Cognitive risk perception system for obstacle avoidance in outdoor mUAV missions

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Abstract

Robotics has undergone a great revolution in the last decades. Nowadays this technology is able to perform really complex tasks with a high degree of accuracy and speed, however this is only true in precisely defined situations with fully controlled variables. Since the real world is dynamic, changing and unstructured, flexible and non context-dependent systems are required. The ability to understand situations, acknowledge changes and balance reactions is required by robots to successfully interact with their surroundings in a fully autonomous fashion.

In fact, it is those very processes that define human interactions with the environment. Social relationships, driving or risk/incertitude management... in all these activities and systems, context understanding and adaptability are what allow human beings to survive: contrarily to the traditional robotics, people do not evaluate obstacles according to their position but according to the potential risk their presence imply. In this sense, human perception looks for information which goes beyond location, speed and dynamics (the usual data used in traditional obstacle avoidance systems). Specific features in the behaviour of a particular element allows the understanding of that element’s nature and therefore the comprehension of the risk posed by it. This process defines the second main difference between traditional obstacle avoidance systems and human behaviour: the ability to understand a situation/scenario allows to get to know the implications of the elements and their relationship with the observer. Establishing these semantic relationships -named cognition- is the only way to estimate the actual danger level of an element. Furthermore, only the application of this knowledge allows the generation of coherent, suitable and adjusted responses to deal with any risk faced.

The research presented in this thesis summarizes the work done towards translating these human cognitive/reasoning procedures to the field of robotics. More specifically, the work done has been focused on employing human-based methodologies to enable aerial robots to navigate safely. To this effect, human perception, cognition and reaction processes concerning risk management have been experimentally studied; as well as the acquisition and processing of stimuli. How psychological, sociological and anthropological factors modify, balance and give shape to those stimuli has been researched. And finally, the way in which these factors motivate the human behaviour according to different mindsets and priorities has been established.

This associative workflow has been reproduced by establishing an equivalent structure and defining similar factors and sources. Besides, all the knowledge obtained experimentally has been applied in the form of algorithms, techniques and strategies which emulate the analogous human behaviours. As a result, a framework capable of understanding and reacting in response to stimuli has been implemented and validated.
La robótica ha evolucionado exponencialmente en las últimas décadas, permitiendo a los sistemas actuales realizar tareas sumamente complejas con gran precisión, fiabilidad y velocidad. Sin embargo, este desarrollo ha estado asociado a un mayor grado de especialización y particularización de las tecnologías implicadas, siendo estas muy eficientes en situaciones concretas y controladas, pero incapaces en entornos cambiantes, dinámicos y desestructurados. Por eso, el desarrollo de la robótica debe pasar por dotar a los sistemas de capacidad de adaptación a las circunstancias, de entendimiento sobre los cambios observados y de flexibilidad a la hora de interactuar con el entorno. Estas son las características propias de la interacción del ser humano con su entorno, las que le permiten sobrevivir y las que pueden proporcionar a un sistema inteligencia y capacidad suficientes para desenvolverse en un entorno real de forma autónoma e independiente.

Esta adaptabilidad es especialmente importante en el manejo de riesgos e incertidumbres, puesto que es el mecanismo que permite contextualizar y evaluar las amenazas para proporcionar una respuesta adecuada. Así, por ejemplo, cuando una persona se mueve e interactúa con su entorno, no evalúa los obstáculos en función de su posición, velocidad o dinámica (como hacen los sistemas robóticos tradicionales), sino mediante la estimación del riesgo potencial que estos elementos suponen para la persona. Esta evaluación se consigue combinando dos procesos psicofísicos del ser humano: por un lado, la percepción humana analiza los elementos relevantes del entorno, tratando de entender su naturaleza a partir de patrones de comportamiento, propiedades asociadas u otros rasgos distintivos. Por otro lado, como segundo nivel de evaluación, el entendimiento de esta naturaleza permite al ser humano conocer/estimar la relación de los elementos con él mismo, así como sus implicaciones en cuanto a nivel de riesgo se refiere. El establecimiento de estas relaciones semánticas -llamado cognición- es la única forma de definir el nivel de riesgo de manera absoluta y de generar una respuesta adecuada al mismo. No necesariamente proporcional, sino coherente con el riesgo al que se enfrenta.

La investigación que presenta esta tesis describe el trabajo realizado para trasladar esta metodología de análisis y funcionamiento a la robótica. Este se ha centrado especialmente en la nevagación de los robots aéreos, diseñando e implementado procedimientos de inspiración humana para garantizar la seguridad de la misma. Para ello se han estudiado y evaluado los mecanismos de percepción, cognición y reacción humanas en relación al manejo de riesgos. También se ha analizado como los estímulos son capturados, procesados y transformados por condicionantes psicológicos, sociológicos y antropológicos de los seres humanos. Finalmente, también se ha analizado como estos...
factores motivan y descenden al las reacciones humanas frente a los peligros. Como re-
sultado de este estudio, todos estos procesos, comportamientos y condicionantes de la
conducta humana se han reproducido en un framework que se ha estructurado basadan-
dose en factores análogos. Este emplea el conocimiento obtenido experimentalmente en
forma de algoritmos, técnicas y estrategias, emulando el comportamiento humano en las
mismas circunstancias. Diseñado, implementado y validado tanto en simulación como
con datos reales, este framework propone una manera innovadora -tanto en metodolo-
gia como en procedimiento- de entender y reaccionar frente a las amenazas potenciales
de una misión robotica.
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<tr>
<td>$\psi$</td>
<td>Yaw angle</td>
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<tr>
<td>$\xi_x$</td>
<td>Error in $X$, understood as the difference between to measures of the $X$ magnitude</td>
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<tr>
<td>$h_x$</td>
<td>Relative altitude; height of the element $X$</td>
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<td>aaH</td>
<td>Anchoring and adjusting Heuristics</td>
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<td>aH</td>
<td>Availability Heuristics</td>
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<tr>
<td>apL</td>
<td>Ability to prevent/avoid the lost/damage</td>
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<td>confidence in the Fuzzy Clustering value</td>
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<td>ToF</td>
<td>Time of Flight</td>
</tr>
<tr>
<td>WP</td>
<td>Waypoint</td>
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Executive summary

Introduction

Risk is present all around, in every event or situation. It potentially affects any human operation, threatening the security of the operator, the integrity of the system or the success of the mission. Therefore, one of the robotics’ main goal in any area should be to support and assist the risk reduction efforts in dangerous, difficult or unapproachable environments.

Although several efforts have been carried out to define risk management procedures, most of them have been based on statistical values or probability figures. However, despite these approaches success in many situations, they are not able to adequate their response to changing circumstances or unconsidered environments. This adaptability, inherent in nature, results from the combination of perception and cognition and, at many different levels, has allowed human beings, animals and plants to survive in an unstructured an ever-changing world.

In engineering, versatility comes from integration and multidisciplinarity. Thus, within this frame, the present Thesis focuses on the eyesight-based human mechanisms that allow people to detect, evaluate and avoid risks. The main goal has been the reproduction of those cognitive processes and avoidance behaviours in an aerial robotic platform, setting out an adaptive risk-aware system.

Risk management

As introduced above, the research presented in this Thesis focuses on changing the “obstacle sense and avoidance” paradigm by the “risk avoidance” one. In other words, it has been researched how to deal with elements in the scenario basing not only on their position but also on their nature and implications to safety. In this sense, Chapter 1 motivates and supports this change, also presenting a study of the most common risk management architectures. Since this study revealed weaknesses and shortages in the potential application of these methodologies to robotics, the human performance at risky situations was also studied and analyzed.
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As a first contribution from this thesis -besides the comparative analysis-, the human mental processes involved in reaction to risk has been integrated into the common risk management structures. As a result, a cognitive architecture defining the processing workflow of the system has been proposed. Depicted in Figure 1, it integrates the human neurobiological processes (i.e., perception, cognition, reaction) into the traditional structures and requirement cases.

Figure 1: Thesis workflow and modular structure

Figure 1 illustrates the developed system, which has been structured in four different blocks or modules, each one corresponding to a chapter of this thesis. Risk identification (Chapter 2) focuses on both the external and internal requirements and limitations imposed to the system. The rest of modules have been based on the limitations described in this one.

Subsequently, Chapter 3 presents the work carried out integrating the human perception (i.e. identification and characterization of the relevant elements in a scene) in a robotic platform. Chapter 4, focuses on how those detected elements are evaluated and converted into risk stimuli. Finally, Chapter 5 shows how risks perceptions unleash and motivate reactions to avoid those risky elements.

**Risk identification** is usually the first step of any risk management architecture. It frames the risk analysis within the particular mission and platform, defining the potential risks according to the limitations and requirements of the operation. Thus, Chapter 2 analyzes and classifies the potential hazards -both external and internal- affecting to the setup considered in this thesis: the operation of a mini unmanned aerial vehicle (mUAV) in an outdoor scenario. The specific hazards derived from this layout have been studied and presented, as well as the applying regulations and restrictions.

The main contributions of this chapter are, on the one hand, the analysis, categorization and synopsis of the current air legislation. On the other hand, the application and customization of these protocols in a real mUAV outdoor mission, which implies the breakdown and evaluation of internal and external hazard sources.
Risk perception refers to the scene analysis, situation understanding and element identification. In this regard, as the substitute of the traditional Risk Management Architecture (RMa)'s modules for hazard identification and assessment, Chapter 3 presents the research done to detect and assess the events, situations and elements defined in the previous section.

To achieve this goal, both the traditional risk estimation methods and the human perception of danger have been examined. As a result of this study, a linear workflow has been proposed, implemented and validated. It reproduces the human neurophysiological processes (i.e. acquisition, detection, clustering, identification and characteristic extraction) in a robotic platform as follows:

- Considering the sense of sight as the main source of information, the acquisition process has been reproduced using a stereo camera and complemented with other stimuli sources (i.e. RF communications and ultrasounds).
- Detection refers to the relevant element identification. It has been emulated according to the Recognition-by-Components theory, which establishes an entropic search. It has been implemented using a combinative multilevel segmentation.
- Clustering associates, if necessary, different elements into the same entity. In this sense, and based on the Gestalt theories, clustering has been developed by employing a dynamic iterative search which associates elements according to their contiguity, proximity and similarity metrics.
- Human identification has been divided in two different processes: tracking and recognition: Firstly, tracking -of detected elements over time- employs a cost function designed based on typical human evaluation parameters (according to TMM, FAM and Morland’s theories, position, luminosity, area and motion). The use of these metrics in a recursive algorithm has provided with robust tracking capabilities (> 80% object detection percentage) in real scenarios. Moreover, these results have been combined with a fuzzy-logic recognition process capable of identifying/classifying the danger type (among the potential risk defined during the identification). This integrative method succeeded in > 90% of the analysis with a > 80% confidence on the estimation.
- Characteristics extraction tries to understand the behaviour and nature of each one of the detected elements. In this sense, this module has been designed based on the Ecological Theory: Several metrics have been proposed (load distribution, time-to-contact, variability and observability), implemented and validated (the last two ones being original from this Thesis).

As a result of the combination of all of the above, the human perception system has been accurately reproduced. As it is shown in Figure 2, this perception module
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transforms the raw images from the camera into a virtual representation of the scene, providing an estimation of the nature, conditions and characteristics of the elements on it. In this regard, the main contributions from this chapter are twofold: On the one hand, the analysis of the human perception and its workflow establishment. On the other hand, the adaptation and design of new methods to reproduce these processes including several new algorithms of visual intelligence.

![Perception workflow and modular structure](image)

**Figure 2:** Perception workflow and modular structure

**Risk cognition** implies the ability to determine both the quantitative and qualitative value of risk in a given situation. Chapter 4 has focused on assessing the risk level implied (both for the platform and for the mission) by each of the elements detected in the previous modules. In this sense, the study of the traditional risk assessment methodologies has revealed that these methods are not complete enough to understand the risk implications of the analyzed elements. Therefore, the human mental processes involved in risk evaluation have been researched.

Psychological, anthropological, sociological and neurological theories related to risk evaluation have been studied and analyzed. Among them, the common underlying variables have been extracted (i.e. familiarity, benefit perception, knowledge, observability, etc.). Their correlations have been theoretically analyzed and their relevance (both individual and combined) studied. To achieve this goal, a neurocognitive framework has been developed to conduct a psychophysical experiment. This experiment has been divided into three phases:

- In Stage I, a huge collection of scenarios have been simulated in the experimental framework. Using the number of collisions, the time-to-contact (TTC) and distance to the obstacles as risk metrics, the unambiguous risk level of different situations has been calculated.

- In Stage II, these evaluated situations have been presented to several subjects, in order to evaluate their psychophysical response. This phase has allowed to establish a relationship between risk and some human physiological responses, such eye movements, transpiration level, respiration rate and heart beat. Furthermore,
the connection between these variables and the risk intensity has been analyzed so as to define a relationship that describes this relationship.

• In Stage III, a new set of situations have been defined in order to evaluate the cognitive variables extracted from theory. They have been presented to a new group of people. The relevance of each variable in the global risk assessment has been obtained by evaluating their psychophysical responses using the equation extracted in Stage II.

The results of Stage III -about the relevance of each variable- have been used to train a set of artificial neural networks. The cognitive system has been structured in three meta-parameters according to the traditional risk assessment methodologies (i.e. probability of risk, severity of damage and probability of avoiding the damage) and implemented as a unified module. Its inputs are the characteristics extracted in Chapter 3 and the output states the risk level estimated for each one of the elements. The performance of this system has been validated with an additional experiment, where both the module and human subjects have evaluated the risk of different situations. An error on the estimation smaller than < 6% has been obtained, therefore verifying the suitability of the system based on the comparison of its performance with a human’s.

Thus, the main contributions of this chapter are: i) the analysis of both neurophysiological and socio-antropological factors related to risk perception and the extraction of their common underlying variables; ii) the association between these variables and the visual characteristics perceived; iii) the analysis of the relevance of each variable through the conduction of different psychophysical experiments; and iv) the integration of the results in an intelligent algorithm capable of evaluating the risk of real-world scenarios.

**Risk avoidance** refers to the ability to evade risk or limit the effect of potential damage. To this effect, Chapter 5 presents the work carried out towards employing the risk estimation obtained above as a behavioural motivator.

In this sense, after studying the current risk reduction procedures and sense & avoidance techniques, human behaviour has been analyzed. As a result, an innovative algorithm named Potential Wavefront Dynamic Propagation (PWDP) has been proposed. It combines different traditional algorithms to reproduce human behaviour when dealing with risk. In fact, as presented in Figure 3, PWDP performs a potential field-like search over the integrated danger map. In case of risk detection, a secondary search is performed: in the same way people look for solutions to problems, a wavefront analysis is propagated, with an orientation consistent with the risk gradient obtained earlier. Besides, with the complement of a human-inspired control of the propagation, PWDR provides the indication of the direction and intensity of the suitable response.
This performance has been verified by using a realistic simulation that has included different elements (trees, buildings, kites, helicopters, UAVs, etc.) and conditions (combinations of both static and dynamic elements, including different speeds, types of trajectories, etc.). Furthermore, the simulated missions have been carried out by both the autonomous system and actual human pilots. The comparison between their behaviours (difference < 5%) has validated the performance of the system and the quality of the approach.

The main contributions of this part of the research are related to the analysis of the human conduct and its translation into reactive algorithms. The combination of the hazards to generate a dynamic danger map and the integration of those well-known techniques in a behavioural architecture are both remarkable contributions. Furthermore, the extensive verification process increases the value of these milestones.

**Discussion and conclusions**

As presented in this document, the main goal of the Thesis has been successfully accomplished. On the one hand, the most relevant theories related to human risk perception, cognition and reaction have been deeply analyzed. From them, the underlying principles, procedures and mechanisms have been extracted and compared to the traditional risk analysis methods. This assimilation has allowed to detect weaknesses and strengths, as well as synergies that have resulted in the design of a cognitive risk avoidance framework.

On the other hand, the implementation of this approach in a robotic platform - within a real mission context- has allowed to validate the system. The individual subsystems and algorithms developed have been proved and verified both individually and working in combination. Besides, the comparison with real human responses has also validated the similarity of the integrated system with the natural behaviour. As a result, an adaptive cognitive procedure has been released, customized for risk de-
tection in mUAV outdoor missions but adaptable to any other robotic platform and environmental situation.

Thus, it is possible to conclude that the system designed and developed (named Cognitive Risk Avoidance System, CRAS) is an actual alternative for the traditional RMAs. This cognitive architecture has proved to enhance the environment understanding, increasing therefore the risk avoidance capabilities. Moreover, the results obtained from the simulations and experiments carried out have showed that the cognitive functionalities provide the system with a higher adaptability degree. Hence, CRAS supposes an innovative and effective approach to deal with risks in robotic systems.
“Originality is nothing but judicious imitation.”
— Voltaire

“Human behavior flows from three main sources: desire, emotion, and knowledge.”
— Plato

“What we think, we become. All that we are is the result of what we have thought.”
— Buddha
Chapter 1

Risk management

1.1 Introduction and motivation

Understanding robotics as “the intelligent connection of perception to action” -as M.Brady and R. Paul stated (6)- Asimov’s Three Laws of Robotics would prescribe that this intelligence must guide any robot towards a safe state. One of the branches on robotics studying how to guarantee that is named “Sense & Avoidance”.

The first surveys in this field were made by W.G.Walter in 1948 (7). When his Machina Speculatrix’s robotic turtles, named Elsie and Elmer, found a light source, they moved towards it avoiding the obstacles on their way. They only had one light and one contact sensor (the first one for setting the target, the second one for avoiding the obstacles), but it was enough to prove that logical and functional behaviours could arise from a simple design.

Over the years, not only the sensors but also the behaviours have been improved: lasers, cameras, ultrasounds have replaced the simple sensors W.G.Walter used. Probabilistic paths, potential maps or decision trees have substituted the direct attraction. Nevertheless, the underlying idea has remained: a computational answer to the impulse detected. A proportional reaction, more or less modulated, to the magnitude acquired.

These techniques are especially relevant when considering autonomous unmanned aerial vehicles (UAVs). In addition to the multiple problems that a normal (ground) crash implies, air units have the obvious problem of falling down with potentially disastrous effect. What is more, the 3D space instead of the planar one, and the unpredictability of the air elements (e.g. birds) suppose a challenge broadly addressed these days. Many labs and researchers are integrating a variety of lasers, sonar, lidar or cameras in UAVs. Nevertheless, they almost all use techniques similar to the one explained above. And they usually work well, providing responses that make it possible to avoid the obstacles in almost every situation. However…
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If one pays attention to how people avoid obstacles, one would notice that we do not behave in the same way: when driving, people do not stop when another car is in front. We assume that the other car would keep moving and we continue driving. The same behaviour is observed when entering a mall though automatic doors, where we do not stop because we “know” they will get opened. It is also observed in sports or in many other situations in life. However, we do not always behave in the same way: if the car previously mentioned starts to brake and accelerate intermittently, swerving between among lanes, we will probably be cautious and keep a safe distance. The same happens if it is known that the automatic doors are usually not working properly. So, what is then the underlying reasoning, the underlying thought? It could be thought that people do not avoid obstacles only according to their proximity, but also take into account other factors and characteristics. This Thesis is based on the assumption that people do not avoid obstacles but the risk they imply.

How people perceive, understand and react to threats have been studied and analyzed. In this regard, the first difference in the perception process. While most of the robotic systems only provide the location of an obstacle, human beings are able to perceive not only its presence but also a first estimation of which type of the elements they are. Even more, we are able to distinguish which are the most relevant ones: In a baseball game, the catcher is able to find the ball among the rest of elements in the scene (spectators, baseball bat, birds, lights..), and also to estimate some basic dynamics (if it is moving or not, the time to contact or the direction, for example). All his attention focuses there.

The second main difference comes from the comprehension of what the element implies. In other words, to understand what the ball “means”: if you are a spectator, a baseball flying in your direction probably translates as danger, you need to avoid it. Instead, if you are the batter, the ball is the element you have to hit. Conversely, if you are the catcher, the ball is your target: the object you have to catch. Infinite more examples could be provided. As many as situations and people exist, since all this comprehension derives from our experience, from our social learning, from the context and from our basic instinct: We do not brake when the car in front of us is being driven normally because we estimate that it is not a risk. It is behaving normally. However, if it starts to behave erratically, we will assess it as a hazardous element and will try to avoid it, with an intensity proportional to the danger it represent to us.

Finally, also how people react is worth studying: many feelings, conditioning and prejudices are intermingled in our reactions when facing risky stimuli. Questions like “Are we prepared to loose part of our autonomy/power in order to avoid a risk?” or “Would we react in the same way if there were someone looking at us?” have a deep significance since they invoke societal restrictions, innate behaviours and mental guidelines. The answers to these questions reveal our priorities, set of values and main
fears. Thus, the causal relation they imply define how we react. In this last part, it has been analyzed and presented how the reactions are addressed, how the ways out are interpreted, how the risk intensity is translated into movement and which conditioning make us to choose one option over others.

1.2 Obstacle sense and avoidance

As previously described, almost all the techniques developed for safe navigation in aerial robotics try to avoid obstacles. Most of the authors integrate the input of different sensors in order to extract flight characteristics, predict potential collisions or estimate avoidance ratios. They mainly use computer vision (8, 9), stereo pairs (10, 11), radar (12, 13) and laser (11, 14) sensors to perceive the environment. However, despite the accurate representation of the world they extract, almost none of them take into account the element’s nature or behaviour in their analysis. Although they perform successfully in most of the situations, this omission limits the accuracy and flexibility of this approach. Only Cassimatis (15) employs a “knowledge” abstraction layer. Nevertheless, not even this research analyzes the relationship between the drone and its environment. Besides, the knowledge extracted is restricted to the perception layer, where risk has to be analyzed as a whole.

A framework including all the components related with risk (i.e. origin, nature, behaviour, potential damage, etc.) requires an adequate response to avoid not only obstacles but hazards in general. So, the research presented in this Thesis has tried to move from the “sense and avoidance” approach to the “risk management (RM)” concept.

1.3 Risk management

Risk Management may be defined as the process of identifying, quantifying, and managing the risks in order to minimise their potential effect. However, both the name and the definition use the word “risk”. It is well know as an all-rounded term, that changes according to the following parameters: the environmental situation, the background of the speaker and the context where it is being used. In finances, risk is defined as “the probability that an actual return on an investment will be lower than the expected return”. Insurance people may say that it is “a situation where the probability of a variable is known but when a mode of occurrence or the actual value of the occurrence is not”. On the other hand, for the food industry representatives, risk is “the possibility that due to a certain hazard in food there will be a negative effect to a certain magnitude” and in a medical context is “possibility of loss, injury, disease, or death”.

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Politicians, soldiers or pilots probably define risk in other terms or basing their definition on other parameters. Nevertheless, they all understand that the term risk implies a potential loss of ”something” due to the exposition to a certain event or situation. Thus, in this work, Risk will be considered as a measure of safety \(^1\) in a situation where someone or something is exposed to a potential danger (understanding danger as a chance or harm or loss).

Basing on this definition, RM is the process that defines the context, identifies and evaluates the risk, and provides with a course of action to avoid/limit that hazard. The different approaches to combine and define these methods result in several RM architectures (RMa).

1.3.1 Risk management architectures

Even fulfilling all the applicable regulation and observing every aspect of the legislation, there is always a potential risk involved in any process: risks are inherent to action, and it is impossible to completely avoid them. To control, mitigate and/or reduce them is the best that can be done. In this sense, RMa -also known as Risk Analysis architectures (RAa)- focus on this target, trying to identify, classify and evaluate the hazards in order to limit their effects and coverage to an acceptable level. (16).

Considering RMa as an evaluative framework, many authors have reviewed this topic: economists, engineers, consultants or merchants have addressed it, finding common architectures to assist them with their specific needs (17). For example, C.Chapman proposed the PRAM (Project Risk Analysis and Management) technique, focused on executive processes where the risk management is treated as a project in its own. He based the RA on specific questionnaires, that categorize and evaluate the potential risks (18). Despite the fact that PRAM does not have a technical component in any way, it has been used by the FAA in their System Safety Handbook (19):

Focusing properly on engineering processes, event-driven feedbacked methods are the most popular ones due to their flexibility. J.K.Kuchard proposed a structure system based on events, where faults are modeled in terms of occurrences (that have been caused by anomalies, malfunctions, human errors, etc) (20). Its top-down architecture is a particularization of the common Fault Tree Analysis (FTA)(21), that was later used by J.F.Murtha to suggest a standard design for reliable UAVs (22). Oppositely, S.Celik presented a method that focuses on the general view, instead of the specific events. Named Common Cause Analysis (CCA), it allows to identify and associate common errors (events) in order to eliminate redundancies (23). Also a combination of methods have been verified: R.Apthorpe uses both Probabilistic Risk Assessment

\(^1\)Safety is the condition of being safe, free from danger, risk, or injury.
1.3 Risk management

Figure 1.1: Simplified of the ISO 31000:2009 risk management standard.

(PRA) (24) and the FTA decomposition into basic events to estimate the system reliability (25). Used in EUROCONTROL’s Safety Assessment Methodology Initiative, it combines logic models (of the ways systems can fail) with statistical failure rates in order to associate failure probabilities with consequences. In a similar line, Failure Modes and Effects Analysis, FMEA (26); Fault Hazard Analysis, FHA (27); Hazard Operability Study, HAZOP (28); Event Tree Analysis, ETA (29); Statistical Process Control (SPC)(30); Critical Incident Technique, CIT (31) or Systemic Occurrence Analysis Methodology, SOAM (32) try to assess the potential hazards that may be present in the mission.

As a sum up of all of the methods described above, it is necessary to highlight the ISO 31000:2009 standard. Depicted in Figure 1.1\(^1\), it combines most of the strengths

\(^1\)The diagram presented is a combination of the references described in ISO 14.121-1, ISO 31000:2009, ISO/IEC 27005:2011 and ISO/IEC 31010:2009. Nevertheless, the main core is included in
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proposed by the rest of architectures in a modular approach: it provides a flexible and adaptative linear-but-feedbacked RA scheme that analyzes the system reliability in terms of effect-to-cause. It considers both bottom-up and top-down manners (deductive or inductive, respectively), defining the system’s specifications within the first stage of the RA process. Besides, it combines both ’event management’ and ’a priori information’ approaches in the event-based methods, rendering the architecture more adaptable. Finally, ISO 31000 defines the reduction procedures within the analysis process, guaranteeing a higher robustness and suitability degree.

Nevertheless, in spite of its wide scope and flexibility, not even this method considers the dynamics of nature or the relevance of subjective/abstract evaluation: circumstantial, intuitive or behavioural conditions are not taken into account at all in any of the RMAs. However, as described in Chapter 4, these small details are the ones that allow the human being to assess situations with extreme accuracy (33). And additionally, these cognitive details are the ones allowing people to survive in a changing environment, where adaptability is a critical factor. In this sense, their omission in the RA methodologies poses a strong limitation to the adaptability, robustness and suitability of these architectures. Given these limitations they can be used as a base, yet it is necessary to combine them with the cognitive features to enable effective real-time adaptive evaluation.

In order to do this, it is necessary to understand how the human cognition understands and evaluates risk. The following section presents the research performed in this direction.

1.3.2 Human cognition

The cognitive upgrade has to come as an analogy to the human behaviour. Thus, the first step comes from analyzing the human brain and its mental processes.

When starting the analysis, two similar concepts arise related to the risk concept: emotions and feelings. Both terms are usually considered synonyms, but they are not. Studying the differences, James Williams -the father of modern psychology- set out the following question: “do people run from a bear because they are afraid or are people afraid because they run away from the bear?” (34). While the common-sense assumption is that the bear is the source of our fear, he argued that this common-sense interpretation is wrong: since the reaction precedes the evaluation, the emotion arrives before the feeling. These nuances -how and when the stimuli are processed-make emotions and feelings different. As an example, emotion is what makes people remove their hand when touching something really hot; feeling is the subsequent pain, and cognition is the association between the object/situation and the hazard.
1.3 Risk management

According to Richard S. Lazarus, emotions are a complex status of the body that spontaneously prepares itself for action—an automatic and unconscious evaluation of the situation. Oppositely, feelings are defined as a cognitive component of the emotions i.e. a subjective experience of the emotion (e.g. when receiving a present, emotion is the instantaneous reaction to the stimuli -the present-). Afterwards, the primary assessment of the stimuli -if it is good, or bad; cheap or expensive- results in a feeling. This subtle difference is really important in terms of risk management: Emotions release cortisone to the blood stream, that arrives at the hippocampus, interfering in its tasks. They also affect the memory processes, since the amygdala has powerful connections with the sensor cortex (the anterior cingulate cortex and the prefrontal ventral cortex). As a result of this, most people are not able to perform complex tasks under stressful situations—even remembering the most basic things is a hard job. All the body’s efforts are made available to the reaction. Even more, the perceptive capacities are also eroded. Sight and auditive ranges decrease and the environmental signals attention is lost. The body is focused on the most important -stressful- element.

Emotions maximise survival chances in wild environments, where reaction is the most important parameter. However, they usually dull judgement in the rest of the occasions, providing in many times incorrect -but extremely powerful- clues and masking the logical answers. According to this, emotions have been taken into account only in the reaction stage: since pure logic hampers the decision taking, emotions are required as a reaction trigger. Nevertheless, they have not been taken into account in the evaluation of cognitive processes, emulating the “cold” mind processes expected in an elite athlete, an expert survivor or an special corps soldier.

The stimuli they found in the environment -captured by the eye’s retina- are firstly processed by the thalamus (the visual thalamus, in the case of the sight) and then forwarded to the neocortex (the primary visual cortex, specifically): the thalamus is in charge of characteristic filtering, segmentation and feature extraction, while the primary visual cortex assesses shapes, location or motion. The combination of both area’s processes provides a fast and coarse approach to the elements in the scene and their characteristics. In this thesis, this low level processing has been named “perception”.

This perceived information is distributed along the limbic system and five different layers of the neocortex, distinguishing two different main activities. On the one hand, the amygdala and the nucleus accumbens are related to feelings and autonomous reactions: While the first one provides intuitive judgements and a priori impressions, the nucleus accumbens is related to lower level feelings. It is not as well known as the amygdala, but studies have proved that it is connected with the interpretation of fear, pleasure, rewards or laughter. In both cases, the hippocampus -related to memory and past experience- serves as a database. It has, in addition, an updated mental map of
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the environment (In fact, some specific cells are only activated when the individual is following a specific direction or located in a specific place (37).

On the other hand, the prefrontal lobe and secondary visual cortex are in charge of the logical side of cognition. The first area is in charge of analysis, planning, and other tasks that require high level processing. It is also in this area (more specifically in the lateral side of the right hemisphere, or CPFLd) where the behavioural rules and societal inhibitions are placed (38). Oppositely, the secondary visual cortex correlates the data provided by the primary visual cortex with the information stored in memory (namely in the visual memory association area). It allows the extraction of higher level information (i.e. implications, experiences, etc.). In general, it could be said that all these regions analyze the implications that elements pose, according to past experience, self-defined values, etc. Thus, in this thesis, this low level processing has been named “cognition”.

Finally, reactions can also be split into two different levels: Firstly, the autonomous and immediate reactions, derived from emotions. Both the hypothalamus and the amygdala manage these fast responses that allow people to survive in extreme situations; and secondly, the frontal lobe follows the same line as the prefrontal lobe: makes decisions, evaluates the alternatives and determines how to carry out the plans. Anyhow, both areas lead into the motor cortex (both primary and premotor) who is in charge of generating the necessary stimuli to the muscles.

Analyzing this flow, three main processes arise, equivalent to the three different levels of risk management: perception, cognition and reaction (see Figure 1.2)

1.3.3 Proposed solution: a cognitive approach

As presented in subsection 1.3.1, most of the methods based on events do not include the specifications of the system and the reduction procedures within the analysis process. To avoid this restriction, in this Thesis, ISO 31000:2009 and 14.121-1 standards approach has been redefined according to the mental processes analyzed in subsection 1.3.2.

As can be observed in Figure 1.3, both the requirements and limits of the system remain: requirements/system definition is the one associated to the personal goals and wishes, as well as to the environmental setup. On the other hand, system limits (i.e. regulation, normative) refer to the limitations imposed externally, as well as to the environmental constraints. The requirements defined for this thesis is presented in section 1.4, while the environmental constraints are referred to in Chapter 2.

The first noticeable change between the different approaches affects hazard detection: While ISO 31000 separates hazard identification and risk estimation, the human mind understands both processes as a whole. In this sense, chapter 3 presents the work carried out towards the reproduction of human perception and its transformation to
1.3 Risk management

Figure 1.2: Cortical brain regions, based on Kiernan’s taxonomy (1)

adequate it to a RA-based scheme. However, the main change is located in the following stage: while in the RMas risk assessment is a static and limited measure of safety, for human beings it is a dynamic meta-parameter. It results from the combination of many variables such as culture, past experiences and so on. Besides, the human risk assessment does not provide a specific value but rather a multi-threshold level (equivalent to “adequate or not”) based on the person’s self-defining values and priorities. The work done analyzing which values are involved in the assessment process and their relevance according to the mindsets is presented in chapter 4.

Regarding the reaction to avoid the hazard, RMas understand it as a refinement/dealing process. However, for the human being, it is an integrated action. As it is a part of instinct, it does not deal with the environment but adapts behaviour in accordance to it. Thus, it provides with a response proportional to the risk perceived.

Finally, it should be taken into account that the feedback loop has been split by using the memory. It implies that (the result of) the actions not only affect the expectations/requirements people have, but also the way they understand the world. This contextual learning is presented in chapter 4, since it is the base of the "cognition" concept (both social and psychological).

However, the most significant difference refers to the evaluation schedule: while
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Figure 1.3: Cognitive architecture derived from the ISO 14.121-1

for the RMas risk assessment is a procedure carried out once at the beginning of the mission, in this Thesis it is understood as a task performed in a loop. Perception, cognition and reaction are continuously parsed, updating the assessment every instant according to the environment and the inner state of the individual. Figure 1.4 depicts this loop, where each action is observed, perceived and analyzed. Besides, the same figure also depicts the mental areas associated to each one of the processes.

1.4 Goals

As explained before, current avoidance methodologies do not employ any kind of cognitive evaluation, neither do they analyze the implications of the risk. Nevertheless, although these considerations make this approach undoubtedly richer, it is not that
clear if they make it better: current sense and avoidance techniques have proved their effectiveness, while risk-oriented approaches have always been partial and limited. Furthermore, it is neither evident if the inclusion of the cognitive parameters enrich the perspective or if they just jam it (i.e. by introducing prejudices, fears, etc.). Thus, it can be said that the main objective of this research is evaluating the suitability of the human cognition in its application to a robotic system. Summarizing this approach in a sentence, this dissertation aims to answer the following question:

"Is the human way the best method to evaluate threats, or a pure and logical assessment would provide with better results?"

In order to be able to address this challenge, the environment had to be limited. To this purpose, a mini unmanned autonomous aerial vehicle (mUAV) working in an outdoor unstructured scenario has been selected as the target of the RMa implementation described. Based on that, five more specific objectives have been defined and addressed:

- Understand how humans perceive the World and emulate this high-level perception into an image processing algorithm.
- Isolate the main parameters (i.e. sociological, anthropological, psychological, etc.) that define how humans assess risks and evaluate their relevance and importance.
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- Recreate this cognitive evaluation method in a computer system, generating an environmental risk interpreter.

- Understand how people react to avoid the potential risks and reproduce this behaviour in an mAUV based system.

- Compare the traditional sense-and-avoidance methods and the cognitive one proposed in order to conclude their strengths and weaknesses.
“A ship is safe in harbor, but that’s not what ships are for.”
— William Shedd

“Silence is the safest policy if you are unsure of yourself.”
— La Rochefoucauld, Maxims
1. RISK MANAGEMENT
Chapter 2

Risk identification

2.1 Introduction

Human beings are not able to imagine or dream about things they have never seen before. They can create “new” things by modifying known ideas/elements or by combining many of them yet it is impossible (or at least very hard) to think about elements that have not previously been modeled or seen. It is extremely difficult to consider elements outside a usual repertoire of known stimuli, memories and different mind sets.

Even the most terrifying monsters are created as the result of combinations of different animal parts, chemicals, and so on: fangs, wings, thorns, fog, etc. Likewise, any risk to be considered is the result of combining models already in mind. In this sense, identification is the acquisition process that creates those memories and models. Regarding risk perception and cognition, the hazard identification earlier mentioned is a critical task, since it establishes a number of possible risks to be found (and hence to evaluate and avoid). It provides with the opportunities, indicators and information that will allow managing the risk. Thus, risk identification can be defined as the process that discovers and categorizes potential risks to be encountered in a specific system.

This process clearly limits and puts end to the potential risks to be considered. Nevertheless, the constraint is important in order to be able to effectively consider the potential options in a limited time. To this end, section 2.3 presents the restrictions that have been imposed to the system. They involve, on the one hand, the safety constraints derived from the study of several countries’ current regulations concerning UAVs (section 2.2). On the other hand, the limitations have been also defined according to the nature of risk and the definition of the scenario. In this sense, section 2.4 presents the evaluations that (has been conducted regarding the potential elements to be found, their appearance, probability and nature. This way, the analysis carried out has allowed
the estimation of their potential harmful effect and, accordingly, assign them a matching theoretical risk level.

2.2 Legal framework

The first item to be considered when evaluating the safeness of any system is the legal framework which applies to the system. These frameworks depend on the nature of the system and the country where they are applied. Nevertheless, in general they contain a preliminary analysis of the safety problem, which mainly results in guidelines and procedures that avoid or minimize risks that may arise from their operation.

The analysis and assessment of regulation regarding the mUAV safeness –(Safety)– have required a deep study in terms of discriminating the applying directives for each individual case (i.e. considering the specific scenario, robot characteristics, etc): on the one hand, it has required the consideration of common regulations which apply to any electric system, machine or electronic device. On the other, it has also been necessary to take into account the specific regulation which concerns to air vehicles -specially the smallest ones-. This study has been specially focused on the integration of these autonomous devices in the (non)segregated airspace.

However, current air legislation for mini Unmanned Aerial Vehicles (from here on "mUAV") is still in the early stages of development and therefore is still likely to change a great deal. The great diversity of systems and the quick evolution of the technology make difficult the normative consolidation process. In this sense, the common guidelines regarding the mUAV future regulation have been analyzed. Although many of them remain in an early stage of development, the evaluation the course shown in the current work-in-progress has allowed to define the system and mission limitations in Section 2.3.

2.2.1 Common applying normative

As previously stated, even before analyzing the air-related aspects of the UAVs, it is important to analyze their constrains from a higher point of view: firstly, considering their nature as vehicles or mobile machines. Secondly, even more abstract, attending to their definition as complex systems that interact among them (both internally and externally). In this sense, the present regulations referring to machinery and engineering systems are the following ones:

2.2 Legal framework


Besides, from the systemic point of view, the UAV have also to be considered as a collection of electronic devices. In this regard, the regulations regarding to electromagnetic compatibility, EMC (IEC/TR 61000-3-2 (44)), radio frequency and communications (ISO/IEC 18000-1:2008 (45)), or those referring to tracking, location, navigation and geographic information in general (ISO 19133:2005 (46)) must be observed.

### 2.2.2 UAV regulatory policies

Since the emergence of Unmanned Aerial Vehicles is a relatively new phenomenon, the regulation and legislation in its regarding is mostly under development yet (47). Besides, due to the military origin of the UAVs, global standardization has been postponed many times, turning out lately to be a difficult issue (see subsection 2.2.3: each country have its own regulation, being in many cases inherited from the military policies.

<table>
<thead>
<tr>
<th>Initials</th>
<th>Name</th>
<th>Mass</th>
<th>Range</th>
<th>Max. altitude</th>
<th>Endurance</th>
</tr>
</thead>
<tbody>
<tr>
<td>u</td>
<td>Micro</td>
<td>&lt; 5kg</td>
<td>&lt; 10km</td>
<td>150m</td>
<td>&lt; 1h</td>
</tr>
<tr>
<td>m</td>
<td>Mini</td>
<td>5-15Kg</td>
<td>&lt; 10km</td>
<td>250m</td>
<td>&lt; 2h</td>
</tr>
<tr>
<td>CR</td>
<td>Close Range</td>
<td>25-150kg</td>
<td>10-30km</td>
<td>3000m</td>
<td>&lt; 4h</td>
</tr>
<tr>
<td>SR</td>
<td>Short Range</td>
<td>50-250kg</td>
<td>30-70km</td>
<td>3000m</td>
<td>&lt; 6h</td>
</tr>
<tr>
<td>MR</td>
<td>Medium Range</td>
<td>150-500kg</td>
<td>70-200km</td>
<td>5000m</td>
<td>&lt; 10h</td>
</tr>
</tbody>
</table>

**Table 2.1:** Small UAV classification according to (4, 5).

However, the authorities and regulatory institutions have recently become aware of the importance of UAVs in civilian applications. So, a major global effort have been undertaken in order to give shape to a common regulation that may allow UAVs to fly globally: Cross Atlantic cooperation started in 2005 between the US Federal Aviation Authority (FAA), the European Aviation Safety Agency (EASA) and Eurocontrol. Two main topics were agreed upon: firstly, a common classification for the UAVs (see Tables 2.1 and 2.2 (4)). Secondly, a set of metrics and procedures that define the main lines for the common policy (48). In this sense, based on only six characteristics (i) mass, ii)maximum fight ranges, iii) relative altitudes, iv) flight endurance, v) wing-type\(^1\) and vi)flight control scheme \(^2\), two different scopes were defined: Class I and Class II in Table 2.2.

---

\(^1\)Rotatory of fixed wing  
\(^2\)Autonomous adaptive/non-adaptive, monitored, supervised, and direct
2. RISK IDENTIFICATION

<table>
<thead>
<tr>
<th>Class</th>
<th>Type</th>
<th>Mass (MTOM)</th>
<th>Altitude</th>
<th>Range</th>
<th>Endurance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class I</td>
<td>Micro</td>
<td>&lt;1.5Kg</td>
<td>&lt;150m AGL</td>
<td>&lt;500m from pilot</td>
<td>Flight in VLOS</td>
</tr>
<tr>
<td>Group A</td>
<td></td>
<td>&gt;1.5Kg &amp; &lt;7kg</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group B</td>
<td></td>
<td>&gt;7Kg &amp; &lt;20kg</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group C</td>
<td></td>
<td>&gt;20Kg &amp; &lt;150kg</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Class II</td>
<td>Micro</td>
<td>&lt;1.5Kg</td>
<td>&gt;150m AGL</td>
<td>&gt;500m from pilot</td>
<td>Flight beyond VLOS</td>
</tr>
<tr>
<td>Group A</td>
<td></td>
<td>&gt;1.5Kg &amp; &lt;7kg</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group B</td>
<td></td>
<td>&gt;7Kg &amp; &lt;20kg</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Group C</td>
<td></td>
<td>&gt;20Kg &amp; &lt;150kg</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2.2: Light UAV classification according to (4)

The most significant difference between Class I and Class II vehicles is that the second ones are subjected to the Rules of the Air and in coordination with the Air Traffic Management (ATM).

Based on this the FAA has imposed in the US a two-step certification process before allowing any vehicle to operate within the National Air Space (NAS): firstly, an airworthiness certification is required. Then, a waiver (Certificate of Authorization, COA) regarding the operability of the system and its collision avoidance capabilities have to obtained (49, 50).

- **Operational approval**: Applies to drones class I. It consists on a certifying safe flight capabilities, licensing, training and limitations of the system.

- **Full regulations**: Applies to drones class II. It requires a certification of airworthiness, vehicle registration, design certification etc.

In the same line, European legislation has defined a similar procedure. Nevertheless, since the cooperation focused only on big-medium UAVs, EASA’s scopes have been focused on addressing UAVs with a take-off weight (MTOW) over 330lb/150kg (51): small UAVs (also called Light UAVs, LUAS) regulation has been diverted to the corresponding EU Air Authorities. In this regard, the most advanced civil frameworks for regulating the safe operation of UAVs (either civil or military) are located in the UK, France and Austria. On the other hand, from the military point of view, regulations in Germany, Croatia, Czech Republic and Sweden should be highlighted (52): They regulate common aspects, focused mainly on the dynamics of the vehicle and the safety of the environment. In the first aspect, common rules are defined, such as the maximum velocity (90kts \(\sim\) 46m/s), the maximum kinetic energy on impact (95KJ), or the maximum height above the surface (400ft \(\sim\) 122m). Other regulations are not
2.2 Legal framework

standard, and differ depending on the country air authorities: ii) the maximum distance
to the operator (e.g. 500m, 1km or Visual Line-of-Sight, VSL), and ii) position
lights requirements.

This data agrees with other countries regulations:

- Australia (CASA): Civil Aviation Safety Regulations, CASR. Part 101 (53)(54).
- France (DGA): UAV Systems Airworthiness Requirements (USAR) (55).
- Israel (CAII): UAV Syst. Airworthiness Regulations (56).
- Japan (JUAV): Safety standard for commercial-use, unmanned, rotary-wing air-
craft in uninhabited areas, (57).
- USA (FAA): AC91-57,AFS-400 UAS Policy 05-01 (59).

However, despite the operational/environmental restrictions having a common base,
they have been specified differently on each country: For example, the maximum dis-
tance to populated areas (between 150m and 500m), the distance to people (between
50 and 200m), the maximum distance to airports/military zones (between 2Km and
5Km) or the suitable areas for taking-off/landing (60) have quite different values. Fur-
thermore, beyond the minimums established by the FAA-EASA cooperation, the some
of the issues considered by each regulation are really diverse. Table 2.3 presents the
comparison that has been done regarding those considerations.

2.2.3 On-going regulation

As it has been presented in subsection 2.2.2, the international picture regarding to the
mUAVs regulation is fragmented and divided. However, efforts are being done in this
direction: despite a common normative does not seem to be achieved in a short/medium
period (61), many organisms and organizations are involved in the mUAV regulation.
In this sense, apart from the national air authorities, there are many groups gather-
ing manufacturers, users, designers and researchers attempting to establish a common
frame to regulate safety on UAV operation. They all establish guidelines and/or pro-
vide with recommendations. Nevertheless, it is necessary to highlight the work done by
EUROCAE (Specifically the Working Group 73)\(^1\), USICO\(^2\), JARUS (Joint Authorities

\(^{1}\)https://www.eurocae.net/wgs/active/?wg=WG-73
\(^{2}\)http://cordis.europa.eu/project/rcn/62821_en.html
2. RISK IDENTIFICATION

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>AUS</td>
<td>(N)</td>
<td>CASA</td>
<td>X</td>
</tr>
<tr>
<td>ESP</td>
<td>(P)</td>
<td>MDE</td>
<td>X X X X X X X X X X</td>
</tr>
<tr>
<td>FRA</td>
<td>(N)</td>
<td>DGA</td>
<td>X X X X X X X X X X</td>
</tr>
<tr>
<td>GBR</td>
<td>(P)</td>
<td>CAA</td>
<td>X X X X X</td>
</tr>
<tr>
<td>GER</td>
<td>(N)</td>
<td>BWB</td>
<td>X X X X X X X X X X</td>
</tr>
<tr>
<td>ITA</td>
<td>(P)</td>
<td>ENAC</td>
<td>X X X X X X X X X X X X</td>
</tr>
<tr>
<td>ISR</td>
<td>(U)</td>
<td>CAAI</td>
<td>X X* X X* X X X X X X X X</td>
</tr>
<tr>
<td>JPN</td>
<td>(P)</td>
<td>JUAV</td>
<td>X X X X X X</td>
</tr>
<tr>
<td>SWE</td>
<td>(P)</td>
<td>FMV</td>
<td>X X X X X X X X</td>
</tr>
<tr>
<td>USA</td>
<td>(U)</td>
<td>FAA</td>
<td>X X X* X* X X X X</td>
</tr>
</tbody>
</table>

Table 2.3: Comparison of the current UAV proposals/legislation.

In the table, (1) corresponds to the classification of the drone according to its weight (< 150kg); (2) if the maximum flight speed is 36m/s; (3) if the maximum distance to the pilot is 500m; (4) if the maximum relative height is 121m; (5) if the maximum kinetic energy on impact is 95KJ; (6) if the minimum distance to populated areas is 150m; (7) if the minimum distance to any individual person is 100m; (8) if it is required an aero-plane modeling license; (9) if the drone should always flight under VLOS; (10) if it is not allowed to drive people or animals; (11) if an ATM civil certification for flying in a non-segregated airspace is required; (12) is an airworthiness official requirement; (13) if the drone must be equipped with FGS and lighting systems; (14) Official flight authorization required in private areas/fields.

for Rulemaking on Unmanned Systems\textsuperscript{1}, ICAO (International Civil Aviation Organization)\textsuperscript{2} and UVS International\textsuperscript{3}: although their documents have no official validity, they are taken into account when defining the official regulation. Even more, they are usually used as common guidelines until the legislation releases.

Besides, both the official organisms Joint Aviation Authority (JAA) and Eurocontrol have assembled a joint group named UAV Task Force. It has aimed to issue a proposal report -regarding to safety requirements- according to the suggestions of the aforementioned partners (62). As a result of this, it has been established a common criteria for determining the direction of the future common regulatory policy: “UAVs must comply with an equivalent level of safety (ELOS) compared to conventionally manned aircraft” (63). So, considering the air traffic standards, this delineation has established the minimums required for the development of the future policy.

\textsuperscript{1}http://jarus-rpas.org/
\textsuperscript{2}http://www.icao.int
\textsuperscript{3}uvs-international.org/
2.3 Limits statement

Contour and system restrictions refer to the limits imposed to all the elements involved in the mission (i.e. UAV, participants, scenario, etc.). They have been defined according to the regulations specified in the previous section and considering the possible consequences of a potential accident or failure (64). In this regard, it is possible to divide these limits according to their nature: physical, temporal, environmental, and behavioral. The requirements for both physical and temporal limits are partly derived from the manufacturer’s specifications, and also from experimental tests that have been carried out (65). On the other hand, both environmental and behavioural limits are set by the scenario conditions, by the regulation, the pilot confidence and the common sense. Thus, restrictions have been not only imposed to the equipment, but also to the environment and flight procedures. A detailed description of the limits of operation has been summarized as follows:

Physical limits: unit and components These restrictions refer to the kinematic and dynamic limits imposed to/by the drone. Their origin is derived from i) the physical restrictions of the machine itself, and ii) the dispositions of the legal framework. For example, the maximum payload (or the equivalent Maximum Take-Off Weight, MTOW) and the maximum speed are clearly related to the drone’s specifications. On the other hand, other limits are set according to the applying normative in each airspace (see section 2.2: maximum/minimum height, maximum kinetic energy on impact, etc. Along this Thesis, all these parameters have been defined according to the characteristics of the mUAV considered and the conditions of the mission (EU airspace).

The values defined have been the following:

- Maximum take of weight (MTOW): 5Kg (payload included).
- Maximum payload: 3 Kg, centered.
- Maximum speed: 10 m/s.
- Maximum altitude: 120 m above the surface.
- Minimum operating height: 3 m above the surface.
- Maximum kinetic energy on impact: 95 KJ.
2. RISK IDENTIFICATION

Temporal limits: life time  Time-related restrictions are those derived from the degradation or lost of efficiency of the system’s components. According to the moment when they come out and their temporal behaviour, short and long term restrictions have to be considered: short time restrictions refers to momentary events or aspects regarding to the development/execution of the mission. In this sense, i) maximum flight time, ii) commands response time, iii) maximum delay in the communications and iv) sensors acquisition time have been taken into account. On the other hand, long time restrictions focus on the limits imposed by the temporal degradation. So, the restrictions related to engines and battery degradation have been considered.

The parameters defined for the operation are:

- Maximum flight time: 25 minutes.
- Commands response time: 2 ms.
- Communications latency: 400 us.
- Acquisition time: 125 us (min - IMU) 50 ms (max - camera image).
- Maximum number of cycles of the batteries: 200 cycles.
- Engine operating life: 250 hours.

Environmental limits: flight location and conditions  Similar to physical limits, environmental constrains are imposed by the own drones or/and by the legislation. Nevertheless, in this case, they do not refer to requirements of the drone but of the environment: in the former, limits such as, wind speed, minimum ambient light or the presence of dust/rain have been considered (i.e. climatological conditions). In the latter, limits such as the minimum distance from populated areas or from airports/military installations, the inclusion of the drone in the non-segregated airspace or the GPS coverage have been also taken into account (i.e. geo-topological conditions).

The requirements that have been established for the operational scenario are the following:

- Maximum operating height: 70 m above the surface.
- Maximum operating distance: 500 m (VLOS).
- Minimum operating distance: same as nominal operating height(3 m).
- Minimum distance to EMC sources (power plants, inhibitors): 100 m.
- Minimum distance to airports/aerodromes: 5000 m.
2.4 Hazard identification

- Minimum distance to military areas: 3000 m.
- Minimum distance to private infrastructures: 100 m.
- Maximum wind speed: 18 Km/h.
- Maximum operating temperature: 40 C.

**Behavioral limits: operation and procedures**. These limitations mainly refer to flight constrains applied during the operation, affecting the procedures and actions of the pilot (both autonomous and manual). In case of manual flight, it might be included into this topic the distance limitation operator-vehicle, whereas in case of autonomous, the algorithmic and sensing capabilities of the vehicle.

2.4 Hazard identification

The limitations established in section 2.3 play a significant reducing hazardous situations. Nevertheless, since these limits are static, they do not cover all the possible hazardous situations that may arise in a real dynamic scenario. In this sense, it is possible to scale down the hazards (by constraining the flight conditions) but not to avoid them completely. Thus, it is necessary to find out the potential risks in order to be able to control/manage/reduce their effects. Assuming that the operation conditions satisfy the applied normative, two main hazardous sources can be distinguished: external and internal sources.

2.4.1 External hazards

External risks are those whose behavior and/or presence is not related or connected with the mUAV itself. Since they are no manageable, their presence suppose an extra risk that should be considered. The interference of third-party agents (e.g. animals, humans, other equips, EMC emitters, etc.), the environmental conditions (e.g. wind, temperature, GPS signal quality..) or the presence of dynamic elements -where both relative movement and interaction should be considered- are the main sources of external hazards (66, 67).

Table 2.4 presents the analysis done regarding to the acquittance of the external hazards. As it can be appreciated, an outdoor natural environment has been considered. Over it, three different types or hazards (according to their nature and dynamics) have been analyzed, finding out the most relevant sources of risk for each one of them.
2. RISK IDENTIFICATION

<table>
<thead>
<tr>
<th>Nature</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Static elements</td>
<td>Buildings, trees, marquees, electricity pylons/transmission tower, lamps</td>
</tr>
<tr>
<td>Third party agents</td>
<td>Humans, birds, commercial planes/helicopters, other UAVs or RC devices</td>
</tr>
<tr>
<td>Environmental conditions</td>
<td>Wind, humidity, dust, temperature, GPS signal, EMC emitters</td>
</tr>
</tbody>
</table>

Table 2.4: Analysis of hazards’ external sources.

<table>
<thead>
<tr>
<th>Stage</th>
<th>Activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preparation</td>
<td>Manufacture, Load, Transport, Assembly, Handle, Packaging</td>
</tr>
<tr>
<td>Startup</td>
<td>Setup, Assemble, Adjustment, Connections, Test, Installation, Integration, Assembly</td>
</tr>
<tr>
<td>Operation</td>
<td>Piloting, Human intervention, Setup, Supervision, Human manipulation, Violations of safety procedures, Verification, OS hung up</td>
</tr>
<tr>
<td>Maintenance</td>
<td>Settings, Cleaning, Conservation, Lubrication, Periodicity, Suitability, Cleaning, Charging process of batteries</td>
</tr>
<tr>
<td>Design</td>
<td>Materials, Components, Physical stability, Resistance, Compliance, Software</td>
</tr>
<tr>
<td>Control</td>
<td>Algorithmic stability, Time of response, Refresh rate, Accuracy, Error handling</td>
</tr>
</tbody>
</table>

Table 2.5: Analysis of hazards’ internal sources.

2.4.2 Internal hazards

Internal risks are those related with the drone’s operation/performance, or derived from one of more procedures associated to the application. The analysis and evaluation of these connections should allow to determine the main sources of risk for each system, making possible their control (or, if necessary, their redesign).

Table 2.5 presents that study that have been done analysing activities related with the flight. As a result of this, it has been determined that the major sources of risk can be encompassed within the physical breakdown category (68, 69). They vary a lot depending on their source but, in general, they can be classified depending on its origin: Table 2.6 presents the classification of hazardous events done according to their nature. Based on the work of Hayhurst (70), it present a relationship among the sources, nature and the consequences of the most probable breakdowns.

Besides, classification problems presented by Hayhurst have been also analyzed: on the one hand, the interrelation among hazards/consequences (i.e. a hazard cane be classified in several different groups) have been taken into account. Table 2.6 has been organized according to the hazard occurrence probability (71). On the other hand, the origination of new hazards to the consequences of the previous ones has been also considered (e.g. a mechanical problem -mechanical, friction- causing a hazard of new
### 2.4 Hazard identification

<table>
<thead>
<tr>
<th>Nature</th>
<th>Sources</th>
<th>Consequences</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mechanical</td>
<td>Impacts, Emissions, Give-offs, Collisions, Breaks, Friction, Pressure, Inadequate balance/stability, Mobile parts</td>
<td>Run over, Crush, Cut or section, Drag or entrapment, Hook, Friction or abrasion, Impact, Injection, Puncture, piercing</td>
</tr>
<tr>
<td>Power supply</td>
<td>Violation of maximum absolute ratings, No energy, Perform variation, Short circuit, Polarization</td>
<td>Decelerations, Accelerations, Burn, Overheating, Falls, Motor stop, Saturation</td>
</tr>
<tr>
<td>Thermal</td>
<td>Overheat, Flames, Freeze, Abrasion, Explosions</td>
<td>Burn, Freeze, Battery problems, CPU auto switch-off, Injuries from radiation heat, Dehydration</td>
</tr>
<tr>
<td>Electronic hazards</td>
<td>Saturation, Overflows, Derives, Isolating inappropriate, Synchronization, I/O errors, Disconnection</td>
<td>Overheating, Sensors confusion, Radiations, Control loose, Short circuiting</td>
</tr>
<tr>
<td>EMC &amp; Radiation</td>
<td>Electrostatic phenomena, Interferences, Ionizing radiations, Spectrum saturation</td>
<td>Disorientation, Failures in active components, Overheating, Erroneous reception/send, Interferences in the communications, Drone out of control, Sensors incongruence</td>
</tr>
<tr>
<td>Algorithmic</td>
<td>Infinite loops, Inadequate values, Values out of range, Delayed process, Sequencing, Overflows, Synchronization</td>
<td>Drone out of control, Reception/send wrong parameters, Synchronization failures</td>
</tr>
</tbody>
</table>

Table 2.6: Analysis of the breakdowns according to their nature and sources.

type ‘thermal, flames’). They have been completely broken away, being considered their relative sources as a chain of individual breakdowns.
“But the eyes are blind. One must look with the heart.”
— Antoine de Saint-Exupry, The Little Prince

“Seeing is not always believing.”
— Martin Luther King, Jr.

“There is no truth. There is only perception.”
— Gustave Flaubert
Chapter 3

Risk perception

3.1 Introduction

“Perception” comes from the Latin word *percipio*, composed by *per* (“through”) and *capi* (“capture”, “size”, “understand”). In this regard, it refers to the ability or capacity of identifying something (the environment, for example) and extracting conclusions, characteristics or features from it: in short, to interpret it.

It is one of the oldest disciplines of Psychology, its origin dating back to Ancient Greek. As its etymology points out, it focuses on understanding how stimuli from the world interact with human sensing capabilities (forming visual, auditory, tactile, olfactory, and gustatory), providing representations of the World. In this sense, when talking about risks, perception implies the identification process people make based on the characteristics of the element, without performing an assessment of these features.

Although some definitions combine both perception and cognition inside the perception concept, as previously mentioned (see subsection 1.3.2), during this thesis the blurry frontier between them has been set in the “implication” term: During the perceptive phase the features related to dangers are extracted and analyzed. Also, the elements in the scene are “understood”, making it possible to distinguish among several different objects. Furthermore: the perceptive system of the brain is also in charge of stabilizing the image of the World around, even though the information acquired may be incomplete or unstable. As Rodney Brooks (72) says in his paper: to be able to know that a chair is a chair, independently of the number of legs, shape, size or material. Or, retaking the example depicted in the introduction, the catcher is able to recognize the ball among the rest of the elements in the baseball stadium.

Nevertheless, cognition goes further, assessing and evaluating which the implications of this elements are and also what underling risks it could involve. In other words, if
the chair previously mentioned poses a source of risk or not (as it could be hot, dirty, broken, etc.). This issue will be addressed in the next chapter.

Considering all the above, this chapter presents the work undertaken towards this goal. Perception has arisen as a fundamental piece of the system since it is the input for the rest of the modules. It has been defined following the structure of both human and animal perception system/brain: firstly, the human systems for acquiring information from the environment -distal stimulus- have been studied (Subsections 3.3.1 and 3.3.2) and reproduced in terms of sensing devices (subsection 3.4.1) and detection algorithms (subsection 3.4.2). Then, the research has considered the higher-order perceptive levels (identification and characterization). To this effect the human processes involved in these phases have been studied (subsections 3.3.4 and 3.3.5, respectively) and then reproduced by designing and implementing equivalent computer vision algorithms (subsections 3.4.4 and 3.4.5). All these modules have been verified using real world situations and actual human estimations.

### 3.2 Traditional obstacle detection

Detection refers to the process of identifying relevant elements in a scenario. Many different methods have been developed in this regard, reproducing the human senses: touch, sight, hearing or even smell have been reproduced in many different ways (73, 74, 75, 76). Nevertheless, regarding to obstacle detection, not all of them have been considered: defining an obstacle as an object that “stands in the way of or holds up progress” and considering a mobile system, an obstacle detector has to detect these elements soon enough not to get blocked or crash into them (77). Thus, only remote sensors have been employed (mainly vision and audition-based ones, since odor is not applicable to machines).

Regarding to sound-based detectors, multiple technologies have been developed and tested by different systems and means. Since few obstacles emit detectable sounds, most of these systems base on emitting their own waves and analyzing the alterations of their reflexes. Similar to the navigation used by bats (78), radar (79, 80), sodar and ultrasonic sensors (81, 82) sensors have been widely applied in detection: they are based on analyzing the degradation of the radar signals (i.e. energy or power of the waves) due to the reflexion of the scattering in some elements. By analyzing the power loss, it is possible to estimate their range, altitude and location. Besides, by using the Doppler effect, it is also possible to determine the direction and speed of the objects (83).

On the other hand, lots of computer vision methods, devices and algorithms have broadly dealt with the obstacle detection issue. In this regard, both hardware and software get fused to provide with a representation of environment in terms of distance
3.2 Traditional obstacle detection

(i.e. visual disparity) or images. Thus, both active and passive systems capable to provide with this type of information have been studied:

**Time of Flight Cameras (ToF)** - The ToF principle is based on measuring the difference between an emitted signal and its reflex. In this sense, applied to the image acquisition, a ToF sensor a matrix of photo diodes captures simultaneously reflected light and evaluates the distance information. This is done by correlating the emitted signal with the received signal -using the time spent or the phase variation-. Typical ToF cameras use intensity modulated infrared light, being able to capture the entire scene with each light pulse. It allows covering ranges of a few meters up to about several kilometers (5-10m is the average), providing even with sub-centimeter resolution. The main advantage of these cameras is their high image rate (greater in some cases than 100 images per second) and their acceptable weight and size (around 500g). The principal disadvantages are the expensive cost of the devices, the high power consumption and the image resolution in commercial equips (around 200x200 pixels) (84, 85).

Principal manufacturers and commercial devices are, among others, Fotonic (models C70, C40, T300)\(^1\), Mesa Imaging (SR4000)\(^2\) or PMD Technologies (CamCube)\(^3\).

Besides, basing also in the same principle, other techniques measure the distance by analyzing the phase interference provoked by reflexes in obstacles. For example, interferometry illuminates the scene with coherent light and measures the phase shift of the reflected light relative to the light source. In this sense, assuming that the true range image is a continuous function of the image coordinates, interferograms obtain the depth of each point by using phase-unwrapping. Nevertheless, due to their time-delay and their high power consumption, they are not commonly used for obstacle avoidance (86) but for navigation or topographic applications (87, 88).

**Stereo cameras** - A stereo pair is a system composed by two separated and calibrated cameras (i.e. two independent lenses and sensors). This set up allows to reproduce the human binocular vision, generating disparity images -those that depict the distance map between each pair of corresponding points in the left and right image of a stereo pair-. These pixels do not lie co-planarly, so an image rectification is required in order to be able to compute the images together. In this sense, by using linear transformation, it is possible align both images and generate three-dimensional images basing on the disparity map (89).

\(^1\)http://www.fotonic.com
\(^2\)http://www.mesa-imaging.ch
\(^3\)http://www.pmdtec.com
3. RISK PERCEPTION

Multitude of systems and brands manufacture both professional and amateur stereo system. Their main advantages regard to the stereo pairs are derived from their low cost, power consumption and weight. Despite they require a powerful computation and suffer from a great dependence on the calibration and the prior information (e.g. size of the elements), they provide easily with good estimations of the distance (10).

Structured light - Structured light bases on the changes of a projected 1D/2D light pattern over the elements in the scene. By analyzing the deformation of the pattern when striking surfaces, the camera is able to extract the depth and surface information of the objects in the scene.

The simplest pattern is a line, which is swept across the field of view to gather distance information one strip at a time. A camera, slightly offset from the pattern projector, looks at the shape of the line and uses a technique similar to triangulation to calculate the distance of every point on the line. The system work equally by using a two-dimensional pattern (i.e. a grid or a line stripe), where the camera captures the deformation of the pattern (90).

The main advantage of structured-light scanners is derived from its speed: instead of scanning one point at a time, structured light scans the entire field of view at once. It allows to reduce/eliminate the problem of distortion from motion (91). Even more, considering their acquisition rates (40-60fps), the simultaneous acquisition allows to successfully detect moving obstacles in real-. Nevertheless, although the accuracy provided by these systems is really high in close distances, it is poor when the range increases (due to depth values at non-illuminated points have to be derived via interpolation). Also, the distance range is not actually wide, not being applicable in outdoor environments either.

Main manufacturers and commercial devices are JAI/PULNiX (models TM-6740x)\(^1\), Point Grey (Dragonfly Xprs, Grasshopper)\(^2\), Prosilica (GE680)\(^3\) and Texas Instruments (DLP series)\(^4\).

RGB cameras - Video cameras are well known devices, capable to acquire capable information from the environment and convert it into RGB images. This raw data can be processed in many different ways to extract information, depending on the goals on the application: on the one hand, it is possible to extract information from each images by using employing feature tracking (92) or different types of segmentation (93).

On the other hand, it is possible to take advantage of the differences between contiguous frames to evaluate changes in the scenario. For example, it is possible to

estimate elements’ motion by using optical-flow or similar approaches (94). Besides, it is also possible to reconstruct 3D scenarios by using inter-image stereo compensation. In this sense, Sinopoli or Howe employ the movement of the camera to reproduce a virtual stereo pair and reconstruct the tridimensional shape (95, 96). It allows to determine distances, and even navigate while building an scenario using SLAM-like algorithms (97). Although they don’t provide with a high accuracy, these methods are enough for allowing mUAVs to autonomously navigate in different contexts.

**Laser sensor** - A laser range-finder is a device which uses a laser beam to determine the distance to the elements in a certain plain. The most common form of laser range-finder operates on the ToF principle: as the ToF cameras, lasers send a signal towards the object and measures the time taken (by the pulse to be reflected off the target and returned to the sender). Nevertheless, it is distinguished from them due to the narrowness of the pulse beam: it allows to concentrate the energy, providing with greater accuracy, distance range (5-100m) and the possibility to be used outdoors (98).

Besides, due to this power concentration, they are not light conditions dependent. It implies that laser sensors are really suitable for working outdoors (99). On the other hand, same reason implies that they are, in general, extremely power consuming. Besides, as they concentrate the energy in one plane, they are only applicable in conditions where the elements to be found are all at the same height.

Most relevant manufacturers for mUAV are Hokuyo\(^1\) (models URG-04x and URG-30x) and SICK\(^2\) (LMS100), which focus on light-weight models. They both have been used in many different detection missions, as in the works of Shim (100) and Ferrick (98).

**Flash LiDAR** - Flash Light Detection And Ranging technology (Flash LIDAR) bases on the laser-radar paradigm: Similar to the ToF technology, it uses single laser pulses to illuminate the field of view creating an whole frame. Nevertheless, Flash LIDAR sensors have a prism where the laser beam goes through, making it to diverge and cover all the scene. Besides, they fuse this information with the one provided by radar waves, combining in this sense the advantages of both laser rangers and ToF cameras.

In this sense, this devices provide with a 3D point cloud -absolute range- and intensity data -albedo- at really high rates (e.g. an 100 meters scenario capture requires from around 1 microsecond). It enables real-time 3D sensing without motion distortion or scanning artifacts (specially useful when considering moving vehicles or platforms, where blur-free imaging are required). Besides, due to their solid state composition,
their weight is reduced and their range really wide (from 5cm to hundreds of meters) (101, 102).

On the other hand, Flash LIDAR systems are really expensive and have a considerable power consumption. In this sense, it has been trained reproduce their performance using virtual reconstruction (103). Nevertheless, it has been not possible to achieve the performance of ASC’s devices \footnote{http://www.advancedscientificconcepts.com/} (models Tigercube, Peregrine or Goldeneye) or Ball’s \footnote{http://www.ballaerospace.com/} Total Sight.

As it is possible to appreciate, all the algorithms and techniques described above provide with efficient localization methods. Nevertheless, although the provide with the position and motion characteristics of the elements, they do not provide with any other information. Nevertheless, it is these additional characteristics and features where the risk implications can be found. The element’s nature, behaviour and attitude define its meaning and allows the further steps to evaluate the danger level they suppose. In this sense, it has been studied how human beings extract this information. Section 3.3 presents the conclusions extracted about the human perception, focusing on the characteristics that may imply potential risk. Subsequently, section 3.4 explains how the computer vision methods have been adapted and redesigned in order to match the human vision, in order to provided with similar meaningful information.

### 3.3 Fundamentals of human perception

The “perception” concept embraces the interpretation and understanding of the feelings or sensations provided by the sensory system. This definition can be applied to all the human senses. Nevertheless, along this research, the two main ones have been considered: vision and audition \footnote{Although the touch is the most important sense regarding to the survival, sight and hearing are the main ones when considering the perception of far events}. These two senses are able to perceive the same objects in the world in different way. The combination of both of them (audiovisual system) provides with a clearer understanding of the environment (104): by comparing, vision dominates the human perception due to its reliability and the huge amount of information it provides. It is is optimally suited for noticing objects and geometries, while hearing is optimally suited for the perception of dynamic close events.

Audition provides with a warning system unbounded by line of sight: a time ordered and sequenced danger could be perceived from any direction -even regardless of obstacles between us and the danger-. Besides, the presence of the sound is maintained even when the origin disappears, flowing in time. It may suppose a problem due to
the jamming, but provides at the same time a reference of the recent past that can be useful when evaluating the environment (105). Nevertheless, since vision is responsible for four-fifths of all the information the brain receives, this research has focused on it: Visual perception is an organizational process that integrates the *stimuli* in order to be able to analyze it and obtain a meaning (106): it recognizes shapes, patterns and environments. It is also able to notice changes among structures or similarities among elements, distinguishing and identifying objects belonging to the same group. Furthermore, perception also interprets movements and behaviors, although it is limited when trying to understand the implications of the elements/event have: the perceptual system it is not able to supply information about the relationships it involves (107). That information is generated by the cognitive system (see Chapter 4).

According to the latest neuroscientific researches postulate that this organizational flow is divided into four different stages of increasing complexity (108, 109): during the first one, the images are processed in terms of colour, depth and forms, so as to determine basic components, pulling out the relevant objects in the scene. These elements are grouped during the second stage to improve the object segmentation. These two first stages can be understood as the low level visual processing, finding their equivalences in the filtering, segmentation and clustering tasks.

The remaining two steps imply a higher level of intelligence and complexity (110): during the third stage, the representation of the objects detected is matched with descriptions in memory, in order to identify the type of element. Finally, semantic attributes are applied to the visual representation in the last step, providing with individual properties, belonging and, ultimately, understanding. These both are processed almost in parallel, sharing between them features and results.

Different theories try to explain how these stages are performed:

### 3.3.1 Stimuli acquisition

As in any other sense, perception starts with the acquisition of information thought the sensing systems. In this sense, considering the visual perception, eyes are the responsible os providing with information to the brain: composed by , eyes reacts to light in such a way that forms monocular representations (111).

Although the human vision involves many other processes and characteristics (e.g. eye movements), the main aspects defining the vision capabilities are the ones associated to the optics (i.e. crystalline lens - cornea) and the acquisition (i.e. retina): the first one, by changing its shape, allows the light refraction to be focused on the retina. On the other hand, the retina itself is in charge of providing with the representation, by converting the light received into electrical signals. These are generated by rods and cones -light and color sensing organs, respectively- and transmitted though the optic
nerve to the rear back of the brain (112). There, according to the stated in subsection 1.3.2 is where the rest of processes start analyzing the stimulus.

Taking all this into account, the human eye can be modeled as a low-pass sensor (limited number of rods in human eye) which provides with images of the environment. It is light predominant (since the there are fewer cones in human eye than rods) and capable to detect motion basing on contiguous changes of texture/contrasts. Besides, as a system, human physical vision is characterized by its disparity/binocularity, which provides with depth to the perception.

3.3.2 Detection

During this first stage, the image is acquired and the relevant elements in the scene are selected from the background. This extraction simplifies the representation of the images in something more meaningful and easier to analyze. In terms of Human Visual System (HVS), it is the result of the fixation process, that identifies the attention points on each of the relevant objects in the scene (113).

According to the Feature Integration Theory, stimuli are registered automatically and in parallel, while objects are identified separately (114). This difference is defined by the attention focus, which behaves according to the Helmholtz principle: the human brain is able to detect large deviation from random actions, events or visual stimuli (115). In these cases, structure is perceived. These deviations can take the form of colours, alignments (edges), depths or shapes, following a coherent feature: Livingstone proposes a model that combines color, contrast, movement and depth (116), while Regan substitutes the contrast by the alignment for defining these characteristics (117) and Schiele focuses on the lighting variations (histogram) (118).

Nevertheless, they all use these features in order to define shapes. In this sense, all the studies have revealed the preponderance of the forms in the detection process (119). This hypothesis was firstly postulated by I. Bierederman in 1987: According to his Recognition-by-components theory (RBC), the segmentation is performed by assimilating the elements to simple forms. The combination among them defines the nature of each of the objects (120), providing with the segmentation. This approach was also confirmed by Perception Organization Theory (POT), Cerella’s Particulate Feature Theory (PFT) or Edelman’s Chorus of Prototypes (CoP) (121). So, in all the cases, the shape interpretation can be interpreted basing on two parameters: low pass filtering using chromatic stimuli and band pass employing luminance ones (122, 123).

3.3.2.1 Recognition-by-components theory

Despite of its name, the recognition-by-components theory (RBC) does not focus on the recognition process but in the detection one. This bottom-up process, proposed by
3.3 Fundamentals of human perception

I. Biederman, states that the human being divides objects into small basic elements. Like this, detection comes from the logical organization of sets of basic components (120).

These main elements, capable to be distinguished in the scene, are named 'geons' (the objects main component parts). According to the RBC theory, there are 36 different types of geons, resulting from the combination of 3 basic dimensional shapes (i.e. prism, cylinders, cones.). Thus, people identify the combinations of these components, detecting actual elements when the set of geons and their spatial configuration make sense. (This is one of the main differences compared to the rest of theories mentioned above, since RBC is the only one considering the spatial organization).

This aggregative approach explains why people is able to successfully recognized occluded objects or degraded images: RBC provides with three levels of invariance. Since it assimilates the elements distinguished to known geons, it provides with identification despite changes in the size, position or orientation/viewpoint (124).

3.3.3 Clustering and segregation

Clustering corresponds to the second stage in the perception flow. It is related to the interconnection among elements, in an attempt to put together the elements corresponding to the same reality. It gives a meaning to elements that, by themselves, have different implications (e.g. crystal, steel or wheels do not mean equally when they are taken individually or taken as on in a car). In fact, it has been proven that the human cerebral cortex has specialized regions with preferential activation to discrete categories of objects (e.g. faces, body parts, tools, animals and buildings)(125, 126).

Many theories have focused along the time on analyzing how individual elements are grouped to become an unique entity: David Hume stated in 1974 (127) that the three main basic principles underlying the human associative process are similarity, causality, and dimensional and temporal contiguity. More recently, these principles have been extended, but all HVS associate theories have remained (128).

The Gestalt psychology is the theory that summed up all these contributions and unified all the structuring principles:

3.3.3.1 Gestaltism

Gestalt psychology or gestaltism (from the German word Gestalt - ”essence, configuration, totality or shape of an entity”) is a perception theory that tries to explain how the human being acquire and maintain stable percepts from the noisy World. It emerged
in Germany in the early XX century around the work of K. Lewin, M. Wertheimer y K. Koffka, among others (129, 130). They stated that the mind configures -by using different principles or laws- all the phenomena that arrive to the brain through the different sensory channels (including the memory). The result of this process (the perception) arises after complex interactions among various stimuli, beyond the aggregation of these ones. This process is holistic, parallel, analog and with self-organizing tendencies.

Most of the principles base on the idea that the human eye captures the objects as a whole before perceiving their individual parts. The result, as said, is greater than the sum of its parts. The main theoretical principles are the following:

- **Closure law**: When an object is incomplete or a space is not completely enclosed, human mind fills in the missing information to get a complete/meaningful shape. It uses stored information. When the viewer’s perception completes a shape-as in the “circle” or the “rectangle” in Figure 3.1 a)- closure occurs, providing a full impression from a set of individual segments.

- **Principle of similarity**: The mind groups elements according to their similarity: all else being equal, perception lends itself to seeing stimuli that physically resemble each other as part of the same object, and stimuli that are different as part of a different object. This allows people to distinguish between adjacent and overlapping objects. In Figure 3.1 b) most people will distinguish black and white points as different patterns or groups, despite the fact that they are placed at the same distance and have the same size.

- **Proximity principle**: When elements are placed close together, they tend to be perceived as a group. In Figure 3.1 c), the elements in the left seem to be together, while the elements in the right looks like being split in 3 different groups. So, the element clustering is defined according to their relative distance.

- **Principle of totality**: The perception is considered as a global experience (by taking into account all the physical and mental aspects of the individual simultaneously). It is because the human brain considers each component as part of a system of dynamic relationships.

- **Principle of continuation** Human mind seeks for smooth continuation in shapes and objects, trying to avoid sudden or unusual changes in the profiles. Where there is an intersection between objects and the eye is compelled to move through one object and to another element, individuals tend to perceive the two objects as two single uninterrupted entities.
3.3 Fundamentals of human perception

- **Principle of pregnancy**: Also known as the Law of Good Gestalt, it is understood as “pregnant with meaning, not with child”. It states that the perception always tends to adopt the simplest shape/meaning possible. Also proposes that individuals eliminate complexity and unfamiliarity stimuli during the acquisition process. Observing the World in its most simplistic form, helps the mind to create meaning that implies a global regularity (often mentally prioritized over spatial relations).

\[ \text{Figure 3.1: Gestalt principles} \]

3.3.4 Identification

Identification is the process whereby the characteristics of an object are compared (wholly or partially) with the attributes of a model in order to establish a correspondence among them. The aim of the identification is to define if both elements correspond to the same entity.

In order to do that, two main approaches can be found depending on the nature of the characteristics: pattern-based methods -when intrinsic parameters are used-, or dynamic methods, if they focus on extrinsic characteristics.

The first of the alternatives focuses on the remarkable human ability to recognize patterns (131). This approach was firstly introduced by Hubel (132), who demonstrated the specialization of the neurons to recognize patterns (some neurons responded only to horizontal lines, others to diagonal lines, etc). However, along the time, more accurate theories have emerged to explain the identification of more complex patterns: those can be specified as visual templates, sets of features or structural relationships, but always focus on the intrinsic properties of the elements. According to that, Neisser (133) proposed a Template Matching Model (TMM), where the brain directly compares the elements to various stored patterns (literal copies that are stored in memory) in order to find a match. Likewise, Prototype Model provides a more flexible version of template model since it uses a diffused model, where the match does not have to be exact. Nevertheless, this flexibility leads to a greater possibility of false positives and lower accuracy on the identification.
Likewise, Feature Analysis Model (FAM) states that identification comes from the combination of elementary features (e.g. for the alphabet, features may include horizontal lines, vertical lines, diagonals, and curves). In opposition to TMM, FAM does not compare the whole set of characteristics but makes discriminations/discards based on these distinctive features.

On the other hand, semantic properties have proved to be a self-sufficient identification method for identifying elements. Morland (134) describes colour, motion and luminance as the most relevant parameters, being the first two ones perceptually associated. That association comes from the expression of different stimulus attributes in activity of functionally segregated visual areas of the brain. Thus, the information in point-light stimuli might be sufficient and similar for both features, requiring the “motion” one the integration of information over time (135) (1st order perception and contrast associated to the 1st order beta movement; texture and flicker associated to the second order one). Besides, it was also proved that the percepts of brightness, dissociated from the other ones, is as relevant as the other ones (122). It is origin of the contrast patterns that, going one step further, define the element’s texture, features, etc. However, the own luminance distribution has information enough to be significant itself.

3.3.5 Characteristics extraction and behavioural analysis

Last stage in the perception chain is the feature extraction and behavioural analysis. Here, semantic attributes are associated to the elements identified, providing them with a meaning.

In 1977, James. J. Gibson proposed a new approach to perceive the environment that stressed the relation between perception and action (136). His hypothesis-known as the ecological approach or environmental psychology- is nowadays well accepted. It asserts that the World is full of information, being possible to perceive all the required data by detecting higher-order stimulus variables: oppositely to reductionist or constructivist views, the ecological approach proposes a system-based approach to perception and control of aspects that determine the success or failure of concrete behaviors (i.e. the element and the environment should be studied together). It focuses the perception on the relation between the organism and its environment, trying to predict the behaviour according to this observation. He supported the direct perception and direct realism, rejecting the information processing view of cognition. According to this, lots of significant variables could be directly extracted from the images. These parameters determine the “character” and the identity of an element.

On the one hand, identity refers to the features that distinguish an element from the rest of the elements in the group. It implies that this process focuses -in opposition to identification- on the characteristics that individualize the element from the other
3.3 Fundamentals of human perception

ones, instead of the ones that make him part of the group. Blakemore (137) firstly stressed the relevance of size and orientation when discovered neurones in HVS selectively sensitive: area, contour and shape are useful markers for individualizing elements and estimating non-measurable data (e.g. weight (138)). Moreover, the relationships among them are also remarkable: the distribution axes are aligned with the moments of inertia, while major axes tend to align with gravity (139). Both relations suppose a good descriptor of the dynamic of the system. Conversely -in contrast to the its potential preponderance in the segmentation stage-, colour plays a secondary role in the characterization process. It has proved to be useful in disambiguation tasks, but dispensable under normal circumstances (140).

On the other hand, the term “character” (speaking about safety) refers to the characteristics that define the relationship among the observer and the object. It involves the distance among them, their relative movement (141) or the time to contact (in case of potential collision). According to Gibson (142), the first two variables only consider rotation and translation when evaluating rigid obstacles, being the relevance of both parameters beyond reasonable doubt. Regarding to the time to collision (TTC), its definition and validity as HVS mechanism provoked a great controversy. However, Lee (143) finally established the relation between the TTC and the way its size is observed: the ratio of an objects image size to the rate of change of size coincide with the physiological definition of TTC (also know as $\tau$). It corresponds with the inverse of the rate of expansion of the object’s retinal image, what provides a simple and fast method to estimate the time to arrival.

Furthermore, “character” refers not only to the actual relation but to the future one. It implies that it is also related to the predictability of the element’s behavior. As Jakobson (144) proved, variability (both in size and distance) is one of the main factors related to the capability for estimating the future: the greater the stability of an object, the bigger the stability of perception and the capacity to predict/estimate the future behaviour (145). Besides, Shuman also proved that there is a direct relation between the variability of the objects and the numerosity of elements perceived (146). It means, in numerical cognition, that the representation level of a voluble obstacle is greater than the one of an static object. Even more, it also affects to the observation itself: predictability is also a function of the element’s visibility (being visibility a representation of measurability), both in social (147) an visual terms (148). Several studies have shown that the visibility degree affects to the attention selectivity and the perceptual load (149), being the representation accuracy balanced by the observability degree. It results in a lower accuracy in the description and the details provided. The lower the visibility the worse predictive capacity. It implies that the predictability is a direct function of the visibility, being this, in turn, a function of measurability.
3. RISK PERCEPTION

3.4 Risk perception processing system

Trying to reproduce the human perceptive system, the whole HVS has been tried to be emulated by using a modular architecture: Firstly, the physical visual organs have been substituted by an equivalent sensing system (see subsection 3.4.1). Then, the four phases of perception have been reproduced in a four step image processing system. The result of these stages has reproduced the human perception, providing with a basic interpretation of the elements in the scene.

3.4.1 Sensing system

The sensing system is the first piece in any robotic application. It is the input to the rest of the modules, so all the system depends on its quality and suitability. So, the main goal of this subsystem is providing with information from the environment. In this sense, it has been tried to reproduce the most relevant human sensors: eyesight and audition. In this sense, according to the fundamentals of human perception studied in section 3.3), a multilayer sensor layout has been defined: on the one hand, a ultrasonic-based hearing-like system has been implemented covering the robot (up, down, left, right and behind). It provides with low-level fast omni-directional information about potential risks. On the other hand, vision-like sensors have been analyzed, in order to select the most suitable system to acquire information of the environment. It should provide with a rich and accurate spatial view of the World, complete enough to be analyzed in the following stages.

In this sense, Table 3.1 presents the comparison that has been done regarding to the different types of sensors presented in section 3.2. As it is possible to appreciate, the metrics considered have been the ones related to the operation of an UAV in an outdoor environment. In this sense, weight (due to the payload restrictions), outdoors operability and power consumption (due to the batteries limitation) have been considered hard restrictive conditions. Taking that into account, a combination of a simple RGB camera and a stereo pair has been selected: one of the cameras of the pair is constantly operating, providing with a video stream used to evaluate the environmental stimuli. The remaining camera has been only employed when an obstacle has been detected: it allows to estimate the distance to the elements detected in the following steps by using disparity and stereo reconstruction (see subsection 3.4.5).

3.4.2 Segmentation and blobbing

Three different processes correspond in computer vision to the human object detection: filtering, segmentation and blobbing. The first one sets the image up, while the segmentation divides a digital image into multiple segments. Blobbing, for its part, aims
3.4 Risk perception processing system

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<td>Structured light</td>
<td>++</td>
<td>+++</td>
<td>+</td>
<td>+++</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

Table 3.1: Sensor comparison
The number of ‘+’ denotes the benefit perceived for each category, being + the minimum and +++ the maximum level.

to detect regions in a digital image basing on their properties: it labels of each one of the regions defining them as independent elements.

**Filtering:** As described in section 3.3.2, human segmentation results from a combination between colour an luminance filtering. It can be understood as an entropy search (150) that focus on the homogeneity of gray level values in a region. In order to reproduce that process, a noise reduction filter together with a colour enhance filter has been used (151). This filter emphasizes the green levels (and also a bit the red ones) while diminishes the blue channel\(^1\), according to the human spectral sensitivity (152). As in the case of the humans, it maximizes the distinction among the objects and the sky.

**Segmentation:** A thresholding process has been applied over that filtered image (converted to gray scale). More sophisticated approaches -as the ones based on Markov random fields (MRF)(153), k-means clustering or wavelets (154)- have appeared over the time. Nevertheless, the HVS not only uses a general view segmentation but also a focused one defined by using the attention points. Here, a coarse grain segmentation (i.e. sky-ground) has been performed by using a common threshold. Nevertheless, as it is possible to appreciate in the center picture of Table 3.2 a), this standard segmentation provides with good results but is not able to detected softer details: It is enough for distinguishing the land and the sky but not for identifying dark moving obstacles, like

\(^1\)In a natural environment, most of the surrounding elements are natural, so they tend to have green-red pigmentation. [http://hyperphysics.phy-astr.gsu.edu/hbase/vision/colcon.html](http://hyperphysics.phy-astr.gsu.edu/hbase/vision/colcon.html)
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UAVs. Even more, its strong dependency from the lighting conditions makes it too context-dependent for a general use.

On the other hand, the adaptive thresholding methods focus on the smallest details providing with more accurate results. Methods like the maximum entropy, maximum variance, histogram analysis or k-means clustering\cite{155} provide more specific segments. Among them, Otsu’s should be highlighted: It performs a histogram shape-based image thresholding by maximizing the between-class variance of pixel intensity \cite{156}. Nevertheless, as can be observed in (see the images b) of Table 3.2, the use of a gaussian weighted sum as a threshold value provides a a good contour detection, really useful for detecting the borders among regions but not the segments themselves. Like this, the fine-grain segmentation regions are able to detect the objects but do not consider the general view.

The combination of both methods results in a fully segmented image that contains both the details obtained when minimizing the intra-class variance and the coarse grain quantization that provides the absolute threshold. The blending percentage has been estimated experimentally, and it is adjusted dynamically according to the luminance of the situation. It ranges from 50%-50% to 70%-30%, providing with good results in many different ambiental conditions (i.e. cloudy, sunny, dawn, etc.). The center image at Table 3.2 c) presents the result of blending them.

Blobbing: Finally, after splitting apart the elements of the image, the last process in this area is the actual detection of the elements in the scene (also known as blobbing). The slight line between “regions” and “blobs” is located in the identification of the elements. In this sense, the regions extracted could be also be understood as “blobs” as far as they get an unambiguous and unique identity. Thus, blobbing algorithms are in charged of individuating the regions and assigning a reference to each one of them. In this thesis, the blobbling method has been implemented considering the I. Bierderman’s approach based on shapes: by using morphological reconstruction (i.e. connectivity), it has been assigned a label to each pixel according to their connectivity degree with the rest of element that share certain visual characteristic. It is the closest approximation to the human segmentation described in subsection 3.3.2. Although more specific methods have been proposed in literature -such as the Laplacian of Gaussian (LoG), Difference of Gaussians (DoG), Determinant of Hessian (DoH) or Maximally stable extremal regions (PCBR)-, the shape-based approach has proved to be a valid solution for the target scenario \cite{157}. In this manner, it is easy to determine which pixels are connected by using a seek-based propagation algorithm over the multi-range segmented image. Each seek, that surely has its origin inside one of the segmented regions, defines a blob/node \cite{158}. Moreover, it is also possible to fill holes inside the elements using a flood fill algorithm, providing with compact objects.
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The results of this process are illustrated in the leftmost column of Table 3.2.

<table>
<thead>
<tr>
<th>Real capture</th>
<th>Segmentation</th>
<th>Blobbing</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
</tr>
<tr>
<td><img src="image4.png" alt="Image" /></td>
<td><img src="image5.png" alt="Image" /></td>
<td><img src="image6.png" alt="Image" /></td>
</tr>
<tr>
<td><img src="image7.png" alt="Image" /></td>
<td><img src="image8.png" alt="Image" /></td>
<td><img src="image9.png" alt="Image" /></td>
</tr>
</tbody>
</table>

Table 3.2: Segmentation of the scene. Blobbing

For the same image (depicted in the leftmost column), the different rows present the results when applying different methods of segmentation. The first one uses a normal static threshold; the second one an adaptative threshold based on Otsu’s; The last one corresponds to a combination of the previous methods. The column in the middle presents the results after the segmentation process. The leftmost column shows the outputs of the blobbing procedure.

3.4.3 Clustering

Clustering refers to the process of grouping and combining several elements corresponding to the same reality into a single blob. It plays a fundamental role from both the
meaning and processing points of view: during the identification and characterization stages, the estimation of some parameters (e.g. the aspect ratio, the real size or the element or inertia, among others) depends on the entity definition. Thus, its correct interpretation (i.e. the element is complete. It is not only a part of a bigger object) is critical.

According to the precepts described in subsection 3.3.3, the HVS clusters the elements according to the Gestalt principles: similarity, proximity and continuity. On this sense, an iterative method has been implemented basing on that. Firstly, for each pair of bounding-boxes, an overlapping/distance analysis is performed. It provides with a simple, fast and computational-efficient way to estimate the probability of belonging to the same set. If the probability is high enough, a second step is carried out: the minimum distance between both contours is calculated and their histogram compared. According to the combined value, both blobs get integrated or remain independents. It is important to highlight that every time that a joining is performed, the algorithm is dynamically restarted in order to reevaluate the connections taking into account the new element. It guarantees that all necessary bonds are finally established.

The images in Figure 3.2 presents a comparative of the method applied to the scene depicted in 3.2a: Figure (3.2b) corresponds to the raw output provided by the blobbing extractor module. It contains 8 elements, takes ms to process it and is used as the input of the cluster processor. In contrast, the image in 3.2c is the output of the associative module: it finally provides 4 elements. In the 10 cases tested, the averaged grouping percentage has been higher than 50%.

Furthermore, given that each blob is processed independently and generates a multi-register of ancestors, an excessive subdivision increases the computational cost ($O(5n)$), specially in terms of memory usage. However, at the same time, the grouping process sometimes requires an exhaustive use of the CPU -specially when there are many elements too close-. Considering that the system will be embedded on-board (and then
it is expected that the computing resources to be limited), the clustering value should result from a deal of the benefit-cost ratio.

![Comparative perception performance](image)

**Figure 3.3:** Performance comparative using or not the dynamic clustering method

The Figures 3.3 and 3.4 present the analysis carried out to estimate this ratio and the suitability/efficiency of the clustering method. As it is possible to appreciate in Figure 3.3, the clustering task supposes around the 3% of the CPU consumption (measure in CPU ticks), as well as the re-analysis does (Analysis II, performed over the new integrated blobs). This 6% could be saved if not clustering. Nevertheless, it has a significant impact in subsequent processes: as could be appreciated in the Fuzzy Analysis, Update and specially in the Optical Flow tasks, the grouping reduces the number of CPU ticks since there are less elements to analyze, process or send.

However, this assumption is not always-as could be appreciated in Figure 3.4:- the computational suitability is really context dependent, according to the number, distribution and size of the obstacles. As Figure 3.4 a) presents, the computational consumption difference increases with the complexity and density of the scenario. Nevertheless, it has been though that the clustering module is useful due to i) the great relevance of the clustering task in the identification process; ii) the small variation in the memory usage (see Figure 3.4 b)), and assuming that iii) the CPU consumption difference is not quite significant and that iv) the outdoor scenarios are not expected to be complex and dense environments.

### 3.4.4 Identification

Although human beings perform identification as a single process, computer vision requires from, at least, two different tasks clearly differentiated. Firstly, it is required to guarantee the correspondence among the objects detected along the time (i.e. associate target elements in consecutive video frames). It implies following an object along frames
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<table>
<thead>
<tr>
<th>Real capture</th>
<th>Contours found</th>
<th>Segmentation processed</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image" /></td>
<td><img src="image2.png" alt="Image" /></td>
<td><img src="image3.png" alt="Image" /></td>
</tr>
<tr>
<td><img src="image4.png" alt="Image" /></td>
<td><img src="image5.png" alt="Image" /></td>
<td><img src="image6.png" alt="Image" /></td>
</tr>
<tr>
<td><img src="image7.png" alt="Image" /></td>
<td><img src="image8.png" alt="Image" /></td>
<td><img src="image9.png" alt="Image" /></td>
</tr>
<tr>
<td><img src="image10.png" alt="Image" /></td>
<td><img src="image11.png" alt="Image" /></td>
<td><img src="image12.png" alt="Image" /></td>
</tr>
</tbody>
</table>

**Table 3.3:** Processing of real flying scenes
The left column corresponds with the raw image captured; the center present the contours found in the scene and the right one shows the final segmentation for each scene. The videos from UAVRF @ GeorgiaTech. Used with permission.
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a) CPU tick count analysis

b) CPU memory usage analysis

Figure 3.4: Comparative among scene using or not the dynamic clustering

Scene refers to the scenarios presented in Table 3.3

guaranteeing that it is the same all along the sequence. Known as “tracking”, this process is critical when estimating movement, speed, variability, etc.

The second process is the identification itself, although it could be also named “matching”: the elements are here classified according to their nature, defining their belonging to a group or class. The matches models stored, being here where the system becomes aware of the type of element it is facing (e.g. a tree, a building, an UAV, etc.).

3.4.4.1 Tracking

The aim of a tracking algorithm is to monitor the movement of an object over time by locating its position in every frame of the video sequence. Many strategies can be followed to perform this task. However, according to (159), they can be grouped in three different categories: The first one refers to point/blob tracking, where the elements detected are represented by sets of points. The association between elements detected in consecutive images is determined by the relationship of the points composing them. If the prediction comes from a linear prediction (e.g. based on proximity, structural properties or common movement, etc.), the association is considered deterministic. On the other hand, if the prediction bases on a state space representation, it is considered as statistical, as in the cases where a Kalman filter or a Particle filter are applied to the position, location or speed. Their main disadvantage comes from the low adaptability of this algorithms in complex situations (i.e. occlusions, misdetections, entries, and exits of objects, etc.)
In opposition to the individualization of point tracking, kernel/feature tracking understands the elements as a whole, unlike blob, which refers to the collection of points composing it. Thus, kernel tracking bases on the intrinsic characteristics that define each one of the objects. In this sense, both the motion and the features have been considered: on the one hand, methods for motion estimation (e.g. optical flow, SLAM, etc) allow to monitor a trajectory and, hence, a behaviour; on the other, algorithms as KLT (160), SURF (161) or KAZE (162) provide with (scale and rotation invariant) enough features to perform a 80-90% success correlation. The main disadvantage of the kernel tracking is due to its high computational cost.

Half-way between individual points and complete sets, region/silhouette-based tracking algorithms try to find the object region in each frame by using an object model generated in the previous frames. This model can be based on the information contained on the region itself (e.g. size, luminance, structure, etc) or in the contour (163). Among the methods basing on this second characteristic, also a division may be done: those which analyze the silhouette (mostly edge and shape analyzers), and those that try to find a direct correspondence among the contours in consecutive frames (most basing on heuristics or variational methods). Also statistical analysis methods -such as SSIM (Structural Similarity) or Peak Signal-to-Noise Ratio (PSNR)- can be considered here. They all region-based approaches are resilient to noise and flexible. Nevertheless, they lack of accuracy compared to other methods.

Considering all the above, and relating it with the human characteristics described in subsection 3.3.4, different factors have been chosen: area variation, position/ displacement, illumination characteristics and the predictions done over these parameters.

**Area variation:** Since the capacity to alter the own structure during the operation is really low, the area of an element is one its most distinctive attributes. Nevertheless, it is, at the same time, a very voluble and changing variable: it is really dependable from the quality of the segmentation. It should be also taken into account that different views of the same obstacle -or changes in its illumination- may provide with different size measures. However, despite of this fact, the area-based approach has been widely use (164, 165), since it is more suitable for tracking unknown moving target scenarios (166). Besides, it is also more efficient and flexible than model-based approaches, although it is considered weak because its based on "target undergoing a rigid body motion". Thus, by employing Normalized Cross-Correlation (NCC) of the area variation, it has been considered useful and stable the value the area variation contribution.

**Displacement and (ego)motion estimation:** Regarding to the position metric, the among-frames displacement can be thought as the first intuitive approximation: The closer a object is to another’s previous location, the greater the possibility of both
3.4 Risk perception processing system

elements to be the same. Nevertheless, this method is not very robust neither reliable when evaluating objects with high relative speeds, shaking movements or overlapped elements. It requires more sophisticated techniques: Optical flow (OF) refers to the apparent pattern of motion of the elements in an scenario due to the relative movement between them and the observer. This concept was introduced by the J.J. Gibson in his Ecological Approach (see subsection 3.3). There, he stated that this is the way not only people but also animals perceive the movement. It is based on the analysis of two consecutive scenes, where the same points (in general, surfaces, corners or edges) are located and their displacement measured. Besides, this stimuli is also a key factor for the perception of the shape and distance, as well as for the control of locomotion. In this sense, he addressed the importance of OF for affordance perception (See Subsection 5.3.1).

As this feature has proved to be really useful in robotics/vision (in motion detection, object segmentation, time-to-contact analysis, motion compensated encoding or stereo disparity measurement applications, for example), several methods to compute the OF have been developed: from phase correlation techniques -that use the normalized cross-power spectrum- to block-based methods, which try to minimize the sum of squared/absolute differences. Nevertheless, the most popular algorithms are based partial derivatives: known as differential methods, they estimate the OF estimating optical using local Taylor series approximations of the image signal and/or the sought flow field.

There are many different type of differential methods, according to which features do they consider and how they process them (e.g HornSchunck, Buxton-Buxton). Among them, in this work, the Lucas-Kanade one has been chosen: The LucasKanade method was developed by B.Lucas and T.Kanade (167) in 1981 to provide a fast estimation. For this purpose they assumed that the flow is essentially constant in a local neighborhood of the pixel under consideration. They method solves the optical flow equations for all the pixels in that neighbourhood following a least squares criterion. Besides, it also uses the information from several nearby pixels is combined in order to resolve the inherent OF ambiguity (168).

It has been specially useful when applying this technique to every single blob extracted from the scene: the local search performed by Lucas-Kanade’s have been constrained even more, limiting it to the concrete blob’s bounding box (plus a margin). It has speeded up the search and avoid potential errors. Even more, it is also usable as a complement for the variability calculation.

The images presented in Figure 3.5 depict the results of the implementation of this technique: The first one (3.5 a)) presents the results from an off-board observation, where the camera is static but the obstacle (a quadrotor) is moving. In the next one (3.5 b)), the situation is the same but both the obstacle and the ground are moving
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-with different speeds and directions-. In the following two images (3.5 c) and d)) the results of processing the on board video are shown. In the first case, an slow movement en yaw is analyzed, while in the second one a fast movement in both yaw and roll were being performed. So, it has been possible to identify individually different speeds and movements in the scene. The speeds have been classified in a fuzzy way, considering its angular component: null/slow for movements between 0 and 0.2 rad/seg, medium between 0.21 and 0.5 rad/seg and fast for movements faster than 0.5 rad/seg ¹.

![Figure 3.5: Optical flow analysis.](image)

The red and blue points in the images represent the features/points tracked (past and present, respectively). The green vectors represent the direction and magnitude of the movement, while the thickness of the bounding boxes -in blue- proportionally represents the variability of the movement (less thickness, less variability).

**Illumination and colour:** Regarding to the illumination characteristics, both colour and lighting have been considered. Regarding to the first one, colour, as size, is a really good estimator that, nevertheless, varies a lot. It varies according to illumination and

¹The distance has been also defined in a fuzzy way, by using the stereo rectification. So, the angular speeds are approximated
attitude, resulting really challenging its continuous tracking. Many works have focused on this challenge, generating algorithms to estimate the colour variations: colour models (169), probabilistic schemes (170) or even adaptative algorithms based on particle filters (171). However, almost all of them finally relay in predictions done over the illumination evolution. In this sense, illumination has been directly considered, using the histogram comparison as the reference metric. It has been chosen due to its scale- and rotation-invariant nature, despite its high sensitivity to changes in the saturation, lighting or tone. Nevertheless, since it is a representation of the distribution of data, it has been considered as a good estimator in conditions where the motion is reduced.

Illumination is as well behind contrast, who is mainly the determining element when performing feature analysis. As previously said, the feature search methods provide with outstanding results in most of the cases. Nevertheless, they have been also considered and evaluated despite their great CPU consumption due to their performance and their relevance in motion tracking.

**Prediction:** Block-motion matching, batch estimation or phase correlation methods are broadly use in order to predict movement or actions. Nevertheless, among the motion prediction algorithms, the Kalman filter (KF) is undoubtedly the most popular one: it is Linear Quadratic Estimator (LQE) based on the work of Rudolf E. Kalman (172). It uses a series of measurements observed over time -containing noise, random variations and other inaccuracies- to estimate the internal state of a linear dynamic system. In a recursive way, it produces estimations of unknown variables that tend to be more precise than those based on a single measurement. Besides, as it is a recursive estimator, only the previous frame’s estimation and the current measurement are needed to compute the estimation for the current state. Besides, in contrast to other techniques, no history is required (173, 174).

So, a Kalman filter with four dynamic parameters and two input parameters has been employed to estimate the movement. 2D location of the blob and its speed in x and y axis have been defined as the dynamic parameters, while the new 2D location of the candidate blob is set as the measurement one. The Figure 3.6 presents some examples of the results obtained (in green, the real trajectories of the objects; in red, the estimations performed).

**Final tracking comparison and selection:** Methods described above have been evaluated in order to i) validate their suitability, and ii) estimate their relevance in the overall process. Both Tables 3.5 and 3.4 present some of the results obtained in the experiments, that has been carried out both using static images and videos.

According to these results, and basing on the HSV configuration studied in subsection 3.3.4, finally the combination has been the one established in equation 3.1,
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<table>
<thead>
<tr>
<th></th>
<th>SSIM</th>
<th>PSNR</th>
<th>Histogram</th>
<th>SURF</th>
<th>Proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Confidence</td>
<td>34.9%</td>
<td>12.3%</td>
<td>50.1%</td>
<td>88.5%</td>
<td>80.2%</td>
</tr>
<tr>
<td>CPU time</td>
<td>0.26</td>
<td>0.15</td>
<td>0.12</td>
<td>9.3</td>
<td>0.18</td>
</tr>
</tbody>
</table>

Table 3.4: Performance of the different tracking methods evaluated

\[
\text{min} = K_{\text{disp}} \cdot \frac{\Delta x + \Delta y}{2} + K_{\text{pred}} \cdot \frac{\epsilon_{x_{\text{pred}}} + \epsilon_{y_{\text{pred}}}}{2} + K_{\text{area}} \cdot \Delta \text{Area} + K_{\text{hist}} \cdot \text{HistComp} \cdot (1 - \frac{\Delta x + \Delta y}{2});
\] (3.1)

where, \( \Delta \) corresponds to the variations in the variable \( \epsilon \) denotes the error estimated and ‘x’ and ‘y’ refers to the location of the CoG of the element. \( \text{HistComp} \) is the histogram comparison performed using the OpenCV’s \( \chi^2 \) method. Finally, ‘\( x_{\text{pred}} \)’ and ‘\( y_{\text{pred}} \)’ are the positions estimated by the Kalman filter. Regarding to the different Ks, they stand for the different constants employed. They have been empirically calculated along the experiments, obtaining \( K_{\text{disp}} \sim 10, K_{\text{area}} \sim 2 \) and \( K_{\text{pred}} \sim 4 \) for an suitable and reliable performance.

3.4.4.2 Recognition

This identification process (recognition) is similar to the one performed during the tracking. However, instead of associating the object to the elements detected in the previous images, it is compared to the mental models stored in memory. Thus, recognition is the subprocess of identification whereby a person assimilates a property or attribute from an element and matches it with the models in his mind.

![a) Smooth continuous trajectory b) Angular trajectory c) Curve formation flight](image)

Figure 3.6: Kalman filter applied in different scenarios

The green dots depict the actual trajectory of the drones. The red dots present the estimation performed by the Kalman filter.
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<table>
<thead>
<tr>
<th>Image</th>
<th>Results</th>
<th>Image</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original Lena</td>
<td><strong>SSIM:</strong> 100 100 100</td>
<td><strong>PSNR:</strong> 0.000000</td>
<td><strong>HIST dif:</strong> 0.000000</td>
</tr>
<tr>
<td>Displacement</td>
<td><strong>SSIM:</strong> 50.3752</td>
<td><strong>PSNR:</strong> 9.763828</td>
<td><strong>HIST dif:</strong> 1.835953</td>
</tr>
<tr>
<td>Colour change</td>
<td><strong>SSIM:</strong> 84.5052</td>
<td><strong>PSNR:</strong> 15.013872</td>
<td><strong>HIST dif:</strong> 76.664718</td>
</tr>
<tr>
<td>Borders broken</td>
<td><strong>SSIM:</strong> 92.4372</td>
<td><strong>PSNR:</strong> 12.971462</td>
<td><strong>HIST dif:</strong> 9.752642</td>
</tr>
<tr>
<td>Section top</td>
<td><strong>SSIM:</strong> 78.0046</td>
<td><strong>PSNR:</strong> 8.136719</td>
<td><strong>HIST dif:</strong> 25.712767</td>
</tr>
<tr>
<td>Size increase</td>
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<td><strong>PSNR:</strong> 10.522944</td>
<td><strong>HIST dif:</strong> 14.068098</td>
</tr>
<tr>
<td>Spatial distortion</td>
<td><strong>SSIM:</strong> 50.8171</td>
<td><strong>PSNR:</strong> 8.778074</td>
<td><strong>HIST dif:</strong> 19.227690</td>
</tr>
<tr>
<td>Rotation</td>
<td><strong>SSIM:</strong> 49.8349</td>
<td><strong>PSNR:</strong> 10.260928</td>
<td><strong>HIST dif:</strong> 4.668361</td>
</tr>
<tr>
<td>Desaturation</td>
<td><strong>SSIM:</strong> 93.6824</td>
<td><strong>PSNR:</strong> 19.664616</td>
<td><strong>HIST dif:</strong> 62.153688</td>
</tr>
<tr>
<td>Holes</td>
<td><strong>SSIM:</strong> 89.693</td>
<td><strong>PSNR:</strong> 12.733913</td>
<td><strong>HIST dif:</strong> 11.582545</td>
</tr>
<tr>
<td>Blurring</td>
<td><strong>SSIM:</strong> 67.0977</td>
<td><strong>PSNR:</strong> 19.631611</td>
<td><strong>HIST dif:</strong> 28.565448</td>
</tr>
<tr>
<td>Size decrease</td>
<td><strong>SSIM:</strong> 57.2324</td>
<td><strong>PSNR:</strong> 5.5969</td>
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</tr>
<tr>
<td>Leno</td>
<td><strong>SSIM:</strong> 52.6384</td>
<td><strong>PSNR:</strong> 53.0213</td>
<td><strong>HIST dif:</strong> 49.610619</td>
</tr>
</tbody>
</table>

Table 3.5: Comparison of the feature-based tracking approaches
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However, it is really difficult identifying generic elements an unstructured environment. Works have been carried out in this direction, but even limiting the types of obstacles to a concrete one -human beings, for example (175)-, the process is challenging. Besides, even restricting the number and kind of the obstacles, the multiple variations each one of them may have -shape, size, color, etc.- make really hard the identification process. Nevertheless, it is possible to provide with good approximations or generalizations basing on their characteristics: if we find a medium/big-size, unmoving-but-maybe-oscillating, tall and unreactive element, it may be thought that is a tree. Even if it is not, the behaviour of the unknown object will probably be similar to the tree one. Likewise, the risk a fast moving, small and variable object entails will be probably the same both if it is bird or an RC plane.

Despite the complexity of the problem can be reduced with this simplification, the definition of the characteristics to recognize is not an easy problem: how big should be an object to be considered big and not medium-size? how many oscillations and with which amplitude should an object move to be considered unstable? Fuzzy logic (FL) has been considered the best mathematical approach to deal with these definitions since it substitute the traditional digital keypoints by analog ranges.

Proposed by Lofti A. Zadeh in 1965 (176), is an attempt to imitate the human reasoning: He realized that people are capable of highly adaptive control without requiring accurate numerical information. This is performed by using soft transitions instead of sharp thresholds. Thus, in opposition to the traditional logical, where key points define the swap among conditions (if the value of the variable overcomes the threshold, the output is set to true/false, and viceversa), FL proposes a gradual logic. This way, the values in FL are not ‘true’ or ‘false’ but partially true o partially false. It provides with smooth and progressive changes, guarantying a suitable integration with the analog human mind processing system.

According to this, a fuzzy logic system has been designed an implemented in order to perform the recognition. Three different aspects have to be taken into account for that: i) Definition of the FL models, ii) Definition of the fuzzy variables, and iii) FL Association between models and variables:

**FZ models** As said, first step performed has been the determination of the potential elements to be found. In this sense, an analysis has been run considering the most typical elements that can suppose a risk in an outdoor environment (92, 177), as well as the characteristics defining them:

- Ground: Present in all the scenarios, ground is both a reference and an obstacle. Nevertheless, due to its permanence and immutability along the time, it supposes a low risk even in its obstacle role. In most of the cases it supposes the “least
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worst” solution when no way is found to avoid a collision (Assuming the non-presence of human beings and a padding natural terrain).

- Walls, buildings, high voltage pylons or general infrastructures: They are usually large, rough and completely static. Their non-reactivity and immobility make them easy to be avoided, and thus, not quite dangerous. Nevertheless, their natural hardness implies a probable critical (and mutual) damage in case of collision. Since they are a private property, the third-party potential damage should be taken into account as a aggravating factor.

- Trees, awnings or marquees: Despite of being static obstacles, they can be slightly swayed by the meteorological conditions. It makes greater the risk they imply when comparing with the previous static elements. However, they are usually softer. This cushioned feature diminishes the potential damage for both the drone and the obstacle, resembling the global risk to the rest of static obstacles.

- Flying devices/vehicles: Multiple elements can be grouped under this topic, such as UAVs, RC models or manned systems (helicopters, light aircrafts, etc.). However, despite of this diversity, their expected behaviour maybe similar: they are all fast and variable elements, with highly maneuverability. Nevertheless, they are all controlled (manually or autonomously), so they are expected to have smooth behaviors and avoidance capabilities. It implies that the risk they imply is not as much as it could be thought.

- Kites, balloons, paragliding wings, etc.: Similar to the rest of flying elements, they are distinguished nonetheless due to their unpredictability: although they are expected to have lower speeds and the movements constrained, this mitigating circumstance is balanced with their dependency from the wind and their leak of control. It assimilate them to the rest of flying obstacles.

- Birds and other animals: As in the previous cases, the complete unforeseeability of the animal behaviour is compensated by the natural capacity to escape from menaces. Besides, it should be taken into account that the behaviour of a flock is the same of the one of its members. Thus, the classification is valid for both an individual bird and for a swarm of them.

- Fleets UAVs: The main exception that may be applied to the flying elements is the one corresponding to the drones of the fleet: despite they are as fast and variable as the other elements, their behaviour is completely predictable or at least controllable. It makes them much less risky than the rest of flying units, even considering the high risk any mobile robot implies.
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- Aggressive elements: Although no aggressive obstacles are expected, there is a chance of finding elements that may try to attack the own drone. For example, frightened birds or commercial flights may be interpreted as belligerent elements. In these cases, the reaction should not be and avoidance maneuver but an instinctive reaction.

As it is possible to observe in the previous list, some of the elements are defined by common features or, likewise, by the risk they imply. Thus, they can be gathered, resulting 5 different categories (the four ones resulting from the combination between the parameters defined in ISO 13.849-1, plus the one corresponding to the aggressive objects): the lower risk level (RL) corresponds to the ground, which would match, in the aerial regulation, to moderated damage and low probability (since its predictability is really high). The following level refers to the static elements, as buildings, trees or high voltage pylons (damage moderated and medium probability). Above that, the flying elements are split according to their reactiveness: the less dangerous ones -controllable/predictable ones (UAVs from the fleet)- are in lower step of the dynamic scale (high potential damage and low probability). The neutral obstacles (other UAVs, RC models, manned flights, etc.) are in the intermediate position (high potential damage and regular probability), while the aggressive ones are considered as the most dangerous ones (not considered in the regulation).

**FL variables** Once found the models, second step has consisted on defining the variables to associated to the models. As it could be appreciated during the description of the models, almost all the definitions basically focus on the kinematics and movement profile: attached to the ground or not, aspect, size, speed, variability and reactiveness have been considered the most relevant ones.

![Figure 3.7: Geometric distribution of the input variables’ fuzzy terms](image)

The terms at the sides correspond, geometrically, with a [0, 0.5] and [0.5, 1] shoulders, respectively. The term in the middle is a [0.25, 0.75] triangle centered in 0.5

As can be appreciated in Table 3.6, each one these variables have been defined with shoulder-triangular-shoulder term structure, evenly distributed in a [0-1] range (see Figure 3.7). On the other hand, the output has been composed using five terms (shoulder-triangular-triangular-triangular-shoulder) corresponding to the five different

---

1ISO 13.849-1 defines the potential damage according to the elements involved. Situations with third-party elements involved are considered riskier than other where only the own drone suffers the damage.
3.4 Risk perception processing system

classes or risk levels. As Table 3.7 presents, all the terms have been equally distributed in a [0-5] range.

<table>
<thead>
<tr>
<th>Human variables</th>
<th>Fuzzy variables</th>
<th>Fuzzy ranges &amp; terms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spatial variability</td>
<td>Variability</td>
<td>SMALL - ShoulderTerm [0, 0.5],</td>
</tr>
<tr>
<td>Dimensional variability</td>
<td></td>
<td>MEDIUM - TriangularTerm [0.25, 0.75]</td>
</tr>
<tr>
<td>Transversal speed</td>
<td>Speed</td>
<td>HIGH - ShoulderTerm [0.5, 1]</td>
</tr>
<tr>
<td>Longitudinal speed</td>
<td></td>
<td>SMALL - ShoulderTerm [0, 0.5]</td>
</tr>
<tr>
<td>Tau</td>
<td></td>
<td>MEDIUM - TriangularTerm [0.25, 0.75]</td>
</tr>
<tr>
<td>Grounded</td>
<td>Grounded</td>
<td>HIGH - ShoulderTerm [0.5, 1]</td>
</tr>
<tr>
<td>Aspect ratio</td>
<td>Aspect ratio</td>
<td>NO - ShoulderTerm [0, 0.5]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>PARTIAL - TriangularTerm [0.25, 0.75]</td>
</tr>
<tr>
<td>Size x</td>
<td>Size</td>
<td>FULL - ShoulderTerm [0.5, 1]</td>
</tr>
<tr>
<td>Size y</td>
<td></td>
<td>SMALL - ShoulderTerm [0, 0.5]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MEDIUM - TriangularTerm [0.25, 0.75]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>BIG - ShoulderTerm [0.5, 1]</td>
</tr>
<tr>
<td>Reactivity</td>
<td>Reactivity</td>
<td>BAD - ShoulderTerm [0, 0.5]</td>
</tr>
<tr>
<td>Communications</td>
<td></td>
<td>NONE - TriangularTerm [0.25, 0.75]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>GOOD - ShoulderTerm [0.5, 1]</td>
</tr>
</tbody>
</table>

Table 3.6: Gathering of the extracted characteristics I

(Human variables) for provide rational inputs to the fuzzy estimator (Fuzzy variables). For each one of these, Fuzzy ranges & terms present the associated terms and ranges describing the operator.

**FL classification** Finally, the association among the features and the risk resulting from their combination naturally emerges. It is presented in table 3.9

**FZ results** Table 3.9 presents the performance results of the fuzzy classifier (FC) applied over a collection of situations (see Figure 3.10). For each one of the risk levels (RLs), the second column presents the mean number of positive identifications provided by the algorithm. As can be observed, the FC manages identifies properly the obstacles in most of the situations (92 % average probability).
3. RISK PERCEPTION

<table>
<thead>
<tr>
<th>Output</th>
<th>Fuzzy acquittance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GROUND</td>
</tr>
<tr>
<td></td>
<td>STATIC</td>
</tr>
<tr>
<td></td>
<td>DYNAMIC I</td>
</tr>
<tr>
<td></td>
<td>DYNAMIC II</td>
</tr>
<tr>
<td></td>
<td>DYNAMIC III</td>
</tr>
</tbody>
</table>

**Table 3.7:** Gathering of the extracted characteristics II

*(Human variables)* for provide rational inputs to the fuzzy estimator *(Fuzzy variables).* For each one of these, *Fuzzy ranges & terms* present the associated terms and ranges describing the operator.

<table>
<thead>
<tr>
<th>Class</th>
<th>Obstacle</th>
<th>Variability</th>
<th>Speed</th>
<th>Grounded</th>
<th>Aspect ratio</th>
<th>Size</th>
<th>React.</th>
</tr>
</thead>
<tbody>
<tr>
<td>G</td>
<td>Tree</td>
<td>L/M</td>
<td>Low</td>
<td>Full</td>
<td>L/R</td>
<td>M/B</td>
<td>None</td>
</tr>
<tr>
<td></td>
<td>High vol.</td>
<td>Low</td>
<td>Low</td>
<td>Partial</td>
<td>R/T</td>
<td>X</td>
<td>None</td>
</tr>
<tr>
<td>S</td>
<td>Fleet</td>
<td>X</td>
<td>X</td>
<td>No</td>
<td>L/R</td>
<td>S/M</td>
<td>Good</td>
</tr>
<tr>
<td>DII</td>
<td>Other mUAV</td>
<td>X</td>
<td>X</td>
<td>No</td>
<td>L/R</td>
<td>S/M</td>
<td>None</td>
</tr>
<tr>
<td>DII</td>
<td>Air veh.</td>
<td>L/M</td>
<td>X</td>
<td>No</td>
<td>L/R</td>
<td>X</td>
<td>None</td>
</tr>
<tr>
<td></td>
<td>Balloon, kite..</td>
<td>L/M</td>
<td>Low</td>
<td>No</td>
<td>X</td>
<td>Small</td>
<td>None</td>
</tr>
<tr>
<td>DIII</td>
<td>Bird</td>
<td>X</td>
<td>X</td>
<td>No</td>
<td>X</td>
<td>S/M</td>
<td>N/B</td>
</tr>
</tbody>
</table>

**Table 3.8:** Definition of the potential obstacles’ characteristics and the associated fuzzy rules for their acknowledgement.

The different obstacles are grouped in the five output or fuzzy categories: 'G' stands for GROUND, 'S' for STATIC, 'DII' for DYNAMIC I, 'DII' for DYNAMIC II and 'DIII' for DYNAMIC III. Inside the table, for the parameters *Variability (Variab.)* and *Speed*, 'L' refers to LOW value, 'M' to MEDIUM one, 'H' to HIGH figure; in the variable *Grounded* 'F' represents a FULL value, 'P' a PARTIAL one while 'No' means that it is not grounded at all; for *Aspect ratio (Asp. Ratio))* 'L' represents a LONG aspect ratio, 'R' a REGULAR one and 'T' a TALL value; the alternatives for the *Size* variable are 'S' for small, 'M' for MEDIUM and 'B' for BIG or large sizes; Finally, the *Reactivity* figure is represented by 'G' for the GOOD reactivity, 'N' for NONE reactivity and 'B' for a BAD behaviour. For all the parameters, X denotes any possibility.
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<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.96</td>
<td>0.38</td>
<td>0.67</td>
<td>0.87</td>
<td>0.77</td>
</tr>
<tr>
<td>2</td>
<td>0.94</td>
<td>0.53</td>
<td>0.99</td>
<td>0.82</td>
<td>0.87</td>
</tr>
<tr>
<td>3</td>
<td>0.99</td>
<td>0.19</td>
<td>0.99</td>
<td>0.88</td>
<td>0.94</td>
</tr>
<tr>
<td>4</td>
<td>0.79</td>
<td>0.17</td>
<td>0.79</td>
<td>0.67</td>
<td>0.73</td>
</tr>
<tr>
<td>Mean</td>
<td>0.92</td>
<td>0.32</td>
<td>0.86</td>
<td>0.81</td>
<td>0.82</td>
</tr>
</tbody>
</table>

Table 3.9: Statistical evaluation of the fuzzy acquittance analysis.

RL states for Risk Level; Posit id. refers to the mean percentage of positive identifications, while False pos. to the same ratio of false positives identifications; F conf. refers to the fuzzy confidence value, I conf. to the iterative one and Total conf. to the average between them.

Nevertheless, as can be also observed in column 3, it provides with false positives in many cases (32%). It is due to the similarities among elements and the uncertainty in some of the estimations done. So, a verification system has been required in order to estimate the confidence in the value provided by the FC (cFC): the first metric used is the own confidence figure provided by the fuzzy algorithm. It is a function of the inputs (the more centered the inputs in one of the terms, the greater the confidence; the more ambiguous, the lower its potential reliability). Besides, as a second ratio, it has also been measured the number of changes acquittance (estimated) of the element (the longer the time with the same acquittance, the greater the confidence). The average between both metrics has been used as confidence estimator. The third, forth and last columns of Table 3.9 present the mean values of these variables for each one of the situations. It should be highlighted the higher value of the familiar dynamic elements (DI). It comes from the greater reliability in the communications.

3.4.5 Characterization and behavioural analysis

As presented in section 3.3, according to the latest neurobiology works, characterization is the last stage in the four-stages perception process. It could be understood as the capacity to identify an objects properties (physical or others) and apply semantic attributes to define their entity inside the group they belong to: while the first three ones (i.e. Extraction of characteristics, grouping and recognition with models or descriptions in memory), characterization provides with an element identification: semantic attributes are applied to the representation, providing with entity, meaning and, thereby, understanding (178, 179).

This process is, anyhow, closely related to the identification one, since some of the characteristics are shared: for example, the identification process requires from the variability analysis, that is an intrinsic parameter of the element’s individuality. This,
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<table>
<thead>
<tr>
<th>Original image</th>
<th>Elements recognized</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="Quadrotor flying over grassland" /></td>
<td><img src="image" alt="Quadrotor flying over grassland" /></td>
</tr>
<tr>
<td><img src="image" alt="Plane overflying land" /></td>
<td><img src="image" alt="Plane overflying land" /></td>
</tr>
<tr>
<td><img src="image" alt="Helicopter in hovering over a house" /></td>
<td><img src="image" alt="Helicopter in hovering over a house" /></td>
</tr>
<tr>
<td><img src="image" alt="Tree oscillating" /></td>
<td><img src="image" alt="Tree oscillating" /></td>
</tr>
</tbody>
</table>

#### Table 3.10: Examples of situations analyzed

The real video with the motion analyses information is presented in the left column. Contrarily, the right column presents the results according to the following colour code: Ground is in brown colour, static obstacles in green, predictable moving ones in blue, regular flying elements in red and the most dangerous ones in yellow.
in turn, depends on the $\tau$ measure, composing all of them an interconnected cognitive mesh. Like this, three different aspects can be distinguished regarding to this analysis: Firstly, the one related to the identity of the element to characterize. In this case, as commented above, the physical characteristics standing out the element specific from the rest of the group are looked for. Considering the human mental selectivity described in subsection 3.3.5, area, perimeter, aspect ratio and inertia $^1$ (basing on the image moments as a reflection of weight (180)) have been considered.

The second aspect considered refers to the behaviour of the element in relation with the observer (the drone). This analysis increases the complexity of the system, since involve not only physical properties but also their evolution along the time (i.e. kinematics and dynamics). In this sense, three main metrics have been evaluated: i) the time-to-contact basing on the Lee’s $\tau$ approach; ii) the relative motion among each pair of elements, basing on the optical flow concept (181) and its PyrLK OpenCV implementation (see subsection 3.4.4.1); and iii) the distance estimation, basing on the stereoscopy principle (it was used the projective rectification of the disparity map implemented in the same library).

Finally, the last aspect is the one related to the predictability of the behaviour. Using the data described in the previous, it is possible to estimate the position of the element in the next instant, or even suggest a potential trajectory. Nevertheless, in addition to this calculus (mainly performed during the identification process and in the individualization stage of behavioural analysis), the human brain weights the results of these estimations. As described in subsection 3.3.5, five (plus the number of obstacles) are the main parameters affecting to this balance: weight/load distribution, time to contact ($\tau$), motion, variability and observability. The first two ones have been used and implemented according to the standards used in robotics and computer vision. The last two ones, has been designed and verified from sketch:

3.4.5.1 Load distribution analysis

An image moment describes the distribution of the pixels along the image according to their intensity. It could be assimilated to a certain particular weighted average image pixels’ value, resulting in a good describer of the object (182).

According to the order of the moment, different characteristics can be extracted. Moments of order 0 (spatial or raw moments, $m_{ij}$) are related with the number of active pixels in a B/W image. It could be assimilated to the moment of inertia around the image’s centroid -being the pixels’ intensities analogous to physical density- and contains information about the area and the centroid of the polygon. Sequentially, $^1$Inertia provides visual center of gravity (COG) or orientation. It is evaluated considering statistical regularities of the pixels.
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moments of order 1 (central moments, \(\mu_{ij}\)) are translation invariant and provide information about the image orientation. 3\(^{rd}\) order moments (central normalized or scale invariant moments, \(\nu_{ij}\)) can be constructed to be invariant to both translation and size changes by dividing the corresponding central moment. Finally, Hu added the rotation invariance to the set of moments. The last one (\(I_7\)) is skew invariant, which enables it to distinguish mirror images of otherwise identical images (183). These moments have been combine since they are translation invariant, scale invariant and even rotation invariant.

![a) Tree swinging](image1)

![b) Kite moving smoothly](image2)

![c) Helicopter accelerating](image3)

**Figure 3.8:** Moment analysis.

The blue points corresponds to the moment calculated. The black ones to the CoG.

The results obtained are presented in Figure 3.8. As it can me appreciated, the relative movement of the elements increases from subfigure a) up to subfigure c): from motionlessness to an accelerated movement, through an smooth movement in subfigure
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b). Likewise, the distance between de moment extracted (depicted with a blue point in the left images) and the element’s CoG (depicted with a black point) has been reduced. This relationship matches with the research of Liao (184), supposing a good as stated a good image descriptor.

3.4.5.2 Time to contact

According to the $\tau$-hypothesis described in section 3.3.5, the blobs extracted from the images have been analyzed using the Tau’s ecological approach. The messages defining the obstacles contains -apart from location, area, maximums and minimums- the temporal evolution of the obstacle. It includes not only the instantaneous $\tau$ but also the accumulated one. In both cases, as is depicted in Figure 3.9, positive values of $\tau$ implies a relative approximations while negative $\tau$s a distancing between the obstacle and the observer. Null value indicates a maintenance in the distance.

a) Element is increasing. $\tau$ positive
b) Element is decreasing. $\tau$ negative
c) Element keeps its area. $\tau$ null

Figure 3.9: Time to contact analysis: $\tau$ hypothesis.

The white rectangle corresponds to the first frame, the black one to the second image.

Also the transverse displacement has been included in the analysis, considering the projection of the obstacle together with the size variation. The movement considered has its origin in the Center of Gravity (CoG) of the element. It has been calculated by using a 3$^{rd}$ order moments (see the previous subsection), that provides the mass center. The results obtained along 12 different scenarios have validated the $\tau$ approach, what has been normalized.

3.4.5.3 Variability analysis

According to the Ecological Theory, presented in subsection 3.3.5, the behavioral variability of the elements has a great impact of the perception humans get from them. The first connection comes from the volubility-predictability relationship: the greater the stability of an object, the bigger the stability of perception and the capacity to predict/estimate the future behaviour (145). However, variability is not only related to the stability of perception and the capacity to estimate the future: Miles Shuman
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also proved that there is a direct relation between the variability of the objects and
the numerosity of elements perceived (146). It means, in numerical cognition, that the
representation level of a voluble obstacle is bigger than the one of an static object.

Both reasons have impelled to analyze the behavioral variability of the elements in
the scene. Besides, its relation with the environment has been discussed: it has been
considered that the element’s mood is represented by the object’s fickleness or volubility
in terms of motion and displacement. These parameters-one for the spatial variability
and another for the dimensional fickleness- are a key factor in the risk estimation, since
they provides a good factor to evaluate the reliability of the estimation.

On the one hand, the spatial variability has focused on the evaluating the perfor-
mance of the objects in relation with their trajectories. i.e. if they follow smooth paths
or whether, on the contrary, they move and/or turn abruptly. On the other hand,
the dimensional volubility considers relevant changes in the speed/acceleration on the
approximation vector: as no reliable distance estimation is available, the measure is
performed over the vector that joins the obstacle and the own drone. It implies that
these changes are represented on the \( \tau \) parameter.

The following equations present the way to evaluate both volubilities. They follow,
respectively, the laws described in the Ecological Theory. Thus, they are both based
on the \( \tau \) parameter, standing \( \varepsilon \) for the displacement of the CoG between frames and \( n \)
for the interval considered:

\[
Variability_{Spatial} = VS = \left( \frac{\sum_{j=0}^{n} | displX_{j}^{j+1} + displY_{j}^{j+1} |}{\sum_{j=0}^{n} displX_{j}^{j+1} + displY_{j}^{j+1}} \right)^2 \tag{3.2}
\]

\[
Variability_{Dimensional} =VD = \frac{\sum_{i=0}^{n} | \tau_{i+1} - \tau_{i} |}{\sum_{i=0}^{n} \tau_{i+1} - \tau_{i+1}} \tag{3.3}
\]

Several tests have been done in order to validate these approach and to determine
the number of samples to consider, the regression time and the threshold values. In this
sense, different movements and configurations were tested, as well as different periods,
motion ranges and movements speeds: Figure 3.10 presents the results obtained applying
this equations in a simulation environment: Every 30 seconds, the state changed
from static to dynamic, increasing the variability level (Low, medium and high spatial
variability, and low, medium and high dimensional variability, respectively). The red
line in the first subplot represents the spatial stimulii measured, while the green line
represents the three levels interpreted. Oppositely, the blue line represents the dimen-
sional variability. As can be observed, the first of the factors is completely independent,
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while the dimensional variability is activated in both cases. It is due to the inherent changes in the position due to the binocular vision. In order to correct this, an XOR function has been implemented in order to identify both cases independently. Its result is implemented in the last subchart, following the same colour pattern. As can be observed, it presents an outstanding performance, that includes a 2s maximum delay on the response and a 89% of accuracy in the detection.

Figure 3.10: Results of the variability analysis.
In all the charts, red represents the spatial variability, blue the dimensional variability and green, the activation levels.

3.4.5.4 Visibility analysis

Visibility is a measure of the distance at which an element can be clearly discerned. It can be also understood as a measure of the distinction of an object from the surrounding environment (185). Furthermore, as several studies have shown, it is also a factor that affects the attention selectivity and the perceptual load (186). It implies that the object’s visibility plays an important role in how the attention is focused into the object, and thus, how its risk is perceived. Even more, the marketing studies and techniques have also stated that the visibility is not only related with the attention, but also the memorization: low visibility elements are harder to remember, and thus the familiarization with them is slower (187). Due to all of this, visibility has always played an important role in the risk evaluation: many international flight procedures
have special sections or amendments regarding to low visibility situations (188). Nevertheless, nowadays there are no autonomous visual system or techniques to estimate the visibility of an scene and its elements.

Visual salience (also called visual saliency) is the (subjective) perceptual quality by which some elements are stood out from their neighbors: being possible to apply the salience concept to almost any sensory systems, in the visual experience, saliency typically arises from contrasts between the elements and their neighborhoods. Thus, it can be consider a method to distinguish objects in the environment (189, 190). Thus, along this thesis, the visual salience value has been understood as a measure of the visibility of the element: the lower the saliency is, the higher the difficulty to distinguish the object from the rest of the image.

![Figure 3.11: Analysis of the visual saliency according to the contrast](image)

In order to evaluate its performance, a set of experiments (both objective and subjective) have been run: Firstly, objective levels of contrast have been ranked using the saliency method. Figure 3.11 presents this assesment: in the left, Figure 3.11 a), presents four elements with 100%, 75%, 50% and 25% contrast, respectively (top-bottom, left-right). Oppositely, the figure in the right (Figure 3.11 b)) illustrates how those elements are understood in terms of saliency. As it is possible to appreciate, the borders are the most significant parts since they present the greater differences. At a naked eye, it is easily appreciable that the 100% contrast element (top left) is more
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distinguishable than the 25% (bottom right). Mathematically, the ratio among the sum of the values of the pixels and the area covered also points clearly enough the visibility value. Table 3.11, presents these analyzed values, where both the mean of the sum and the sum of the means have been considered. The result considered is the sum of both values (Forth column).

<table>
<thead>
<tr>
<th>Subj. evaluation</th>
<th>Mean</th>
<th>Sum</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>100%</td>
<td>0.49</td>
<td>0.59</td>
<td>1.08 (H)</td>
</tr>
<tr>
<td>75%</td>
<td>0.20</td>
<td>0.42</td>
<td>0.62 (M)</td>
</tr>
<tr>
<td>50%</td>
<td>0.14</td>
<td>0.19</td>
<td>0.33 (L)</td>
</tr>
<tr>
<td>25%</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05 (L)</td>
</tr>
</tbody>
</table>

Table 3.11: Visibility measure basing on the visual salience value.

<table>
<thead>
<tr>
<th>Subj. evaluation</th>
<th>Mean (Max/Min)</th>
<th>Sum (Max/Min)</th>
<th>Total</th>
<th>Normalized</th>
</tr>
</thead>
<tbody>
<tr>
<td>High</td>
<td>0.58 (0.82/0.22)</td>
<td>0.62 (0.84/0.43)</td>
<td>1.21</td>
<td>0.88</td>
</tr>
<tr>
<td>Medium-High</td>
<td>0.31</td>
<td>0.33</td>
<td>0.64</td>
<td>0.46</td>
</tr>
<tr>
<td>Medium</td>
<td>0.18 (0.19/0.17)</td>
<td>0.19 (0.22/0.17)</td>
<td>0.37</td>
<td>0.26</td>
</tr>
<tr>
<td>Low-Medium</td>
<td>0.09(0.10/0.09)</td>
<td>0.08(0.09/0.07)</td>
<td>0.17</td>
<td>0.12</td>
</tr>
</tbody>
</table>

Table 3.12: Visibility measure basing on the visual salience value.

On the other hand, a subjective experiment has been conducted in order to evaluate the correspondence of the visual saliency with the human perception: a group of people (6 persons, 4 males and 2 females; mean age 25 ± 3 years SD) have been asked to rate, in fuzzy terms (low, medium or high visibility), the visibility of the elements in the scenarios proposed in Table 3.10. Their responses have been correlated with a normalized measure of the salience value, defining a linear regression with a 0.6 slope. It implies a [0-20] range for the low-visibility normalized salience value, [21-50] for the medium one and [51-100] for high salience figure. It verifies that Weber-Fechner Law, that states a logarithmic relationship between physical luminance and subjectively perceived brightness (191).

Finally, Figure 3.12 presents two situations where the observability has been analyzed. In this sense, column b) shows the visual salience map of the scene in column. As it is possible to appreciate, the elements detected are clearly highlighted in opposition to the background. Besides, it is also noticeable that, while in the first scene (top one), both elements have the same visibility level, in the second one the buildings...
3. RISK PERCEPTION

are more clear than the helicopter. As it is possible to observe in column b), it has its equivalence in terms of observability/saliency, were the gray level reflexes this fact.

![Figure 3.12: Observability analysis of two different situations.](image)

3.5 Discussion

The human brain is probably the most efficient, complex and fruitful system known. It continuously evaluates thousands of facets, providing with extremely accurate interpretations of everything surrounding us. A great percentage of these results comes from the visual sense, playing the HSV a fundamental role in almost every aspect related to identification, recognition and understanding (Visual processing involves almost 1/3 of the cerebral regions, what provides with an idea of the visual sense relevance).

The work done regarding risk perception has focused on this guide, aiming to reproduce this workflow in order to evaluate its applicability and impact. Thus, the HSV has been studied from the processing point of view. Its workflow has been analyzed
### 3.5 Discussion

<table>
<thead>
<tr>
<th>Stage</th>
<th>Brain process</th>
<th>Image processing task</th>
</tr>
</thead>
<tbody>
<tr>
<td>Detection</td>
<td>Fixation and point identification</td>
<td>Filtering (colour, noise)</td>
</tr>
<tr>
<td></td>
<td>Attention focus</td>
<td>Segmentation (fixed + context adaptive)</td>
</tr>
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<td></td>
<td>Shape interpretation</td>
<td>Blobbing (morphological based)</td>
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<tr>
<td>Clustering</td>
<td>Associative process (Gestalt)</td>
<td>Contiguity, proximity and similarity iterative union</td>
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<td></td>
<td>Interaction among stimuli</td>
<td></td>
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<tr>
<td>Identification</td>
<td>Element-model correspondence: intrinsic (pattern-based) and extrinsic (colour, motion, etc.)</td>
<td>Tracking: Features analysis (SURF, SIFT) or characteristic analysis (luminance, motion, prediction)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Recognition (model definition and identification)</td>
</tr>
<tr>
<td>Characterization</td>
<td>Semantic attributes: Identity, character (behaviour) and predictability</td>
<td>Identity (area, aspect ratio, inertia, shape)</td>
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<td></td>
<td></td>
<td>Relationship (Distance, TTC, relative movement)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Predictability (Num. of elements, variability, observability, prediction,)</td>
</tr>
</tbody>
</table>

**Table 3.13:** Relationship among the HSV mental processes and the image processing functions used to reproduce them.

and its variables found out. Image processing algorithms have been related to the mental processes, establishing a correspondence among them (see Table 3.13): Well-known methods have been employed (e.g. optical flow, adaptive segmentation) to replicate the brain processes when possible. When there have been no techniques available, others have been reinterpreted (e.g. saliency as a visual measure) or designed (e.g. variability or fuzzy acquaintance), providing with a modular-but-complete image processing system.

The output of this bioinspired module is similar to the inputs provided to the limbic system (thalamus, hippocampus, amygdala, prefrontal lobe, etc.), making possible a brain-like cognitive analysis (focusing on the implications).

Finally, the performance of the system has been analyzed and compared by using the scenarios proposed in Table 3.10. The average processing time oscillates between $5 \cdot 10^4$ and $2 \cdot 10^5$ CPU clock ticks (50ms and 200ms in a common computer, or 17 to 5 images per second), depending on the image size and the number of obstacles to be analyzed. It is lined up with the brain’s processing time (as said in section 3.3, around 300ms).
“When all actions are mathematically calculated, they also take on a stupid quality."
— Theodor W. Adorno. *Minima moralia*

“The world is its own best model and there is no need for internal representations. The robots behaviors should directly connect perception to action, and cognition will emerge”
— Rodney A. Brooks.
Chapter 4

Risk cognition

4.1 Introduction

Risk assessment is the second step in the risk analysis management procedure. It implies the determination of both quantitative or qualitative value of risk in a given situation with a specific hazard or hazards (also called threats).

How is the risk value determined? Traditional approaches start from a static evaluation and study of the scenario. The candidate elements to be present in the scene (i.e. birds and trees in an outdoor location; persons and walls in an indoor one) and the potential hazardous events (e.g. wind, propeller breakage or GPS signal lost) are studied and considered as factors of an equation: the potential damage, the probability of failure and the own capabilities are estimated before taking off, providing a fixed value for the risk of the mission. The presence of obstacles, the setbacks or misfortunes are managed statistically, assigning numerical values to their respective probabilities. This open-loop procedure provides -as in any engineering process- a poor and conservative way to manage the risks and dangers which is effective in most cases but very unadaptive and inflexible. Even worse considering that all these approaches treat the obstacles as a mere no-go zone or vector.

As the motivation of this Thesis describes (see 1.1), the goal of this work is overcoming these static approaches. The challenge is to evaluate the risks as a human being would do. Move from an “obstacle detection” paradigm to a “risk cognition” framework. It implies not only detecting the risks and extracting their characteristics, but understanding what they imply for the safety of the mission.

In this sense, this chapter presents the study undergone to figure out which are the parameters and variables the human mind considers when evaluating a risk. Psychological guidelines, sociological prejudices, anthropological restrictions and innate mindsets
squeeze, modify, twist and mix the characteristics extracted by the perception module. All these factors are intermingled in the cognitive assessment, making it really difficult to isolate the variables and extract independent factors. Only a deep study of the related bibliography made possible the segmentation and independization of the factors. Their isolation, extraction and porting (to variables a computer would be able to understand and process) could be considered one of the main contributions of the Thesis. However, identifying them is not enough for assessing the risk. It is necessary to evaluate their individual relevance in the global risk evaluation. So, a perceptual experiment was carried out to evaluate the weight of each one of these variables in the global assessment. “How powerful is the familiarity feeling?”, “how do we estimate unknown elements?” were -among others- questions answered in this process. It allowed to properly combine all the factors in order to provide a unique and univocal risk value for the elements in the scenario.

4.2 Formal risk assessment

As mentioned above, risk has been traditionally defined in terms of probability, statistics and figures. In fact, according to Lowrance (192) -the most popular definition-, risk is a measure of the probability and severity of adverse effects. In other words, the combination of probability of an event and its consequences, as ISO 2002 defines (193).

In this sense, once the candidate risks sources (see subsections 2.4.1 and 2.4.2) and their nature have been identified, risk assessment (RK) had always implied to estimate the seriousness and severity of their effects. So, according to the risk definition and to ISO 31010:2009, ISO 14121-1:2007 and ISO 12100:2010 -and also to most of the risk evaluation methods (194, 195)-, hazard assessment has always been defined as a function of two factors: the first one refers to the severity of the damage, which evaluates in a fuzzy way the resultant harm from an hypothetical incident (the magnitude of the potential loss, mL). The second factor defines the probability of occurrence (pL), which is mainly determined by the frequency of exposition to the risks. The relationship between these factors determine the risk level of the component.

Furthermore, a third parameter is usually considered in the legislation: the capability to avoid, prevent or limit the damage has to be considered as an attenuating characteristic (apL). All these factors are described in the following subsections. The global risk model results from the integration of the individual risk estimates provided by each of these parameters.

4.2.1 Seriousness of damage

The seriousness of the damage (SoD) evaluates the harm that could result from an accident. Potential damage is a key factor to estimate the risk associated to a com-
ponent, by defining the importance of the processes where the damage has its origins. The seriousness rate is composed by two factors: Firstly, the severity of the injuries or the damage to health. This aspect is usually assessed in a fuzzy way, according not to the percentage of destruction, but also to the evaluation of the impact/importance in the system. The international regulation only contemplates reversible and irreversible damages (196).

The second factor -which it is not considered in the actual legislation but that has been proposed in many classification systems-, relates to the number and affiliation of the agents involved in the event. There should be a distinction between critical and non-critical components, as well as if people or third-party elements have been affected. In this sense, the classification may consider i) components of the unit, ii) the unit itself, iii) the payload (in case it exists), iv) external infrastructures or objects, v) the operator (the pilot or anyone involved in the UAV operation) and vi) external people, as the different elements in the scale.

4.2.2 Probability of damage

Probability of damage (PoD) estimates the frequency of occurrence of a hazardous event (those which imply a risk for the drone or the performance of the mission). Also named “incident rate”, it is a function of the system use, with its value resulting from the composition of two factors (196, 197):

- Exposition to the danger: It evaluates the quantity of risk the systems have been exposed to. To define this ratio, the following issues should be taken into account: i) the exposition time (mean period T of exposition every time it is exposed), ii) the number of agents exposed and the kind of exposition (e.g. manual or not, normal operation or emergency mode), and iii) the frequency of exposition, meaning the time exposed to the risk over the total time of operation (e.g. to the collisions risk, total time when the system is close to another object, over the total flight time).

- Probability of occurrence of a hazardous event: The frequency of incidents in the components could be experimentally determined or/and provided by the manufacturers. The event rate has to be determined by means of statistics and history: statistical reliability, accident history and similarities with other systems. It is also applicable to the event rate derived from human intervention.

4.2.3 Ability to prevent or limit the harm

The probability of damage occurrence depends on the capability to avoid a hazardous situation. Likewise, the severity of the damage is balanced by the possibility of limiting
4. RISK COGNITION

or reducing the harm in case of accident. Thus, the ability to prevent or limit the
damage (APD) is an operator that modifies the parameters presented above (198).

Regarding the capability to avoid the risk, the existence of warnings (e.g. horns,
lights), availability avoidance maneuvers and skills of the control system (both human
or autonomous: reflexes, qualification/experience or agility, on the one hand; response
speed, observability or redundancy, on the other) have to be taken into account.

Halfway between SoD and PoD, the dynamic of the system affects both the prob-
bability of damage and the severity of the potential harm: scenarios where the speed is
high (in any of the elements), clearly increase the potential harm. On the other hand,
systems where the reactiveness level is small suffer from a higher probability of accident
(198).

Finally, referring to the damage limitation, the presence of guards and safety sys-
tems should be considered. In both sides, passive methods effectively limit the potential
damage: parachutes, gliding structures or airbag-like mechanisms, -from the side of the
drone-; absorptive materials, protective nets or dead-man switches, from the external
perspective.

4.2.4 Risk assessment result

According to the regulations mentioned, the three factors described above are used to
provide a general evaluation of the risk. As depicted in Figure 4.1, these factors are
combined using the Kinney method (199, 200) in order to obtain the Performance Level
(PL) metric. PL is employed to manage the assessed hazard and refers to the general
reliability required by the component/system in order to operate under safe conditions
(i.e. probability of a dangerous failure per hour). This metric considers both quantity
(e.g. measurements of reliability, ability to resist failures, etc.) and quality aspects (i.e.
the system’s performance upon failure conditions, failure monitoring, and safety related to
software implementations.

As it is presented in section 5.2, PL is used to determine the level (category) of
avoidance requirements needed to guarantee a safe operation. Nevertheless, since it
is based on a priori (static) knowledge, it is not flexible to adapt itself to a chang-
ing environment. Furthermore, it does not take into account really important facts
(probably because they are hard to quantify): the mood of the pilot, the probability of
gusty winds or the potential bird behaviour which are key factors when analyzing the
likelihood of an accident.

The relevance of these factors can be only assessed performing an analysis that
involves the human comprehension and its relationship with the environment. Thus,
the following section (4.3) presents the study performed towards evaluating the human
cognitive process, in order to apply its underlying principles to risk assessment.
4.3 Fundamentals of human risk cognition

The term cognition stems from the Latin word cognoscere that refers to the knowing action. Thus, cognition can be defined as the capacity of the mind to acquire, process and use knowledge (201). It embraces most of the mental processes - attention, memory, planning, learning, understanding, reasoning and decision making - and has remained a pending issue for centuries: Plato and Aristotle already tried to explain the nature of human knowledge in ancient Greece. And, although their philosophical view remained as the valid one for a long time, experimental sciences provided better approaches in the XIX century: Wilhelm Wundt started studying mental operations systematically from a psychological point of view, while the anthropological behavioristic theory defined an observable relationship between stimuli and behavioral responses. On the other side, computing science started to trying to reproduce the human mind - the Dartmouth Conference in 1956 the seminal event for Artificial Intelligence (AI) as a field -1. Nevertheless, Howard Gardner was the first one to define cognitive science as a unified theory, involving philosophy, psychology, AI, Neuroscience, anthropology, etc., interlacing each field with the rest (see Figure 4.2). Considered the “father of cognition”, his proposal especially focuses on how information is represented, processed, and transformed, both in human (nervous) and computing systems (202, 203).

1Stanford Encyclopedia of Philosophy
Discarding linguistics (not applicable in this scope) and AI (to be considered in the following stages), the rest of the fields have been taken into account in relation to risks evaluation\(^{(204)}\). They have been factorized according to Renn’s taxonomy\(^{(205)}\): psychology and neuroscience have been combined since they both focus on mental processes. On the other hand, considering that both anthropology and philosophy focus on the relationships between people or environments, both approaches have also been joined:

### 4.3.1 Socio-Anthropological approach

The anthropology and social approaches posit that risk perceptions are socially constructed by institutions, cultural values, and ways of life. As Weistein said in 1989, Perception of risk goes beyond the individual, and it is a social and cultural construct reflecting values, symbols, history, and ideology. In this sense, the try to analyze the interactions among persons, or the relationship among persons and the environment the live in \(^{(206)}\).

Different theories try to evaluate how these interactions are performed regarding to risky situations or events:

#### 4.3.1.1 The Cultural Theory of Risk

Culture refers to the human capacity to classify, encode these experiences symbolically and teach such abstractions to others. This capacity is learnt thought a enculturation
process, where the person acquires values and behaviours that are appropriate, common or necessary in his environment. The influences which limit, direct or shape the individual (whether deliberately or not) include parents, other adults and peers, which in turn where compelled and induced by an older generation to reproduce their way of life. It results in an endogamic process, where the fears, doubts and interpretations are similar for all the persons in a concrete society.

The Cultural Theory of Risk (CTR) has it origin in this idea, being the result of the work of anthropologist Mary Douglas and political scientist Aaron Wildavsky (207). They asserted that, as far as Culture is embedded in the persons, the individual risk perceptions should be also balanced by the social aspects and cultural adherence. They analyzed how people perceive and act upon the world around them, trying to “predict and explain what kind of people will perceive which potential hazards to be how dangerous (208).

CTR bases on three assertions that Douglas defined in her previous work: The first one refers to the social function of individual perceptions of societal dangers. She stated that individuals associate societal harms -from natural catastrophes to individual disasters- with behaviours that transgresses societal rules. It allows to maintain the social structures and eliminate subversive behaviors.

The second assumption of cultural theory is that natural systems are full of surprises and uncertainties, so are unpredictable. In this sense, CTR makes no attempt to account for differences in individual perceptions of nature.

Finally, the last aspect of Douglass work is the characterization she did of the cultural ways of life and affiliated outlooks. She proposed two dimensions, called “group” and “grid”. The first one refers to the dispersion of control and to the inclusion of the individuals into a collective, where a high group way of life exhibits a high degree of collective control, whereas a low group one emphasized on individual self-sufficiency. The “grid” dimension refers to what degree a social context is regulated and evaluates the stratification in roles and authority: A high grid way of life is characterized by a well-defined hierarchy, whereas a low grid one reflects a more egalitarian ordering (209).

The integration of these two strands of her thought resulted in a conceptual framework and a body of empirical studies that formed their a theory of risk perception. Woven together, both strands defined a set of certain social relations: The combination among societal hierarchisation (i.e. individual’s voluntariness), the personal autonomy (i.e. degree of control) defines four worldviews or attitudes towards the world: These were named Individualistic (low group and grid cultures), Egalitarian (High group and low grid), Hierarchical (High group and high grid), and Fatalistic (Low group and high grid). All these attitudes have a self-preserving pattern of risk perceptions and perceive things that endanger their own way of life as risky.
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Individualists fear events or elements that might obstruct their individual freedom, while Egalitarians fear development that may increase the inequalities among people. They see the nature as fragile and vulnerable and tend to be alert about situations that might change the state of nature and will provoke a collective damage. Oppositely, hierarchical cultures emphasize the natural order of the society and the perseverance of this order. They fear everything that could alter this situation. Hierarchists have a great deal of faith in expert knowledge, and they accept imposed risk or risky situations if they are justified. Finally, Fatalists take little part in social life and usually are indifferent about risk, being their fears most of the times decided by others. The fatalists do not care about dangers since they assumed that they are not able to avoid them. (210).

4.3.1.2 Cultural cognition

The Cultural Cognition of Risk theory -also known simply as Cultural Cognition (CC)- is the result of the Dan M. Kahan’s work: Basing on the PP’s states of mind and the CTR’s individual values, Kahan employed experimental methods to understand how values shape behaviours over facts (211).

He and his team used general surveys to establish the connection between individuals values and beliefs regarding to risk (212). His experiments suggested that empirical data is usually not the key factor when taking a decision or when asserting a menace. On the contrary, individuals selectively credit or dismiss information in a manner that reinforces their values (which are defined by their societal experience, as CTR stated (213)): for example, the experiment focuses on that the immigration/crime or contamination/climatic change relations. The results proved that the people established the relation between both factors depending on their (societal) prejudices instead of basing on empirical data. Thus, CP experimental data stated that individuals form risk perceptions according with their self-defining values.

Likewise, these values exert a greater influence over risk perceptions than does any other individual characteristic (i.e. race, economic status, religion, gender, or political ideology). It implies that the risk knowledge has a mild relevance when evaluating it. On the contrary, the feelings evoked and the class acquittance defined by the self-defining values totally balance the risk perceived.

Besides, people tend to align themselves with individuals that hold similar values (214). So, as in the case of Cognitive Dissonance (see subsection 5.3.3), hazards in conflict with one’s understanding are perceived as much dangerous that those ones that can be perfectly aligned.
### 4.3 Fundamentals of human risk cognition

#### 4.3.1.3 The Social Amplification of Risk (SARF)

In 1986, R.Kasperson, O.Renn and P.Slovic tried to provide a solution for one of the most perplexing problems in risk analysis: why relatively minor risks result many times in strong impacts on individuals’ perception while hazardous events are many times unnoticed? They stated that the fragmented nature of risk perception makes necessary to combine psychology, sociology, anthropology and communications in order to obtain a global explanation. After several cross-field experiments where analytically compared the responses from different groups when facing the same event, they surmised that the mechanism altering the perception is the communication itself (2). Locating the focus on the transmission process, they proposed a framework that explains how the risk perception is transmitted and how it is altered in this process: named Social Amplification of Risk Framework (SARF), it outlines a risk communication where danger estimation pass from the sender to a receiver through different means and relays.

Figure 4.3 depicts the SARF layout (215). According to the theory, there are four different stages in the communication process, being each one of the intermediate stations a filter that amplifies or attenuates the risk perception. Thus, the raw risk characteristics are firstly amplified or attenuated by individuals, groups, media, etc. (i.e. personal experiences, leader’s opinion, media coverage or pre-existing trust in institutions, for example). This amplification/attenuation is basically defined by the nature of the risk (the degree of control over it), the attention it attracts (attenuated over the time) and the impact it has in the individual’s life (i.e. weather it is imposed or not) (3, 216).

The third filter is known as the “ripple effects”. It refers to the variations provoked in the people’s behaviours in response to the risk. The alteration of routines or decisions in order to reduce the risk exposure modifies, in turn, the societal perception. This interaction reinforces the estimation, generating secondary social impacts, increasing/decreasing the perceived risk as well. Besides, the ripple effects caused by this modification implies enduring mental perceptions, what changes in the familiarity degree. Furthermore, these secondary changes are perceived by individuals and groups, resulting in third-order impacts, that may ripple to other factors.

Finally, in the last stage both the real and virtual impact of the risk are analyzed: The consequences of the perceived risk (e.g. financial losses, loss of confidence in institutions, deaths or injuries, etc.) result in another modification of the perception. Thus, the distortion of risk signals provides with a corrective mechanism by which society assesses a fuller determination of the risk and its impacts to such things not traditionally factored into a risk analysis.
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4.3.1.4 Situated cognition

Situated Cognition (SC) is a sociological theory that explains the nature of culture and knowledge. Firstly proposed by J.S. Brown, it posits that knowledge is inseparable from the action (217): since all knowledge is situated in activity bound to social, cultural and physical events, people need to learn in context because knowledge acquisition and action cannot occur separately.

Thus, according to SC, cultural cognition is defined through situational learning: Knowledge does not come from the accumulation (and retrieval) of concepts but from the maximization of situations experienced. Like this, each one of the situations establish a bond so that knowledge is understood as the individual’s effective performance across situations (218). Being learning the increment of this performance, the repetition of the stimuli is necessary until the knowledge is settled. After that, the learning process gets swamped and the perception stabilized. So, SC encourages a balance between the familiarity and the maximization of structural diversity.

Applying this view to the risk perception, SC addresses the question of why something is or is not defined as a risk (219). In this regard, it states people perceive something as a risk when they establish a relationship so that the risk element is considered -in some way and under some specific circumstances- to threaten the value attached to the object at risk (in general, the health or integrity) (220). Thus, it can be understood that risk perception comes from learning in dangerous situations: The

![Figure 4.3](image_url)

**Figure 4.3:** Risk estimation transmission according to SARF (2, 3).
The numbers on the ripple effects correspond to: 1- individuals involved/affected; 2- Local community/company; 3- Industry/Groups; 4- Society
knowledge acquired in risky situations is the one defining the perception when a similar one emerges.

4.3.2 Neuropsychological approach

Neuropsychological theories rely on comprehension about how the information is processed and knowledge acquired. This interest is as old as the human being. The first news from its addressment date from the IV century B.C., when Plato suggested that the brain was the seat of the mental processes. Along the centuries, other philosophers and scientists continued with this thought - John Locke, Immanuel Kant, Rene Descartes or Santiago Ramon y Cajal, among others-, opening the way to the modern neuropsychology (221).

Different theories have tried to evaluate how the data is sorted out and how the relationships are established: Earlier works maintained a behaviouristic approach, focusing only on observable behaviours. Nevertheless, through the years, neuropsychology has evolved towards the study of mental representations or states, basing on cognitive relationships. According to Kahneman, these bonds can be split in two different levels: intuition and reason (222). In this sense, while reasoning provides with analytical results based on logic, intuition establishes fast relationships resulting from deep unconscious mechanisms. Risks are mainly evaluated in this level, emerging from the combination of numerous abstract factors (e.g. includes dreads, newness, stigmas, etc.) (205, 223).

This section presents the study of the main neuropsychological theories related to risk perception. In this sense, it has been analyzed the different approaches defining the processes and factors involved in the individual’s risk comprehension.

4.3.2.1 Cognitive Psychology

In general, it could be said that psychology bases on the comprehension about how the information is processed. Assuming this, Cognitive Psychology (CP) is the branch of the psychology that studies the mental processes involved in the knowledge acquisition: attention, memory, perception and thinking.

Initially proposed by Ulric Neisser in 1967, it is understood as a whole in the knowledge act (133). By using the scientific method, he tried to define how people understand the World, focusing how the information is processed, stored and used later. In this sense, it embraces all the processes involved in the information transformation to result in knowledge: i.e. how human storage, recovery, recognition, comprehension and organization are combined in such a way that the result in concrete internal mental states.
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Furthermore, CP also focuses in how the cognition leads into acts (understanding that “action” is the results of thinking, and from instinct, necessity or arousal). In this sense, it was experimentally proved that human beings tend to choose the course of action that produces the largest expected information gain (224) (understanding that “action” is the results of thinking, instinct, necessity or arousal). Thus, human planning and aims definition are the result of an utility function that tries to maximize the level of welfare by incrementing the quantity of information (225). It establishes a direct connection between the closeness of the stimuli and the power of the interaction: for example, people express a greater concern for problems which have an immediate effect (lots of immediate information) than for long-term problems because the attention-memory-processing bond is stronger. For the same reason, people is less concerned about events in remote areas of the World than events in their surroundings (226).

In the same line, Noll (225) also posits

4.3.2.2 Representational/Computational Theory of Mind

The Computational Theory of Mind (CTM) is the philosophical/sociological that describes the human mind as an information processing system. It was firstly stated by Hilary Putnam in 1961, when she proposed the human brain as a cognitive form of computing (227).

According to her view, the brain is a computer and the mind is the program (a set of sequential processes) that the brain runs. Besides, as in a computer, the reasoning is an algorithm that process the inputs to provide with an output. Being an algorithm a step-by-step set of instructions, the same inputs always result in the same output. It implies that when a situation has been already experienced, similar situations are expected to result in a similar answer, in a kind of familiarity remark.

Besides, being a computational system, it should be noted that it is not possible to interpret an actual object: CTM requires both the inputs and the outputs (and even the internal variables) to be defined as symbols or representations of the reality (the form of the input, and not what it means). The representations -the elements computed- have to be deterministic (non-random) and formal (non-semantic) way. It implies that should be the representation of the reality (the models) and not reality itself the one analyzed. It leaded in to the Representational Theory of Mind (RTM).

The RTM, developed by Jerry A. Fodor (Putnam’s student), continues with the idea of a mind structured basing on mental representations of the reality. Nevertheless, RTM do no establish a sequential relation among inputs and outputs. Contrarily, it propose an interrelation system, where beliefs, desires, perceptions and thoughts are states used to link different representations (228). These mental states have intentionality -they refer to things, and may be evaluated with respect to properties-. This characteristic implies, in terms of thinking and reasoning, that the mental processes are understood as
4.3 Fundamentals of human risk cognition

a sequence of intentional mental states that divert from one representation into others. For example, in the case of a war, the mental representation of war (the propositional content) involves the desire/opposition to it, the fear to what it implies, etc. (i.e. several relations to the same mental representation). It may lead to representations of guns, demonstrations or dead, since they are connected by the same states (229).

It means the relationship among concepts (representation) is defined according to the feelings (mental states) they brought to the mind. The greater number of mental states shared, the greater chance to connect one representation with the other. It may result in attenuated/exaggerated risk perceptions due to states shared among the representations of the objects, even if the real objects do not share it: for example, an stone will be probably evaluated as more dangerous than a tree because it shares more states with dangerous items (strength, nature, etc.)

4.3.2.3 Heuristic psychology: Intuitive judgment

Many decisions are based on suppositions concerning the likelihood of uncertain events. Individuals’ beliefs assess the probability of these. The research of the psychologists Daniel Kahneman and Amos Tversky (230, 231) focused on assess how lay people evaluate probabilities. They performed a series of gambling experiments, finding that that people use a number of heuristics to evaluate information. They also found that people rely on a limited number of heuristic principles which reduce the complex tasks of assessing probabilities and predicting values to simpler judgmental operations: a bounded rationality perspective (232).

They extracted the three main heuristics employed to estimate probabilities and to predict behaviours: Representativeness, availability and adjustment and anchoring. Nevertheless, despite of these heuristics are usually used as “shortcuts for thinking”, they may lead to inaccurate judgments and systematic assessment errors. In this case, they become cognitive biases:

- **Availability**: The ease with which relevant instances or occurrences can be brought to mind clearly defines the judgment: the decision making process relies upon knowledge that is readily available -i.e. retrievability of instances- rather than examine other alternatives or procedures.

Conducted experiments proofed that instances of large classes are remembered better and quicker than instances of less common classes. Also that likely occurrences are easier to imagine than unlikely ones, and that associate connections are strengthened when two event repeatedly co-occur. Thus, the estimation of the size of a class, the likelihood of an event, or the regularity of co-occurrences is performed by evaluating how easy is to carried out retrieval, construction, or association the mental operation (233). Furthermore, the knowledge of consequences
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associated with an action is directly connected to perceptions of the magnitude of the consequences of that event. In other words, the easier it is to recall the consequences of something, the greater the perception of these consequences will be (234).

- **Adjustment and anchoring**: When an uncertain event arises, people evaluate it starting from an initial estimation or supposition. This piece of information (often extracted from a group classification) provides a starting point to evolve to yield the final answer, in a kind of adjustment approach.

  This behaviour has its origin in the people’s greater capacity to the relative or comparative thinking than absolute one: It is easier interpreting the information around a value than evaluate in an absolute space of possibilities. That is why the initial position is named “anchor”. Its value moors the adjustment, determining the subsequent evolution: different anchors in the same situation provide quite different results (235).

- **Representativeness**: Representativeness heuristics evaluates the probabilities considering the degree to which A is representative of B - i.e. the degree to which A resembles to the stereotype of B-. Questions like “What is the probability that an event A originates an event B?” or “What is the probability that object A belongs to class B?” are usually answered using representativeness judgments.

  This mindset is based on the people’s need to categorize: People tend to judge the probability of an event by finding a “comparable known” event and assuming that the characteristics will be similar in both situations. When it is not possible to fit the element or the event into a defined category, individuals continue trying to find its meaning by assigning it into a secondary level. These categories are sought in a already completed organizational system. -i.e. if something does not fit exactly into a known category, it is approximated to the nearest class available-. That is why events that do not appear to have any logic or sequentiality are regarded as representative of randomness and thus more likely to occur.

  This was already stated by Plato and Aristotle in the Greek Classical era. They *Associationism theory* claimed thought that mental processes operate by the association of one mental state with its successor conditions, especially with regard to the succession of memories. The later British ”Associationist School” -John Locke, David Hume, David Hartley, John Stuart Mill and others- carried on with this idea, asserting that the principle applied to most of the mental processes.

  In this manner, risk perception basically depends on the capability to associate the detected element to the models stored in memory. The higher the bond (due to
recurrence, similarity, etc.), the greater the effect in perception of the stimuli. Besides, this link also reinforces the substitution level (the detected object by the model).

### 4.3.2.4 Memory-Prediction Framework

The memory-prediction framework (MPF) is a theory of brain proposed by J. Hawkins that explains how the information is processed in order to figure out how the predictions are made. It was motivated by the similarities observed in the mammal’s brain structures (especially in the parts related with behaviours): the way the sensory inputs access to the patterns in the stored memory defines how the relations emerge and how the predictions evolve (236). Thus, MPF focuses on figuring out how the predictions come out, since it considers that the risk is a reflex of the potential damage estimated.

According to Hawkins’ theory, the human brain recognizes patterns in the observed World and forms mental representation of the elements in the scene. These models are not specially accurate, but they are enough to recognize faces or elements despite the changes in the illumination, shape or even composition. This coding of the inputs signals is organized following a bottom-up hierarchy (in terms of complexity). Each hierarchy level is associated (“labeled”) with concrete sequences or patterns according to the frequency of apparition. The higher the frequency or the longer the exposition to the stimulus (i.e. familiarity), the better the mental representation/pattern \(^1\), the faster the association and the stronger the stimuli (due to the retrievability) (237).

On the other hand, the memory follows a top-down structure: When an input sequence matches a memorized sequence at a given layer of the hierarchy, the (risk) data associated to that category is retrieved. And what is more, the corresponding label is propagated up the hierarchy looking for relatives. In other words, when a stimuli access to the store memory, the recognition process evokes a series of expectations (named “potentiations”) stored in the memory structure. It enables higher-order sequence learning and increases the invariance of the representations at higher levels. Besides, the potentations interact with the sensory inputs and they together generate predictions for the following (expected) inputs, in a kind of iterative process.

### 4.3.2.5 Psychometric paradigm

As described in section 4.2, normative and risk policies usually define risk in terms of probabilities and potential damages. Nevertheless, most of the people typically take into account other factors in their definition of risk: catastrophic potential, equity, future effects, controllability or involuntariness are only a few examples. In this sense, the work of Paul Slovic, Baruch Fischhoff and Sarah Lichtestein - the origin of the Psychometric

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\(^1\)Better, in this context, means more abstract. Maintaining the accuracy, more abstraction mean a greater capability to relate events or elements
4. RISK COGNITION

Paradigm - aimed to analyze how people judge risks by using the scientific method to evaluate these unconscious factors (238, 239).

The Psychometric Paradigm (PP) is based on the assumption that some characteristics of risks are perceived in a similar way. Basing on this surmise, they carried out a set of experiments (questionnaire survey based) that has been replicated over the years and has become a well-established model for assessing quantitative judgements about risk (240). According to the results of their research, the Slovic’s team asserted that perceived risks are quantifiable and predictable, being possible to assess quantitative judgements about dangers (241).

The analyzed how people -both lay people and experts- judge risks using psychophysical scaling and factor analysis, obtaining quantitative representations or cognitive maps of risk perception: Considering that risk as multidimensional concept, it embraced all the undesirable effects that people associate with a specific cause, origin or event. They computed these data extracting mean ratings for each situation or hazard, and then intercorrelating these means (242). They specially focused in the characteristics the considered to be perceived similarly:

- Voluntariness
- Immediacy of effect
- Risk knowledge
- Chronic vs. catastrophic potential of the risk
- Common vs. dread (It refers whether this was a risk that people have learned to live with and can think about reasonably calmly, or is it one that people have great dread for).
- Severity of consequences.
- Known to science.
- Level of control.
- Inequity.

Some other division and groups have been done along the years. The most accepted one is the D. Gardner’s one, which subdivides the 8 original categories into 18: Catastrophic potential, familiarity, risk knowledge, level of control, voluntariness, children or future generations involved, victim identificability (Identifiable victims rather than statistical abstractions make the sense of risk rise), dread known to science, media attention, accident history, inequity, benefits reversibility (If the effects of something going wrong cannot be reversed, risk rises), personal risk, origin (man-made risks are riskier than those of natural origin) and immediacy (243).
Furthermore, correlation between some of these risk features can be combined into two or three factors using multivariate factor analysis (244). In this case, each factor is composed by several highly correlated items. For example, voluntariness is correlated with controllability, catastrophic potential with inequity, observability with knowledge about the risk, and immediacy with novelty. Former risk perception studies typically identified three major high-order multidimensional factors that explain much of the variance (245):

- **Dread risk**: It includes catastrophic potential, inequitable distribution of risks and benefits and, fatal consequences and dreadful (i.e. seriousness of the damage). It usually does not include people affected by the risk -dispensed as a individual item. Nevertheless, in this context, it is expected that the dread depends on the people involved

- **Unknown risk**: It embraces factors like observability, experts and lay peoples knowledge about the risk, delay effect (immediacy), potential damage and novelty: in brief, the degree to which a risk is understood. In a study on over- and underestimated risk, Sjöberg showed that risks perceived as dreadful and unknown are frequently overestimated risks. On the other hand, risks that rate low on the dimensions dread and unknown risk are often underestimated by the general public.

- **Elements affected by the danger**: It summarizes which kind of elements are affected (kids, adults, animals, infrastructures, etc), and also if the general public or future generations are involved. As well, it takes into account the relationship of the individual with the risk (i.e. explosives expert or soldiers have a closer relationship with bombs, so an incident where they were involved would not be as dramatic as one where civilians are involved)

Alternative approaches to the PP have recently risen up. They try to change the management strategies and add new perspectives about how to dealing with uncertainties. As corollaries of the PP, rather than investing all efforts to increase the knowledge about the different components and characteristics of uncertainty, it has been proposed to develop better ways to live or co-exist with uncertainties and ignorance. In this sense, the previous factors have moved to be “resilience”, “vulnerability management”, “robust response strategies” and similar concepts (246). According to these, risk management is driven by making the social system more adaptive to surprises and, at the same time, allowing only those human activities or interventions that can be managed even in extreme situations (regardless of the probability of such extremes to occur). In the risk management literature these two approaches have been labeled as science-based (247) and precaution-based (248) strategies, respectively.
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4.3.2.6 The biological evolution of risk preferences

Also known has de the Weber-Fechner law (249), is the result of the experiments carried out by Ernst Weber in 1834 (although it was Gustav Fechner the one that gave shape to the theory). The analysis of the results provided with two different laws regarding to human perception: on the one hand, it was found that the resolution of the human perception diminishes according to the magnitude of the stimuli. In fact, it was proved that geometric progressions on the stimuli results in arithmetic progressions on the perception. In other words, the Weber-Fechner law states that subjective sensation is proportional to the logarithm of the stimulus intensity.

On the other hand, Weber also found that stimuli thresholds are a constant fraction of the existing stimuli. For example, when he placed a weight on a person's hand and increased it gradually, he found that the threshold weight increment turned out to be a constant fraction of the existing weight over the normal range of weights a person would handle in everyday life (250).

Both approaches have been also validated regarding to risk. Weber (251), Barron (252) and Sinn (250) confirmed that risk perception fits the Weber-Fechner model. Besides, their researches also stated that experience leads to different non-linear weighting of probability.

4.3.3 Risk-related cognitive variables

Analyzing carefully all the theories and studies presented in subsections 4.3.1 and 4.3.2, it is possible to find common denominators among all the them. In fact, as can be appreciated in Table 4.1 most of them consider the same risks (and sources) but from different focuses or points of view. For example, the well known situations proposed by SC imply a stronger bond in CP and an observable set of instructions in CTM. Likewise, the self-defining value proposed by CC, the stored patterns of MPF, the availability Heuristics and the mental representations of RTM theory refers to the same reality. Thus, it could be though that most of the theories flows up to common results in the end.

These common results imply common characteristics or bases. This way, the different causes and origins defined for the same effects can be understood as different abstractions of the same notions, formalized with different shapes or looks. The identification and matching processes of these underlying features have required a high-level abstraction process. It has implied to drive out the situational and environmental focuses, extracting raw characteristics that could be applied in every situation. The common characteristics that have been found are class membership, variability, unknown risk estimation, damage distribution, closeness pansy, delay effect, justice idea,
### 4.3 Fundamentals of human risk cognition

<table>
<thead>
<tr>
<th>Theory</th>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>CP</td>
<td>Benefit perception, delay effect</td>
</tr>
<tr>
<td>RTM</td>
<td>Class membership, feeling evocation</td>
</tr>
<tr>
<td>CTM</td>
<td>Observability, familiarity</td>
</tr>
<tr>
<td>CC</td>
<td>Class membership, feeling evocation</td>
</tr>
<tr>
<td>CTR</td>
<td>Attitude, degree of control felt, voluntariness, damage distribution, uncertainty</td>
</tr>
<tr>
<td>SARF</td>
<td>Familiarity, voluntariness, degree of control felt</td>
</tr>
<tr>
<td>SC</td>
<td>Familiarity, risk knowledge</td>
</tr>
<tr>
<td>Hp_{av}</td>
<td>Familiarity, feeling evocation, risk knowledge</td>
</tr>
<tr>
<td>Hp_{aa}</td>
<td>Class membership</td>
</tr>
<tr>
<td>Hp_{r}</td>
<td>Class membership, feeling evocation</td>
</tr>
<tr>
<td>MPF</td>
<td>Feeling evocation, class membership, familiarity</td>
</tr>
<tr>
<td>PP</td>
<td>Voluntariness, Risk knowledge, Delay effect, degree of control, observability, damage distribution, benefit perception</td>
</tr>
<tr>
<td>NSc</td>
<td>Variability</td>
</tr>
</tbody>
</table>

Table 4.1: Fundamental variables extracted from the theories mentioned in sections 4.3.1 and 4.3.2.

Hp_{av} refers to the availability heuristics, Hp_{aa} to the anchoring and adjusting heuristic and Hp_{r} to the representativeness one.

benefit perception, risk knowledge, feeling evocation, observability, voluntariness, controllability, familiarity, attitude, uncertainty and awareness.

Nevertheless, as it can be noticed, many of these parameters are closely interlaced. Indeed, the distinction among them is sometimes really slight: the denial of risk defined by PP is only an extreme position of the benefit perception; the control feeling is the result of the interaction between awareness and self-confidence, etc. Besides, some of them are the source or the result of others combination, turning out in the tight mesh of relationships presented in Figure 4.4.

In order to deal with this interdependence and provide with an independent collection of variables, a sifting process has been carried out. Thus, for example, it has been considered that awareness and observability refer to the same reality since they both imply the capacity to notice an event or element. Equally, variability has been understood as a parameter that increases the uncertainty value; uncertainty, in turn, has been considered as a factor that balances the acquittance to a class or group.

On the other hand, it has been thought that the confidence in the own capabilities agglutinates both the perception of control and the attitude towards the risk. Likewise, the denial of risk maybe has been considered as extreme case of the benefit perception, where the benefit observed is that high that the risk perception vanishes. Finally, the
same argument can be applied to the closeness pansy referring to the feeling evocation. The result of this sifting process is presented in Figure 4.5. It illustrates the variables relationship after the sifting process a presents the cognitive variables to be considered in the human-based risk evaluation. Furthermore, Table 4.2 establish the relation among the cognitive variables and the visual characteristics associated to each one of them (each association is deeply described for each one of the variables in the following subsections).
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4.3.3.1 Attitude - Voluntariness

Regarding to risk cognition, attitude is understood as the way the situations are faced or the predisposition to accept risks. It is a measure of the risk aversion and the capability to deal with imposed risks: how people exposed to uncertainty try to reduce that uncertainty.

Long time studied, recent studies present two different approaches towards the risk attitude concept: on the one hand, it has been found that the brain area related with this is the right inferior frontal gyrus (253), where it has been appreciated more or less activity depending of the challenge the situations present. It has been also proved that more risk averse people (i.e. those having higher risk premia) also have higher responses to safer options, establishing a balance between both features.

On the other side, the risk homeostasis theory -developed by Gerald J.S. Wilde- predicts that people compare their risk tolerance to the perceived danger level and adjust their behavior until the two are equal (254). It means that human being tend to maintain a constant level of risk: If the danger of the situation people are facing is under the risk acceptance threshold someone has (different for each individual), that person take more risk. Oppositely, if the risk of the situation is over the threshold, he will take more care.

This matches with the CTR proposals (see 4.3.1.1). It states that the perception of risk is attenuated if the risk is chosen voluntarily, but amplified if it is externally set: human being is much more afraid of a risk that is imposed on us (e.g. the driver in the

<table>
<thead>
<tr>
<th>Cognitive variable</th>
<th>System variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Damage distribution</td>
<td>Size, FuzzyAquitance</td>
</tr>
<tr>
<td>Benefit perception</td>
<td>%MissionAccomplished, missionPriority, distance2NextWP</td>
</tr>
<tr>
<td>Class membership</td>
<td>FuzzyAquitance,</td>
</tr>
<tr>
<td>Variability factor</td>
<td>DimVar, SpaVar</td>
</tr>
<tr>
<td>Delay Effect</td>
<td>Tau, distEstimated</td>
</tr>
<tr>
<td>Observability</td>
<td>distEstimated, vel, visibility, size</td>
</tr>
<tr>
<td>Confidence</td>
<td>FuzzyAquitance, Reactivity, Guards</td>
</tr>
<tr>
<td>Risk Knowledge</td>
<td>FuzzyAquitance,ConfidenceFuzzyAquitance</td>
</tr>
<tr>
<td>Feeling evocation</td>
<td>Databased knowledge as f(Tau, Error yaw, height, battery,distance estimated)</td>
</tr>
<tr>
<td>Voluntariness</td>
<td>MissionPriority</td>
</tr>
<tr>
<td>Familiarity</td>
<td>numIterations, elementsObserved</td>
</tr>
</tbody>
</table>

Table 4.2: Relationship among the cognitive variables and the variables originated by the perception module.
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car next to us using his cell phone) than when we voluntarily expose ourselves to the same risk (e.g. we are using a cell phone while we drive). In fact, people tend to accept risks that are voluntarily chosen even if those risks are approximately 1000 times as risky as accepted involuntary risks (255). In this sense, the risk faced while performing the mission has been balanced according to the options the mission/circumstances offer: the mission priority, in the sense that it impels to act reducing the personal freedom; and the numObstacles and the activation or not of the avoidance protocol, due to constrains in the possibilities offered.

4.3.3.2 Benefit perception

According to the CC, PP, CD and SARF theories, the greater a benefit is perceived, the greater the tolerance for tackling risks. It implies that hazards perceived to have clear benefits are more accepted than risks perceived to contribute with a smaller benefit (255): is more likely that someone goes down to the train tracks to recover a $10,000 check than for getting a $1 bill.

Being a logical concept, the difficulty comes from the definition of benefit and its relevance: since abstract profits and physical rewards are intermingled in the associative cortex, it is really difficult to split them into a part. Besides, as the relevance of the benefit changes according to the circumstances (i.e. optional elements may considered necessaries under some specific circumstances, and in the other way round), it is hard to provide with an estimation of the relevance of benefit associated to an event, situation or element.

This quandary is even more valid when trying to define which the benefit a concrete event or situation for a robot is: the benefit observed depends on the kind of robot and type of mission. In this specific case, the mission priority, the obstacle location (the bigger distance from the center, the greater the benefit because potentially implies a lower deviation) and % mission accomplished parameters have been selected as the variables for defining the benefit. It is because the profit is, in this case, related to the successful execution of the mission.

4.3.3.3 Confidence

According to CTR, CC and PP, risks perceived to be under one’s control are more acceptable than risks perceived to be controlled by others or uncontrolled. In general, out of control situations are unwilled because we lack security and stability under such circumstances: Unconsciously, it is thought that as long as the control is maintained, it is possible at least partially to avoid the hazard or remedy the damage. In this sense, it has been estimated that the confidence level is based on the variables that allows to estimate the independence (degree of control) on the environment: battery level in the
sense that it guarantees independence and movement capability; to the *reactivity* level since human confidence is the outcome of the interaction with the environment; and, finally, to the *historic of successes/failures* when facing that trying to avoid an specific type of element.

Anyhow, it should be noted that this perceived control is not necessarily real control, and socio-psychological studies have shown that people tend to overestimate their capability to control a situation. Besides it should be taken into account that, when overestimated, the confidence can be even more harmful that the danger itself. Wilde’s research verified the impact of overestimated confidence in a 3-year car collisions study (254). He proved that ABS-equipped cars had more accidents that non equipped ones, concluding that drivers of ABS-equipped cars took more risks, assuming that ABS would take care of them. Wild also analyzed the change of the direction of the traffic in Sweden: in 1967, they changed from driving on the left to driving on the right. After a first fatal day, during the first months, it was observed a marked decrement in the number of accidents. Nevertheless, after 18 months the figure returned to the previous values. Wilde suggested that the drivers responded to increased perceived danger by taking more care, returning to previous their habits as they became used to the new rules.

### 4.3.3.4 Damage distribution

According to the Psychometric Paradigm and CP theories, risks perceived to be fairly distributed are more accepted than risks perceived to be unfairly allocated. It means that situation where the own damage is greater than the other’s are hardly acceptable. The same holds true for the distribution of benefits and, of course, the combination of both. The least acceptable situation is when the risk burden has to be carried by one group of people but the related benefit is gained by a different group (e.g. the ancient dispute between the person in the front desk of an office and the one solving the problems in the back: Who solves the mess? Who gets the recognition?). It confirms that, besides the undeniable psychological aspect, the damage distribution also has a social faced: for example, it has been proved that the perception of damage distribution varies according to the social trust. When it is controlled, the relation between risks and benefits perceived diminished (256).

In this sense, apart from the degree of control felt (see subsection 4.3.3.1), both the *size* of the elements and its composition are considered in this approach. In the first case, because bigger objects usually have bigger inertia, being more dangerous than smaller ones (i.e. supposing a negative damage distribution). Secondly, the depending on the composition, profile and character of the element, the damage distribution can be totally altered. It implies that both the element size and the *Risk knowledge - Class
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membership associated play a significant role in the damage distribution evaluation (257).

4.3.3.5 Delay Effect

This mental conditioning was one of the first ones defined by the Cognitive Psychology theory. It basically relates the perception of damage (both probability and quantity) with its temporal closeness to the observer. It has two different variations: on the one hand, it is established a direct relation between the temporal proximity of the danger and the probability of suffering its effects. (e.g. if the astronomers report two potential asteroid impacts with the same probability, one of them tomorrow and the other one in two years, the first one will look like more likely to happen.) Thus, far-off approaching objects with slower speeds will be considered as less risky than closer or faster obstacles.

On the other hand, the second relation refers to the effects derived from the exposition to the danger. It connects the risk perceived with the closeness of it’s effects perception, in the sense that the sooner the effect of the danger appears, the greater the perception of the damage: a nuclear explosion will be considered more harmful if kills instantaneously somebody than killing the same person after X days/weeks/etc. due to the radiation. And what is more: the longer the delay (X bigger), the bigger attenuation of the risk perception.

Other view for the same effect is the dispute between catastrophic and chronic consequences: people tent to be more afraid of things that can cause a huge damage, suddenly, located (all in one place) and violently -such as a plane crash-, than things like heart disease, which causes hundreds of thousands more deaths, but one at a time, over time, and not all in the same place.

In the scenario that has been defined, no one of the potential obstacles or harmful events is able to postpone its damaging effect. So, only the variables related to the ToC have been considered in both approaches: the $\tau$ value and the estimated distance are the variables considered for measure the delay effect.

4.3.3.6 Familiarity

Familiarity is a variable that balances how stable and trustable are the ideas and mind sets. It is performed evaluating how knowledge (and predictions done basing on that knowledge) has evolved along the time: If the behaviour observed has been stable and the predictions have matched the expectations, the knowledge is settle. This process defines a set of assumptions that balances the perception.

Focusing on the risk perception, the Psychometric Paradigm (see subsection 4.3.2.5) postulates that a risk is attenuated along time due to habituation, even though the technical risk remains the same. This is due to a context-free mechanism located in
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in the ventro-lateral region of the frontal lobe that organized in a familiar-fashion the
stimulus observed in the environment (258). This is also valid for risks shown with a
certain frequency, who are also attenuated after several iterations. The combination
of both types of associations explains why known dangers are more accepted than
uncertain risks (255).

Extrapolating this, the dangerousness of the elements in the scene is related with
their continuity there and/or their frequency of appearance. So, when an element is
located, a timer (numIterations) is started and increased along the tracking period
(and while the behaviour is maintained). Thus, this variable provides with value of
the time the element has remained observable and stable. As well, if the element was
previously tracked (the element itself or a similar one), it could be expected to have the
same behaviour: the elementsObserved variable stores the number of elements of the
each one of the types have been located and tracked along the present mission. The
higher the number, the bigger the population/availability of those elements in that
environment, and thus the greater the familiarity value expected.

4.3.3.7 Feeling evocation

Defined as “a call to mind by suggestion”, feeling evocation (FE) refers to unconsciously
summoning associations between events/elements and mind states or considerations
(259). Achieved by representation, the judgements associated to these sensations are
integrated in the actual object’s understanding.

Although it is similar to Risk knowledge (see subsection 4.3.3.9), FE does not
requires from a logical relationship neither from a conscious establishment/learning.
Besides, in the case of evocation, the consciousness is derived from past experiences and
not from bibliography, documentation or analysis. In this sense, weighting is directly
connected to real experiences. According to the RTM, Heuristics and MPF theories,
the feelings evoked are derived from the mental disposition that modify those sensory
experience. Thus, the evocation of feelings or dreads (i.e. both positive or negative)
defines the perception of future risks (260).

The main challenge has come from the definition of the relationships among features
and sensations. Apart from the Fuzzy Acquittance value (the feeling evocation is clearly
related to the nature of the element), also the operation height, the battery, the distance
to home/next waypoint, the estimated time-to-contact and the deviation in yaw have
been considered: the higher the altitude, the greater the potential damage in case of
accident. Likewise, the longer the distance to the next WP or the deviation from the
target (i.e. error in yaw), the smaller the feeling of usefulness and safety; oppositely,
a high battery level entails a greater confidence due to the possibility of compensating
errors. Finally, TTC has been considered -as in the case of the delay effect- as explicit
reminder of the potential collisions.


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4.3.3.8 Observability

The acquisition of information from a situation, event or obstacles clearly defines how those elements are perceived. According to the CTM, the lack of information affects how they are been classified or what their nature is. Likewise, interruptions on the observation potentially modifies the predictions about their behaviour in the future, provoking a feeling of uncontrollability and uncertainty. Thus, observability is also a relevant factor in terms of risk perception.

Although it has been already described regarding to the perception (see subsection 3.4.5.4), it also balances the rest of variables according to the availability of information. In this sense, as in economics (261) or in ethics (262), hazard observability is related to those variables that allow which modify the quality of the information acquisition. The distance to the element (disEstimated), its speed, size, and visibility level estimated are the ones that has been selected regarding to UAV operation. Except the size of the element, they all are inversely connected to the perception (i.e. the longer the distance to the element, the lower the observability), providing with independent fuzzy figures that have been integrated evenly.

4.3.3.9 Risk knowledge - class membership

The identification and recognition processes have been addressed during the perception phase. As it can be observed in subsections 3.3.4 and 3.3.5, these processes have dealt with the acquittance and the classification of the elements according to their nature. Nevertheless, they have not focused on the implications of that association (i.e. what the belonging to a group means/implies) and, without that connection, the knowledge remains incomplete. In this sense, basing on the RTM, CC, Heuristics and SC theories-, the classification and knowledge about a risk have been analyzed considering how the belonging to a group modifies the judgement about the risk.

As previously commented, “understanding” is a task related to the cognitive mechanisms: according to the representative heuristics, the probability that an object belongs to a class is judged according to the similarities with the rest of elements of the category. This pertinence to a group implies that the general prejudices and features attributed to that group are partially expected in every element classified into that class, even though it has not those attributes. In this sense, if an element has been included in a concrete group, the behaviour expected for this element is defined by the abstraction our mind made for the behaviour of the class (e.g. people will always perceive venom as as harming substance, even in the situations when poison is used as a medicine).

On the other hand, according to the Psychometric Paradigm (see 4.3.2.5, the greater the knowledge of a risk, the higher the tolerance to deal with this hazard. It is because a priori knowledge increases the confidence in the potential reaction capacity. Besides,
the same theory postulates that the risk assessment also depends on the confidence figure of the RL belonging estimated: the greater the confidence on the evaluation, the lower the risk perceived. Following with the venom example, people will accept easier a poison-based treatment if they have read something (positive) about than if they totally ignored its employment. As well, they will be more reluctant if the treatment is novel than if it is well known.

Considering all above, the side represented by the class membership has been directly associated to the fuzzy acquittance value. On the other hand, the risk knowledge has been connected to the FA figure and to the confidence in that value -since it has been considered that balances the certainty about the knowledge extracted-.

### 4.3.3.10 Uncertainty - variability

Risk has been defined as” the situation or event where something is at stake and when the outcome is uncertain” (263) or as “an uncertain consequence of an event or an activity with respect to something humans value” (205). So, the incertitude associated to a hazard is clearly related to the risk perception: understood as the lack of confidence or sureness about something or someone ¹, uncertainty is a measure of the assurance about the own judgments. In this sense, the more the information about a risk is trusted or the higher the certainty about our evaluation, the lower the perception of the risk. Likewise, the more reliable and trustable the decision-making process used, the lower the fear provoked.

In this regard, and according to CTR, confidence in the judgements is mainly based on i) the knowledge about the risk, and ii) the estimation about maintenance/variation of the behavior over the time. In line with that, the perceptive variables selected for representing the uncertainty have been those one altering the certainty of the rest of measures: the variability (both dimensional and spatial) observed in the object, the visibility and the confidence in the acquaintance estimation (confidenceFuzzyAcquitance) have been selected. Besides, CTR states that uncertainty/variability reduction implies a lower risk perception. Thus, the relationship established between the four variables and the risk perception is inversely proportional to their value.

## 4.4 Cognitive Risk Assessment Framework

The cognitive parameter identification is a goal itself. However, it was defined as an intermediate aim. The third goal described in section 1.4 impels to use the analysis, generating an artificial cognitive evaluation system. Nevertheless, it implies to evaluate the relevance of the characteristics extracted: without an appraisal of their relevance,

¹Oxford Dictionaries
it is completely impossible to use the variables in a robotic (i.e. logic, digital) system (264).

Sociology, anthropology and psychology bibliography mainly present comparative results providing with useful but not-applicable information. In contrast, as presented before, the static figures most of the works in the engineering fields use are not flexible enough in this case. The compromise between relevance and applicability comes from neuroscience: this interdisciplinary science studies the nervous system, embracing the mental processes and activities analysis from a quantitative point of view.

The brain responses suppose a raw, accurate and unbiased measure of the human perceptions -including risk-. In this sense, brain analysis techniques (Electroencephalography, EEG; functional Magnetic Resonance Imaging, fMRI; Positron emission tomography, PET; etc) provides with huge quantities of incredible complex data. Nevertheless, since its interpretation is still a neurobiology challenge, in this thesis a simpler but highly representative substitute has been used: the low level psychomotor responses -completely unconscious and uncontrollable- provides with strong signs of the mental activity and concerns. Both the eye movements and the physiological responses have proven to be specially good estimators of the human concern (see subsection 4.4.1).

Hence, a multidisciplinary experiment has been designed and conducted -in collaboration with the Laboratory of Visual Neuroscience at the Barrow Neurological Institute \(^1\) and the Perception and Action Group at the Universidad Autónoma de Madrid \(^2\)- in order to obtain a numerical measure of the relevance of the parameters extracted in the risk estimation.

The experiment has been made up of three different stages: during the first one, the aim has been to specify, in an objective way, a set of situations where the risk level is clearly defined (see subsection 4.4.3. These situations have been later presented to group of subjects, who have been monitored and analyzed. This second stage has allowed to define which physiological responses provoke different levels of risk and which is the relationship among them (see subsection 4.4.4. Finally, once the association has been defined, the risk-response connection has been used to evaluate the relevance of each one of the metrics proposed: familiarity, benefit perception, risk knowledge, etc. In this sense, the contribution of each one of the cognitive parameters to the total risk perception has been balanced (see subsection 4.4.5).

4.4.1 Fundamentals of the human psychophysical behaviour

As previously said, low level psychomotor responses provides with strong signs of the mental activity and concerns (265). Furthermore, they have been revealed as extremely

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\(^1\) http://smc.neuralcorrelate.com/
\(^2\) http://www.uam.es/gruposinv/gipym/
4.4 Cognitive Risk Assessment Framework

accurate indicators, since they are hardly controllable or cheatable due to their uncon-
scious nature.

Many different indicators have been used and evaluated: measures of skin conduc-
tance (skin conductance response, SCR; galvanic skin response, GSR), cardiovascular
measures (heart rate, HR; beats per minute, BPM; heart rate variability, HRV; vaso-
motor activity), muscle activity (electromyography, EMG), eye movements (EMs) and
are only part of them (266). Nevertheless, according to Richardson (267), the EM are
the unique ones capable to provide with a real-time index of the mental activity. Thus,
the relationship among the eye movements and the risk perception has been studied:

4.4.1.1 Eyesight response measurement and evaluation

Recently, the diverse metrics associated to eye movements have been found as really
good indicators of the mental concern (268, 269, 270): (micro)saccadic and fixational
movements, gaze dispersion or blinking characteristics have proven to be related with
the arousal or excitement states, as the risk perception. In this sense, according to the
Norton’s scanpath theory, scenes are analyzed by using only six different types of eye
movements (271). Nevertheless, these are reduced to three when focusing on the risk
perception (272): saccadic and fixational movements, and the scanpath itself (smooth
pursuit). It should be added to these metrics the visual-based arousal measurements,
which mainly are blinking and pupil dilation (273). The multitude to studies establish-
ing the relation among these parameters and the risk perception were the base for the
experiment conducted: Huestegge established a direct connection between the number
of fixations and the hazard perceived (274). According to his research, the number
of fixations significantly decreases when the risk increases (around 7.5% between the
high risk and low risk cases defined). This approach was supported by the researches
of Falkmer (275) and Thoernell (276). This last one also found a significant effect
on the fixation duration: the fixational time is almost twice when the risk is obvious
than when it is hidden. It exactly matches with the results of the Underwood’s and
Velichkovsky’s researches (277, 278).

Regarding to the saccadic movements, Huestegge found, in same experiment men-
tioned above, an increment on the saccadic amplitude proportional to the hazard per-
ception (44% variation between high and low risk cases)(274). It matches with the
fixation-saccadic amplitude observed by Unema (279) and Lemonnier (280). Also the
variation of the number of saccades was significant: According to Charlton (281), the
number of saccades increases when the risk perceived also increases, supposing the
variation and increment of 34% saccadic movements. Same conclusions were found by
Matsell (282) and Di Stasi (283). In the case of this last one, the study correlated
subjective mental workload and the risky behaviour. Using this method, 53% differ-
ence between a relaxed (test) situations to a real (risk) ones was observed (283). This
relationship was later verified by Yang (284), who associated searching behaviours with increments in the saccadic rate, duration and amplitude using this method. Besides, using risk perception - mental workload correlation as a metric allowed Recarte to verified that the spatial gaze variability diminishes when incrementing the workload (risk)) (285). Hosking, Chapman and Underwood verified this behaviour, estimating a 45% average reduction of the searching amplitude (277, 286, 287).

Finally, referring to the arousal metrics, Preuschoff’s studies found a high correlation among the pupil size and risk perceived (in terms of uncertainty evaluation). 5 % average differences distinguished the low risk and high risk situations (288). This hypothesis is consistent with the researches of Bradshaw (289), Charlton (290) and Recarte (285), and supports the saccade number - pupil dilation relationship found by Jainta (291). On the other hand, blinking was also revealed as a significant indicator of the risk perception: According to Charlton (290), both the number and total duration of the blinks decreased significantly as the risk rating increased. This decrement was also measured by Kawase (292) Besides, the relationship between both variables -defined as blinking patterns- was also related to hazard perception by Noguchi (293). Besides, the counter effect -i.e., the effect associated to the benefit perception- was found by Ackermann (294), who established a relationship between the saccadic movements and the level of reward perceived.

All these relationships can be summarized in the following equation:

\[
\text{Risk} = 34 \cdot \Delta \text{SaccadicNumber} + 44 \cdot \Delta \text{SaccadicAmplitude} - 50 \cdot \Delta \text{BlinkNumber} + 100 \cdot \Delta \text{FixDuration} - 7.5 \cdot \Delta \text{FixNumber} + 15 \cdot \Delta \text{PupilSize} - 45 \cdot \Delta \text{GazeDisperssion}
\] (4.1)

4.4.2 Experimental framework design

As previously described, the goal of the whole experiment has been assessing and confirming the relevance of the cognitive parameters extracted in section 4.3. Thus, a framework has been designed to provide with a scenario capable to reproduce the conditions defined in subsection 3.3.

It had been initially conceived as a realistic 3D simulator, where the different obstacles and their behaviour would have defined the cognitive situations. Nevertheless, according to main neurophysiological tendencies (283, 295, 296), it has been substituted by a simplified -but not simplistic- approach. According to the precepts of Kirk and Gescheider (297, 298), a 2D plain simulator has been designed, where both the drone and the obstacles are depicted using geometrical shapes: similar to an old spaceships 2D game (e.g. the well-known Space Invaders), it presents a flat screen where the drone can move freely in both the X and Y axis (see Figures ) ote Screen resolution: 1024x600
pixels - WSVGA; Elements size: 60x60 pixels. The movement -speed commands- can be defined autonomously (i.e. autopilot), or responding to a mouse/joystick/gamepad order.

As in the old video games mentioned, the obstacles appear in the top part of the screen and move downwards. They have been organized in waves (adjustable speed and frequency), composed by different types of elements. Both the number of objects and their individual characteristics are customizable for each one of the waves. The parameters to be adjusted are:

- Initial position and appearance time
- Delay before moving
- Vertical speed
- Horizontal trajectory (angle)
- Oscillation degree (amplitude and speed)
- Alpha (transparency) level
- Damage/reward level when colliding
- Time-to-explode after collision and explosion range
- Shape, colour and size

The combination of individual features and collective (wave) characteristics define each one of the potential situations. In the first two stages of the experiment (see subsections 4.4.3 and 4.4.4), basic features have been employed in order to define the risk levels: B/W squared obstacles, where only vertical speed, oscillation degree and number have been modified.

Contrarily, Stage III (see subsection 4.4.5) has employed all the resources available, in order to reproduce the cognitive situations. Figure 4.6 depicts some them, resulting from the combination of the different element characteristics.

### 4.4.3 Stage I: Danger levels identification

As explained above, before using the physiological responses to evaluate the risk, it is necessary to relate the response to the risk level that generated it. Thus, the first step in the experimental process has tried to define a set of scenarios where the danger was clearly defined. The goal has been to establish an absolute risk measure to compare, in the second stage (4.4.4), with the eye movements (EMs) and physiological responses (PRs). This association provides a Risk-EMs/PRs relationship.

As previously commented, three different variables have been employed to define the nature of the obstacle: speed, variability and density/number of the obstacles.
4. RISK COGNITION

(a) Base situation (Stages I and II). Different obstacles on the scene
(b) Different shape: Life points and coins as a reward
(c) Low visibility obstacles
(d) Different shape: flowers as an obstacle
(e) Colour change. Explosion delayed, future shock wave depicted
(f) Color changed. Damage level according to the upper number l

Figure 4.6: Examples of different situation during the cognitive evaluation

(299, 300, 301). Eight different situations have been proposed as the result of the linear combination of these three different parameters. As it can be observed in Table 4.3, each one of the variables assume two different values (LOW/HIGH), resulting in the mentioned eight different scenarios. Aligned with the last researches, it has been hypothesised that the higher values imply a greater risk (Duncan states that relation regarding to the number (299), Brook to the variability (300), and both Ahiel and Renger establish a direct relation between speed and risk perception (301, 302)).
Nevertheless, it has been not defined yet the preponderance of one parameter over the rest: In order to validate the thesis and define the relationship among variables, a risk-blind flight control system has been designed to navigate the controlled drone during the simulation. It defines, for each one of the simulation trials, an evolving random trajectory that takes into account different movement patterns (exactly the same for each one of the situations): from an oscillating horizontal movement up to wall-rebound based trajectory, considering different speeds and variabilities.

<table>
<thead>
<tr>
<th>Situation</th>
<th>Obstacles speed</th>
<th>Obstacles variability</th>
<th>Obstacles density</th>
<th>Number of collisions</th>
<th>Distance to closest obst.</th>
<th>Time to the first impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>1.066</td>
<td>114.7824</td>
<td>1.1924</td>
</tr>
<tr>
<td>2</td>
<td>High</td>
<td>Low</td>
<td>Low</td>
<td>1.115</td>
<td>112.6032</td>
<td>1.1664</td>
</tr>
<tr>
<td>3</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>1.424</td>
<td>101.0880</td>
<td>1.1926</td>
</tr>
<tr>
<td>4</td>
<td>High</td>
<td>High</td>
<td>Low</td>
<td>1.384</td>
<td>104.0320</td>
<td>1.1581</td>
</tr>
<tr>
<td>5</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
<td>3.390</td>
<td>80.3408</td>
<td>1.1670</td>
</tr>
<tr>
<td>6</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>2.388</td>
<td>78.2072</td>
<td>1.1400</td>
</tr>
<tr>
<td>7</td>
<td>Low</td>
<td>High</td>
<td>High</td>
<td>3.102</td>
<td>67.8304</td>
<td>1.1602</td>
</tr>
<tr>
<td>8</td>
<td>High</td>
<td>High</td>
<td>High</td>
<td>2.891</td>
<td>66.8840</td>
<td>1.1358</td>
</tr>
</tbody>
</table>

Table 4.3: Parametrization of the contexts for danger identification
Low speed = [1..3]; High speed = [7..9]; Low variability = [1..3]; High variability = [7..9]; Low density = 6 obstacles; High density = 12 obstacles

As can be appreciated in the last three left columns in Table 4.3, three different metrics have been used to evaluate the absolute risk of each one of the situations. They are based in the formal risk assessment methods described in Section 4.2: number of collisions, distance to the (closest) obstacles and time to the first impacts. By using them, 20,000 situations have been analyzed (2500 trials per situation), obtaining the results presented both in Table 4.3 and subcharts in Figure 4.7. The simulation of every situation -over all the contexts- represents more than 83 hours of real-time navigation, providing with a significant result for risk levels.

As it is possible to appreciate in the charts in Figure 4.7 a), the results are the ones expected: the density directly affects to the number of collisions (the greater the number of elements, the bigger the probability of an encounter) and the distance to the closest element (being the elements randomly distributed across the scenario, the probability of finding an obstacle close to the drone is greater). Although smaller, its effect in the time to contact is also appreciable. It is inversely related with the probability of collision: the greater the probability of finding an object, the greater the possibility of finding it sooner.
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Contrarily, the effect of the variability is observable in pairs, and only in the number of collisions and the minimum distance observed: the higher values of the variability increase the number of collisions, decreasing the distance to the obstacles and the impact time at the same pace.

Finally, the effect of the speed is mainly noticeable in the time-to-first-impact value. As expected, the high speed obstacles impact sooner than the slower ones.

Figure 4.7: Results of the Stage I simulation, using a non-reactive Flight Guidance System (FGS)

The numerical results and the statistical analysis depicted in Table 4.3 and Figure 4.7 b) validate the approach proposed. Figure 4.8 presents the linear combination of the normalized metrics defined (see equation 4.2). The ANOVA analysis \( F = 278.9, p = 0.000 \) carried out over the situations 1 to 8 objectively define scenarios with an increasing level of risk.

\[
Risk = \text{mean} \left( \sum Coll_{num} + (1 - Time_{coll}) + (1 - Dist_{obst}) \right) \quad (4.2)
\]
4.4 Cognitive Risk Assessment Framework

4.4.4 Stage II: Physiological risk estimation

Once the risk levels have been defined, the following step has found out which kind of physiological response the risk elicits. So, it can be said that the goal of Stage II has been establishing a relationship between the risk perception and the EM/PR responses. In this sense, the experiment has been run as follows:

Participants

Twelve participants (6 females, 6 males; all of them naive; mean ± SD age 27 ± 6 years) took part in one experimental session. Four of them were left-handed, and half had a previous experience managing high stress situations (health emergency or piloting). All subjects had normal or corrected-to-normal vision. Written informed consent was obtained from each participant, which received $15 for their participation.

Experimental design

The experiment has used the same framework and conditions presented in previous subsection (subsection 4.4.3). Nevertheless, in this second stage, the autopilot has been substituted by real people: By using a mouse, the subjects have had to navigate avoiding obstacles. It has allowed to measure how their psychophysical responses have been according to the risk level they faced.

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1The Barrow Neurological Institute’s Institutional Review Board approved the study (protocol number 10BN142)
4. RISK COGNITION

Five blocks have been run (10 minutes each), presenting each one 120 trials (in series of 3) eight possible the conditions described in Stage I (see subsection 4.4.3 - 8 possible situations resulting from the combination of 3 bi-level variables). Each block has been displayed in a pseudo-random order, so as to minimize potential confounding factors but guaranteeing the equal distribution of risk levels.

An instruction sheet was provided to the participants, presenting two main tasks: the first one (and more relevant) refers to the obstacles avoidance. They were instructed to avoid every collision, not having any indication of the historical number of collisions (although they knew there was a virtual counter of the life points lost), the behaviour expected for the next trial or the time remaining.

As a secondary objective, the subjects were instructed to remain in the middle of scenario (depicted by a set of green dots that become red when navigating out of the center of the scene). Like this, it was aimed to guarantee a basic behaviour in order for the participants to face the different trials from a similar point of view.

Setup and Procedure

In a darkened and quiet room, the participants rested their forehead and chin on the EyeLink 1000 (SR Research) head/chin support, 57 cm away from a linearised video monitor (Barco Reference Calibrator V, 75 Hz refresh rate). A dark box surrounded the set in order to avoid confounding factors (saccades and microsaccades are sensitive to sudden visual and auditory stimuli). Even though, due to the grey background, the illumination has to be considered photopic. It should be also noted that all the conditions in along the test were isoluminant: the obstacles' lighting was compensated (i.e. same number of black and white obstacles) in order to provide with a balanced number of photons and to avoid any potential confound in the pupil size.

Before starting the experiment, the Biopac probes were connected to the participants. They were composed by a respiratory belt and a photoplethysmography reader (for acquiring the heartbeat and transpiration variation). These sensing probes provided with data to the MP36R 4-Channel system.

After filling in the questionnaires and reading the instructions for the experiment, they run a 2-min training session where two obstacles were presented. Stimuli and timing parameters in the training session were equivalent to those in the actual experiment. It was considered successful when the participant achieved not to collide with any obstacle (if not, the training was repeated).

Setup of the eye tracking system followed the completion of the training session. The head support was adjusted and the eye position calibrated until obtaining an optimum performance. Then, five 10-min experimental blocks were run, repeating the calibration process at the beginning of every one. Each block consisted of 120 trials of 5 seconds each, where the condition changed every 3 trials (i.e. 15 trials per condition,
4.4 Cognitive Risk Assessment Framework

The entire experiment had a total of 600 trials and lasted for approximately 1.5 h. Participants rested between blocks, answering the corresponding questionnaires (see subsection 4.4.4).

This method is summarized in Procedure 1:

**Procedure 1** Stage II experimental design.

**Require:** 12 subjects: 1 session, 1.5h each

**Ensure:** Eye movements, physiological data, performance data

1. **Starting**
   - Consent form reading and signature.
   - Demographic questionnaires
   - Stanford Sleepiness Scale (SSS) (304)
   - Sensation Seeking Scale, Form V (SSS-V) (305, 306)
   - Plutchik Impulsivity Scale (PIS) (307)

2. **Starting**
   - Consent form reading and signature.

3. **Training**
   - Subject runs a 2 min training trial until he/she achieves no impacts (In case of collision, the training will be repeated). The situation presented will have 2 obstacles

4. **Video ranking** (8 videos -1 per condition-, 10 sec. each)
   - Subject watches and ranks the 8 videos with a subjective scale of risk, from 1 to 7 (7-point Likert scale (308)). Videos are displayed randomly.

5. **Experiment: 5 blocks**
   - Before each block
     - Eyelink calibration after each block
     - NASA-TLX (Task Load index) questionnaire (309, 310)
     - Stanford Sleepiness Scale (SSS)
   - Block #i (10 mins. - 40 pseudo-random trials per block, 15 sec. trials - 5 trials per condition)

6. **Video ranking** (8 videos -1 per condition-, 10 sec. each)
   - Subject watches and ranks the 8 videos with a subjective scale of risk, from 1 to 7 (7-point Likert scale). Videos are displayed randomly.

**Questionnaires**

As defined in the experimental design 4.4.4, each subject filled in three different questionnaires before staring the experiment: Firstly, both the sensation seeking tendency and the impulsivity degree were evaluated by using the Sensation Seeking Scale, Form
4. RISK COGNITION

V (SSS-V) (305) and the Plutchik Impulsivity Scale (PIS) (307) questionnaires, respectively. Although risk is not an essential part of these traits, the first personality test allows to establish a connection among them basing on individual differences in terms of sensory stimulation preferences (measure how much stimulation a person requires and the extent to which they enjoy the excitement) (306).

Besides, subjects quality of sleep was subjectively measured using the Stanford Sleepiness Scale (SSS) (304). It provides a global measure of sleepiness, used in order to evaluate the potential effect of fatigue on the risk perception (RP). This questionnaire was also filled in after each block.

Also during the intermissions, participants completed the NASA-TLX (Task Load index) questionnaire (309, 310). Filled in after each block, it indicates the degree of workload they perceived, allowing us to assess the subject effectiveness and performance.

Finally, a video-based questionnaire has been also designed and presented to the participants before and after the experiment: 8 videos (10s each) were randomly displayed to the participants. Each video presented one of the risk levels defined in subsection 4.4.3 and they were asked to order them from less risky to the riskier. Thus, using a Likert-type scale (308), it was evaluated the participant’s subjective risk perception.

Psychophysical responses recordings

The eye-data acquisition has been performed by using the EyeLink 1000 eye tracking system. The system is mainly composed by a high-resolution/high-frequency camera that samples eye movements. It has allowed to track the participants eyes at 500 Hz, providing with a 0.011° resolution, a 0.5° average accuracy and 3.0 msec delay, with a volume of allowable head movement up to 25 x 25 x 10 mm (horizontal x vertical x depth).

During the experiments eye movements have been sampled binocularly using the system’s desktop configuration. The analysis has been performed according to the method employed by Di Stasi (311). According to that, blink periods have been defined as portions of the raw data where pupil information was missing. Besides, portions of data where very fast decreases and increases in pupil area occurred (> 50 units/sample) have been also removed since such periods are probably semi-blinks (312, 313).

Likewise, saccades have been identified using a modified version of the algorithm developed by Engbert (314, 315, 316, 317) with k = 6 and a minimum saccadic duration of 6 ms. Only binocular saccades (i.e. saccades with a minimum overlap of one data sample in both eyes (314, 315, 316, 317, 318) have been considered in order to reduce the amount of potential noise. Additionally, a minimum intersaccadic interval of 20 ms has been imposed so that potential overshoot corrections might not be categorised as new saccades (319). Besides, it should be mentioned that a relationship between
the (micro)saccade magnitude\(^1\) and the i) (micro)saccade duration, ii) (micro) saccade mean velocity, iii) (micro)saccade peak velocity (PV) has been assumed. Thus, a robust linear regressions has been used on the log-transformed data for each subject to obtain the slope for each main sequence.

On the other hand, regarding to the physiological responses, they have been captured by using the Biopac’s MP36R 4-Channel system. It supplies a 24-bit resolution and 100 KHz acquisition speed (per channel), providing with data of the EDA (ElectroDermal Activity), heart rate and respiration rate. All these three factors have been acquired observing the establishing set-up time required by each one of them (321): 1000 Hz heartbeat sampling rate (60-100 beats/s), 150 Hz for the respiration (15-30 inspirations/min) and 300 Hz for the EDA.

The analysis has discarded the delay time to observe the effect of the the variables (EDA 3 s, aprox.). Thus, from each 15 s block, only the latest 12 s have been considered as representative.

Data analysis

As previously presented, the final aim was to establish a correspondence between risk perception and EMs. In this sense, it was analysed the effect of the different situations in the most relevant EM indicators: Fixation (Average number, mean time and duration of fixations), blink (Number and duration of blinks), pupil size (variations in the pupil size), (micro)saccadic movements (Number, magnitude, duration, acceleration, peak velocity and slope) and scan path (Dispersion both the X and Y axis). Besides, the performance was measured using the same variables employed in Stage I: number of collisions, time to the first collision and minimum distance to the closest object.

Considering the 2x2x2 experimental design, it was conducted a two-way repeated measures ANOVA analysis with the three dependent variables (i.e. speed, variability and density) as the within-subjects factors. For violations of the ANOVA assumption of sphericity, P-values were adjusted using the GreenhouseGeisser correction. The significance level was set at \(\alpha = 0.05\). Data across conditions was not collapsed, in order to be able to determine the evolution of the variables and the task performance.

Results

The effect of risk perception on eye movement-based physiological responses has been determined in this second experiment. The statistical analysis evidences the relation between the independent variables (IV) postulated in the first experiment and the EMs considered above. Table 4.4 presents the significant effects of these associations.

\(^1\)Microsaccades were defined as saccades with magnitude < 1° in both eyes (270, 320)
4. RISK COGNITION

<table>
<thead>
<tr>
<th>Variable</th>
<th>Effect/Interaction</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pupil size</td>
<td>Density</td>
<td>4.85</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>Variability</td>
<td>16.73</td>
<td>0.002</td>
</tr>
<tr>
<td>Blink number</td>
<td>Density</td>
<td>14.75</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td>Variability</td>
<td>14.10</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>Speed</td>
<td>38.14</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Variability*Speed</td>
<td>9.21</td>
<td>0.011</td>
</tr>
<tr>
<td>Dispersion X</td>
<td>Variability</td>
<td>12.69</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>Speed</td>
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<td>Variability*Speed</td>
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<tr>
<td></td>
<td>Variability*Speed</td>
<td>9.24</td>
<td>0.011</td>
</tr>
<tr>
<td>Number of saccades</td>
<td>Density</td>
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<td>0.000</td>
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<td></td>
<td>Variability</td>
<td>6.43</td>
<td>0.028</td>
</tr>
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<td></td>
<td>Speed</td>
<td>67.34</td>
<td>0.000</td>
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<td>Density*Variability</td>
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<td>Density*Speed</td>
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<td>Saccadic magnitude</td>
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<td>0.001</td>
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<tr>
<td>Microsaccadic number</td>
<td>Density</td>
<td>7.99</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>Variability</td>
<td>10.40</td>
<td>0.008</td>
</tr>
<tr>
<td>Fixation duration</td>
<td>Density</td>
<td>15.74</td>
<td>0.002</td>
</tr>
<tr>
<td>Fixation number</td>
<td>Density</td>
<td>39.77</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Variability</td>
<td>14.12</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>Speed</td>
<td>42.63</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Density*Variability</td>
<td>6.37</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td>Density*Speed</td>
<td>20.34</td>
<td>0.001</td>
</tr>
<tr>
<td>Fixation</td>
<td>Speed</td>
<td>22.20</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>Density*Variability</td>
<td>5.79</td>
<td>0.035</td>
</tr>
</tbody>
</table>

**Table 4.4:** Significant effects in the acquired variables

As it is possible to observe, more than 24 effects have been found over 10 different EM-related factors. Regarding to this area, the main indicators have been the ones related with fixational and saccadic movements (see Figure 4.9), as well as the arousal pointers (blink and pupil size).

Besides, significant data have been also found the performance data and the physiological responses (see Tables 4.6 and 4.5, respectively). Regarding to the performance,
its behaviour is completely aligned with the one predicted in Stage I. As it is possible to appreciate in Figures 4.10 a) and b), the tendency matches the one observed in Figure 4.7. In fact, the error in the slope is smaller than 4%, defining a powerful correlation between the risk perception and the performance estimation. However, although they confirm the relations pointed by the EM analysis, it has been decided not to use them in the last stage to avoid custom-designed metrics.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Effect/Interaction</th>
<th>Order</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Collision number</td>
<td>Density</td>
<td>1</td>
<td>43.98</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>Variability</td>
<td>1</td>
<td>52.21</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Density*Variability</td>
<td>2</td>
<td>14.40</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>Density<em>Variability</em>Speed</td>
<td>3</td>
<td>7.29</td>
<td>0.021</td>
</tr>
<tr>
<td>Minimum time to collision</td>
<td>Density</td>
<td>1</td>
<td>85.31</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>Variability</td>
<td>1</td>
<td>45.13</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Density<em>Variability</em>Speed</td>
<td>3</td>
<td>4.94</td>
<td>0.048</td>
</tr>
<tr>
<td>Minimum distance</td>
<td>Density</td>
<td>1</td>
<td>132.6</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>Variability</td>
<td>1</td>
<td>7.7</td>
<td>0.018</td>
</tr>
</tbody>
</table>

Table 4.5: Significant effects in the performance variables

Regarding the physiological responses (see Table 4.6), also significant effects have been found in all the magnitudes. They all confirm the hypothesis of the physical
4. RISK COGNITION

a) Number of collisions

b) Minimum time to collision

Figure 4.10: Evolution of the performance parameters according to the situation

response according to the risk, and follow the expected behaviour. However, despite on their proved significance, they do not provide with any additional information. In this sense, and considering their heavy inertia, it has been decided not use them in in the following step either.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Effect/Interaction</th>
<th>Order</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Skin Conductance Responses</td>
<td>Density</td>
<td>1</td>
<td>5.30</td>
<td>0.041</td>
</tr>
<tr>
<td></td>
<td>Speed</td>
<td>1</td>
<td>7.45</td>
<td>0.019</td>
</tr>
<tr>
<td>Heart rate % increase</td>
<td>Density*Variability</td>
<td>2</td>
<td>6.09</td>
<td>0.031</td>
</tr>
<tr>
<td>Respiration rate % increase</td>
<td>Speed</td>
<td>1</td>
<td>5.24</td>
<td>0.042</td>
</tr>
</tbody>
</table>

Table 4.6: Significant effects in the physiological variables

Thus, only the EMs have been taken into account in order to define the association between risks levels and psychophysical responses: this relationship has been established basing on the risk-relation defined in equation 4.2 and the parameters extracted for each one of the variables.

\[
Risk = 5 \cdot (\Delta PupilSize - \Delta USaccadicNumber) + 17 \cdot \Delta SaccadicNumber + 8.5 \cdot \Delta FixDuration - 5.2 \cdot \Delta FixNumber - 4 \cdot \Delta BlinkNumber - 4 \cdot \Delta FixDuration - 0.5 \cdot \Delta SaccadicAmplitude + 52 \cdot \Delta GazeDispersion X
\]  

(4.3)

Table 4.7 presents the associative values obtained for the whole set of variables. Each one of the values defines the variation (in %) of the magnitude according to the
4.4 Cognitive Risk Assessment Framework

<table>
<thead>
<tr>
<th>Variable</th>
<th>Speed (↑)</th>
<th>Variability (↑)</th>
<th>Density (↑)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pupil size</td>
<td>x</td>
<td>4.89</td>
<td>3.54</td>
</tr>
<tr>
<td>Number of blinks</td>
<td>11.25*</td>
<td>-6.24*</td>
<td>-7.86</td>
</tr>
<tr>
<td>Dispersion in X</td>
<td>-38.27*</td>
<td>54.72*</td>
<td>x</td>
</tr>
<tr>
<td>Dispersion in Y</td>
<td>x</td>
<td>x</td>
<td>-8.56</td>
</tr>
<tr>
<td>Number of saccades</td>
<td>-15.55*</td>
<td>-5.56*</td>
<td>15.38*</td>
</tr>
<tr>
<td>Magnitude of the saccades</td>
<td>x</td>
<td>x</td>
<td>11.32</td>
</tr>
<tr>
<td>Number of saccades</td>
<td>x</td>
<td>-14.25*</td>
<td>-26.35</td>
</tr>
<tr>
<td>Duration of fixations</td>
<td>x</td>
<td>x</td>
<td>-11.98</td>
</tr>
<tr>
<td>Number of fixations</td>
<td>-9.69</td>
<td>-8.40</td>
<td>8.44</td>
</tr>
<tr>
<td>Number of collisions</td>
<td>x</td>
<td>-68.11*</td>
<td>-66.59*</td>
</tr>
<tr>
<td>Minimum time to collision</td>
<td>-15.53</td>
<td>63.23</td>
<td>49.57</td>
</tr>
<tr>
<td>Minimum distance to the obst.</td>
<td>x</td>
<td>-14.37</td>
<td>-59.63</td>
</tr>
</tbody>
</table>

Table 4.7: Relative relationship among the psychophysical responses and the metrics defined. The values present the relative increment/decrement (%) observed in each metric when increasing the level of each variable.

changes in the variable. Considering these relations and prioritizing high-order effects over simple relations, the relationship defined in equation 4.3 has been defined. The results according to this metric, depicted in Figure 4.11, are consistent with the studies presented in subsection 4.4.1.1.

Finally, regarding to the questionnaires, the Stanford Sleepiness Scale analysis has showed the expected evolution of subject’s alert according to Hodes and Chervin(304, 322). Thus, it has been significantly concluded (ANOVA F(4,44)=5.6, p=0.00098) that sleepiness did not have a relevant impact along the experiment. Likewise, the expected increasing risk perception has been found in the subjective risk perception video-based questionnaires. Figure 4.12 illustrates this tendency. Nevertheless, despite its clear evolution, it is not significant due to great variability across subjects.

4.4.5 Stage III: Cognitive parameters risk assessment

As described in Section 4.4, the last stage in the experiment tries to evaluate the relevance of different variables on the global risk perception picture: the relevant factor found in subsection 4.3.3 have been reproduced by using the framework used in the previous stages, defining each one of them an specific situation. These situations have been analyzed using the risk-psychophysical responses association that have been found
4. RISK COGNITION

**Figure 4.11:** Results of the risk perception level according to the index specified in subsection 4.4.3.

![Graph showing risk perception level](image)

**Figure 4.12:** Results of the video ranking. Evaluation of the risk perceived.

![Graph showing video ranking](image)

in Stage II (see subsection 4.4.4). As a result, a measure of the impact of each one the variables on the risk assessment have been defined.

The experiment carried out for establishing these relationship has been run as follows:
4.4 Cognitive Risk Assessment Framework

Participants

Sixteen participants (7 females, 9 males; all of them naive; mean ± SD age 25 ± 3 years) have participated, for free, in one experimental session. Four of them were left-handed, and most of them (83%) had a experience in videogaming. All subjects had normal or corrected-to-normal vision. Written informed consent has been obtained from each participant.

Experimental design

The experiment has used the same framework and conditions presented in Stages I (subsection 4.4.3) and II (subsection 4.4.4). By using a mouse, the subjects have had to navigate avoiding obstacles. It has allowed to measure how was their psychophysical response according to the risk level they have faced.

Two blocks have been run (15 + 15 minutes) in each experimental session, presenting 180 trials each in a pseudo-random order (in order to minimize potential confounding factors but guaranteeing the equal distribution of the conditions). 10 different situations have been defined for evaluating the cognitive variables. Except the base one, all of them have followed the HIGH density, LOW speed, LOW variability pattern (Situation 5 in Table 4.3) defined in Stage II:

1. **Base**: Black and white squares have been presented, replicating the HIGH density, HIGH variability, HIGH speed situation from Stage II. This situation has been used as a control trial for assessing the rest of the scenarios (see Figure 4.6 a).

2. **Familiarity**: As previously established, familiarity factor is related to pattern recognition. So, in these situations, obstacles have been presented in well defined pattern (in the rest of the trials the directions and starting points are pseudo-random). It was expected the subjects to degrade the risk level perceived once they got used to the pattern.

3. **Observability**: In this type of trials (see Figure 4.6 c), half of the obstacles have been presented barely visible (1.10 contrast relationship, in opposition to the averaged 4.62 \(^1\) level, according to WCAG 2.0 definition (323)). It was expected that the risk perceived would increased due to the lack of observability.

4. **Benefit perception**: Two different rewards have been presented (one at each time) in this type of situations, providing with $10 and $50, respectively \(^2\). Considering

\(^1\)4.63 corresponds to the AA contrast level according to the 4.5:1 ratio recommended by WCAG 2.0

\(^2\)The probability of occurrence of $50 is 15%. The probability of $10 is 85%
the money collected as a secondary objective, it was expected the risk perception diminished inversely proportional to the benefit presented (see Figure 4.6 b).

5. Damage level: As Figure 4.6 f) presents, half of the obstacles (depicted in purple and known a priori by the participants) have a higher potential damage: instead of subtracting 1 life point, any collision with them provoked a 3 life lost. It was expected that, due to their higher potential damage, the risk perceived in these trials would be also greater.

6. Delay effect: Half of the obstacles have been substituted by red squares (see Figure 4.6 e). Participants a priori knew that, after crashing into these obstacles they did not subtract a life but start a counter; however, after two seconds they explode provoking triple the damage to the elements in its radius (three times the obstacle diameter).

7. Feeling evocation: Associations evoke by different elements balance differently the risk perception. As can be appreciated in Figure 4.6 d), in these trials, one of the B/W squares has been substituted by an image, depicting half of the trials a bomb, half a flower. Both elements behave as normal obstacles. Nevertheless, it was estimated that due to their natures, flowers would be perceived as less risky than bombs.

8. Degree of control: During these trials, the participants have been invulnerable (Participants have been told about this condition. It is depicted by a double circle on the user’s mobile element). The collisions provoked no harm, providing to the participants with a feeling of controllability. It was expected that the risk perceived would be lower due to this fact.

9. Risk knowledge: All the conditions but one have been known by the participants when starting the experiment: Four green squares -unexpected for the subject- substituted the same number of B/W obstacles. Despite of having the same behaviour and characteristics, it was estimated that the participants would evaluate these situation as riskier due to the lack of knowledge.

All the situations present the same density of obstacles and obstacle’s speed an variability in order to avoid potential confounds with the results obtained in Stage II. Except for the familiarity situation, all the obstacles have been presented in a pseudo-random position with a pseudo-random direction seed. In this sense, each trial is completely different from the rest, although each one maintains the characteristic that defines its belonging to a situation.

On this scenario, two main task have been defined: the first (and more relevant) one refers to the obstacles avoidance. The participants have been instructed to avoid
4.4 Cognitive Risk Assessment Framework

every collision in order to preserve their life level (they started each block with 30 life points). The indication of the number of lifes has been displayed in the top left part of the screen. As in the previous stage, the unique sign of the collision has been the obstacle vanished. The second task impels to maximize the number of coins collected (grouped in the so called 'treasure').

Setup and procedure

In a darkened and quiet room, the participants have rested their forehead and chin on the ASL Eye-Trac 6000 (ASL Eye Tracking) head/chin support, 70 cm away from a linearised video monitor. As in the previous stage (see subsection 4.4.4), the illumination has been considered photopic: during the experiments, the luminescence has been controlled -maintained-. Over the grey background, the number of black and white obstacles has been balanced, in order to provide with an isoluminant scene.

It should be highlighted that the colour of the coloured elements has been adjusted according to the spectral sensitivity of human visual perception of brightness: The CIE 1931 standard states that the human eye is more efficient acquiring and processing greenish colors than others. Thus, the different colors presented have been adapted -in order to maintain the isoluminescence- by using the Sharpe, Stockman, Jagla & Jgle luminous efficiency function, depicted in Figure 4.13.

![Figure 4.13: Luminosity function.](image)

Relative response of the human eye according to the wavelength of the stimuli.

After filling in the demographic questionnaire and understanding the instructions for the experiment, the participants have run a training session in order to get familiar with the framework (The situation presents 6 obstacles with random movements. Stimuli
4. RISK COGNITION

and timing parameters in the training session have been equivalent to those in the actual experiment). The training has continued until the participant have claimed to be comfortable with the environment.

The setup of the eye tracking system has followed the completion of the training session: The head support has been adjusted and the eye position calibrated until obtaining an optimum performance. Then, two 15-min experimental blocks have been run, repeating the calibration process at the beginning of every one. Each block has consisted of 180 trials of 5 seconds each, where the condition changed every trials (i.e. 18 trials per condition, per block). The entire experiment had a total of 360 trials and lasted for approximately 40 minutes.

This method is summarized in Procedure 2:

**Procedure 2** Stage III experimental design.

**Require:** 16 subjects: 1 session, 40min each

**Ensure:** Eye movements, performance data

1. **Starting**
   - Consent form reading and signature.
   - Demographic questionnaires

2. **Training**
   Subject runs a training trial until he/she feels conformable with the framework.
   The situation presents 6 obstacles with random movements

3. **Provide the participant with the instructions.**

4. **Experiment: 2 blocks**
   Before each block
   - Eye-trac calibration
   Block #i (15 mins. - 180 pseudo-random trials per block, 5 sec each. 18 trials per condition)

**Psychophysical measures recording**

The data acquisition and analysis has been performed according to the method employed by Aivar (326) and Hayhoe (327). Eye movements have been sampled monocularly at 60 Hz using the desktop configuration of the Eye-Trac 6000 eye tracking system. It provides with a 0.1° resolution, 0.5° accuracy and a ±25° / ± 20°/ visual field (horizontal/vertical, respectively).

As in Stage II, blink periods have been defined as portions of the raw data where both the pupil and the Corneal Reflection (CR) information were missing. Nevertheless, in this last experiment, the eye movements have been analyzed using a Hidden Markov
stochastic model detector. Based on the one proposed by Salvucci (328), it uses the
gaze position as the Markov property, employing the speed and distance between points
as the states/thresholds to discriminate between saccadic movements and fixations. It
uses the tangent of the scanpath and verifies the saccadic movements resulting by using
the speed. Noise has been corrected by using geometric mean (centroid).

Finally, the scanpath data has been computed by using the Krassanakis’ Eye Move-
ments Metrics Visualizations (EyeMMV) toolbox (329). This toolbox has been also
employed for verifying the fixational and saccadic movements.

Data analyses

As described above, the goal of this last stage has been obtaining risk responses that
allow to train an ANN (see section 4.5). In this sense, the statistical analysis has been
carried out only in order to understand how the network is going to behave.

The EMs analysis has been performed using the same assumptions and considera-
tions and described in Stage II (see subsection 4.4.4), considering only the variables that
have been found significant in that phase: fixations (Average number and duration),
number of blinks, pupil size, saccadic movements (Average number and magnitude)
and scan path (Dispersion both the X and Y axis). However, all the analysis done in
this stage have been based on the risk perceived level (RPL)

The RPL has been computed by using the equation 4.3, constructed from the results
of Stage II. It matches with the studies presented in subsection 4.4.1.1 and provides
and effective way to measure the variations on the risk perceived. The RPL values have
been calculated for each subject over the collapsed data and then normalized across
the base situation. The control trials -that have presented the mid-risk fifth situation
from Stage II- have been used to verify the fitting level.

The benefit perception has been computed averaging the benefit perceived in both
types of rewards. The familiarity level, instead, has been split in two -familiarity
low and high, respectively- considering the transition zone where the contribution to
the perception is null. Besides, the independent figure for the delay effect has been
computed by comparing its value with its counterpart (purple obstacles, in terms of
absolute damage). Lastly, regarding to the uncertainty analysis, the first 500ms of the
analysis has been discarded in order to avoid the onset effect. This filter has allowed
to focus only in the expectancy moments, where it is uncertain the restart moment. .

Finally, over the whole set of RPL values, a (two-way repeated measures) ANOVA
analysis has been performed in order validate the independence of the results. The
significance level was set at \( \alpha = 0.05 \). As in Stage II, data across conditions has been
not collapsed, in order to study the evolution of the variables.
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Results

The results found after the analysis follow the expectations of logic and societal reasoning. As can be observed in Figure 4.14, the variables that could be expected to have a positive impact in the risk perception have been, indeed, the ones having resulted positive: feelings of confidence and control, rewards, delays observed in the damaging consequences or positive emotions inherited from previous events reduce the perception of risk. In turn, unawareness (due to lack of observability, unfamiliarity or ignorance about the risk), involuntariness or uncertainty increase the hazard perception in up to 80%.

![Figure 4.14: Computed relevance of each one of the parameters involved in risk assessment.](image)

1 - Control: refers to the control/base situation; 2 - Benefit perception: it combines both the lifes and the rewards; 3&4 - Familiarity: it comprises the familiarity effect (both when it is low, L, and high, H); 5 - Delay effect: it refers to the delay effect while; 6&7 - Feeling evocation: it spans both the positive (FE+) and negative (FE-) feelings; 8 - Observability; 9 - Damage perception: it refers to an unfair damage distribution; 10 - Unknown risk estimation. 11 - Confidence: it refers to situations that are under control. 12 - (In)voluntariness: it comprises the final situation where there is no option to avoid the risk; 13 - Uncertainty

The first column presents the control/base situation. As previously presented, it corresponds to the HIGH density, HIGH speed, HIGH variability situation from stage II. It is ranked in this stage with a risk perceived level (RPL) of 59% according to the normalized metric. According to the same metric, it has ranked 56% in this stage III,
4.4 Cognitive Risk Assessment Framework

supposing a 5.08% difference. Using this value as the typical error, the rest of results have been analyzed taking this into account.

The second, forth, fifth, sixth and eleventh columns (benefit perception, high familiarity, delay effect, positive feelings evocation and confidence in the own capabilities, respectively) present the positive reinforcements. As expected, the maximum risk perception reduction (RPR) has been obtained when obtaining a benefit (the average of high and low benefits have been considered) or when feeling a high confidence in the avoidance capabilities (76% and 53% RPR, respectively). The contribution of the delayed effect is significantly smaller (12%) but appreciable.

![Familiarity evolution](image)

**Figure 4.15:** Mean familiarity evolution in the first block

Regarding to the familiarity and feeling evocation contributions, it has been found that they both have two different sides: firstly, regarding to the familiarity, it has been analyzed independently for each one of the blocks and each one of the trials. As it can be appreciated in Figure 4.15, the tendency of the PRL decreases along the trials. In this sense, the level of familiarity has been divided (Low-High) when both the linear and quadratic approximations cut with the abscissa axis. It happens after 10.19 iterations (i.e. in this context, people get used to an element after seeing it more than 10 times). Besides, as can be observed in Figure 4.16 (right side), it has been also observed that when running the second block, people’s PRL is lower due to the knowledge/habituation acquired during the first block (26% risk reduction, 42% time reduction to get used to the element). The final value considered (presented in Figure 4.14 the left side of Figure 4.16) corresponds to the average value of both blocks.
Likewise, a similar effect have been found referring to the feeling evocation: considering the two stimuli presented (bomb, negative feeling evocation; and flower, positive feeling evocation), the first one fits the expectations while the second one betrays the prospects. In this sense, as it can be appreciated in Figure 4.17 a), the first impression (left column, 74%) is attenuate along the block due to the habituation (right column depicts the average value for the block, 12%), although the negative evocation remains (84% attenuation, when the typical value is 48%). In contrast, the subfigure b) illustrates how the first positive evocation (left column) is overcompensated when people have discovered that the feeling have not matched the reality. Figure 4.17 c) presents both the average effects for both the false positive and the true negative (left and right columns, respectively). As can be appreciated, the negative effect of not matching the expectancies increases more the RPL than the actual negative feeling evocation (56% to 17%), even this has its own increasing effect. Balancing all these considerations, as it can be appreciated in subfigure d) it has been extracted a 27% RPL decrement due to the positive feelings and a 32% increment when evoking negative feelings (considering in both cases mid familiarity levels).

Finally, regarding to the negative contributions (besides the low familiarity and the negative evocation ones), columns eight, ninth, tenth, eleventh, twelve and thirteenth of Figure 4.14 present the effects of lack of observability, unknown element, involuntari-
4.4 Cognitive Risk Assessment Framework

Figure 4.17: Evolution of risk perception according to the feeling evocation

ness/lack of control and uncertainty, respectively. As can be observed, both the lack of control and observation have resulted to provide with the most negative effects (53% and 78%, respectively). The first result fits the expectations of the social behaviour, where restrictions are associated to hazards (see subsection 4.3.1). Oppositely, the result associated to the lack of observability is aligned with the global cognitive science hypothesis, that states that people tend to maximize their welfare/safety thought information (see section 4.3.2).

The rest of results (inadequate damage distribution, lack of knowledge and uncertainty in the estimation) provide with mid range negative values. It could have been expected a higher effect. Nevertheless, it has been reduced due to the learning (a priori knowledge) and the habituation (familiarity) effects (39% reduction from the first contact). They are all presented in Table 4.8. Besides, they have been analyzed by
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using a one-way ANOVA analysis. Presented in Figure 4.18, the invariance analysis has proved the independence of the parameters and their statistical significance \( F = 1.84, p = 0.00405 \).

<table>
<thead>
<tr>
<th>Cognitive variable</th>
<th>RPL variation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control group</td>
<td>0.56</td>
</tr>
<tr>
<td>Benefit perception</td>
<td>-0.76</td>
</tr>
<tr>
<td>Familiarity (low - novel element)</td>
<td>0.65</td>
</tr>
<tr>
<td>Familiarity (high - known element)</td>
<td>-0.48</td>
</tr>
<tr>
<td>Effect delayed</td>
<td>-0.12</td>
</tr>
<tr>
<td>Feeling evocation (positive)</td>
<td>-0.27</td>
</tr>
<tr>
<td>Feeling evocation (negative)</td>
<td>0.32</td>
</tr>
<tr>
<td>Observability (lack of)</td>
<td>0.53</td>
</tr>
<tr>
<td>Damage distribution (unfair, disadvantageous)</td>
<td>0.35</td>
</tr>
<tr>
<td>Risk knowledge (lack of)</td>
<td>0.29</td>
</tr>
<tr>
<td>Confidence</td>
<td>-0.53</td>
</tr>
<tr>
<td>Voluntariness (lack of)</td>
<td>0.78</td>
</tr>
<tr>
<td>Uncertainty</td>
<td>0.32</td>
</tr>
</tbody>
</table>

Table 4.8: Significant effects in the physiological variables

**Figure 4.18:** Results of the ANOVA analysis

\( F = 1.84, p = 0.00405^* \). The numbers in the X axis observe the legend described in Figure 4.14
4.5 Risk cognition architecture implementation

Last step in the process comes from the application of the knowledge acquired to actual robots. In this sense, the goal has been to provide the robots with intelligence enough to recognize and evaluate the risky elements surrounding them using an human-based cognition. In other words, to reproduce the human risk assessment process in a computer-based system.

Many alternatives have been developed within the AI framework in order to deal with knowledge management: expert systems, designed to provide accurate answers in structured fixed environments; fuzzy logic, where the inputs are not pretty well defined; or genetic algorithms, indented to look for original solutions. Nevertheless, among all of them, when trying to provide with answers to unknown stimuli, model complex relationships or finding patterns, Artificial Neural Networks (ANNs) are the best option (330, 331).

Proposed by Minsky and Papert in 1969, ANNs try to reproduce the human information processing paradigm by imitating the human central nervous system (332). In this sense, they are mathematically modelled as a interconnected group of nodes that emulate the actual neurons, where knowledge arise from the relationships among nodes (333). These relationships are defined by training/learning, using situations similar to the ones wanted to evaluate later. So, by associating input to one (or several) outputs, the network establishes/understands the relationships and configures itself (i.e. the connections among nodes).

Thus, in the thesis, artificial neural networks have been employed to reproduce the human behaviour regarding to the risk. A meta-neural network has been designed, according to the perceptual architectures proposed in section 4.3.3. Composed by several subAANs (see subsection 4.5.1), it has been trained by using the data collected on the experiments presented in subsections 4.4.4 and 4.4.5. As a whole, an architecture capable to assess the risk as a person would do has been designed, implemented and validated.

4.5.1 ANN architecture design

In order to provide with a useful and realistic way to manage the risk perception, a structurative process has been required. Thus, as the Psychometric Paradigm (see 4.3.2.5) or the Kinke perceptual architecture (248) do, the cognitive variables have been factorized according to their anchor. The anchors have been defined considering the formal risk assessment methods presented in section 4.2, so as to be able to relate, combine and compare both approaches.

Each one of the meta-parameters that have resulted from this combination process (risk knowledge, risk allocation and self confidence) give shape to one ANN. They have
been modelled according to the human nervous system, resulting on a collection of multilayer perceptron (MLP) nets (334). Each one of them individually evaluate the risk associate to their corresponding magnitude, combining their results in order to provide with a global risk assessment.

4.5.1.1 Influences to the seriousness of the damage: Risk knowledge

Knowledge refers to the information and skills acquired through experience or study \(^1\). It is also defined as the understanding of a subject, element or topic. According to this, Risk knowledge (RK) refers to the emotional parameters and mind sets that directly weights the objective danger assessment. RK provides with an evaluation of the global situation outcome, including a benefit/loss account that considers not only the statistical figures but also emotional concepts. In this sense, it can be equivalent to the seriousness of damage concept used in the traditional approaches \(^2\).

The variables related to RK are the damage distribution, benefit perception, risk knowledge and feeling evocation. As described in Section 3.3, all, feeling evocation, damage distribution and benefit perception balances the perception of the potential damage. It is increased when the benefit is small or the distribution is considered unfair. Likewise, the risk knowledge variable itself empowers or diminishes the meta RK value according to the knowledge available of the risk to be faced. Thus, the values the variables can assume are ranged from 0 to 1, implying 1 a full concordance with the (positive) proposition and 0 the opposite (e.g. Benefit perception = 0 means that no potential benefit is observed, while Risk knowledge = 1 implies that the knowledge about the risk is complete and reliable). An exception has had to be done with the Feeling Evocation variable, who ranges from -1 to 1. It is necessary due to the positive-negative character of this variables. So, Feeling evocation = 1 means a strong positive feeling, while Feeling evocation = -1 entails the opposite and Feeling evocation = 0 a complete indifference (no feeling is associated).

Finally, as can be observed in Figure 4.20, the composition of these variables (obtained by training the ANN using the data acquired in Stage III) balances the damage estimation originated by the traditional approach. This value is estimated considering the scale defined in subsection 4.2.1, that fits with the levels/classes defined in the FuzzyAcquaintance (from 0 to 4). The combination of both approaches (cognitive and traditional), presented in Figure 4.19 defines the Risk Knowledge contribution (from -1 to 5) to the global Risk Perception figure.

\(^1\)Oxford Dictionaries  
4.5 Risk cognition architecture implementation

4.5.1.2 Influences to the probability of damage: Risk allocation

Allocation derives from the Latin verb *allocare*, composed by *ad* (‘to’) and *locare* (‘arrange’, ‘place’, ‘set’). Thus, it refers to the classification of events, elements or actions. In particular, regarding to the risk management, allocation involves all the characteristics related to the way people identify and classify the risks.

Regarding to the identification, it provides with *a priori* information that complement the data analyzed. In the same line, mental listing associates different risk levels to the different groups. Both processes allow to perform estimations about the likelihood of the events and their consequences. In this sense, risk allocation concept can be understood as the cognitive substitution of the probability of damage estimation.

The variables related to this factor are familiarity, observability, uncertainty-class membership and delay effect. The three first ones are associated to the capability to judge/estimate the hazardous event. They allow to balance the likeliness of occurrence. On the other hand, delay effect is related to the capability to predict the events. The sooner the incident (or the stabler the perception), the better the estimation and the more stunning the risk assessment. All these variables are ranged from [0 to 1], representing 0 the minimum level of the magnitude and 1 de maximum one (e.g Familiarity
4. RISK COGNITION

= 1 implies that the element is completely know and familiar, while Uncertainty = 1 entails a complete doubt about the element properties or behaviour).

The ANN have been trained using these parameters as inputs, and establishing the relationships by using the data extracted in Stage III (see 4.4.5). Besides, the result of the computation has been used to balance the Probability of Damage (PD) figure, originated by the traditional approach (see subsection 4.2.2). This value has to be calculated independently for each mission, considering the elements/people present in the scenario and their affiliation. Table 4.9 defines the values for each one of the combinations:

<table>
<thead>
<tr>
<th>Affiliation</th>
<th>Estimated density of elements</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No elements</td>
</tr>
<tr>
<td>External</td>
<td>0</td>
</tr>
<tr>
<td>Internal</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 4.9: Potential damage assessment table

The final component of the risk perception corresponding to the risk allocation results from the training provided to the ANN. It employs the data obtained in the Stage III experiment (see 4.4.5), combined the Damage Estimation value, providing with a value that ranges between 5 and -1.

4.5.1.3 Influences to the ability to prevent: Self confidence

According to ISO 31000, “risk attitude (and its risk criteria) influence how risks are assessed and addressed”. It also states that attitude defines the approach to risk, influencing whether or not risks are taken, tolerated, retained, shared, reduced or avoided.

On the other hand, self-confidence (SC) refers to the certainty degree in one’s personal evaluations and abilities ¹ (to avoid the risks). So, it is, firstly, a reflex of the relation between de subject and the environment. Secondly, it is also a comparison between the subject and the rest of elements in the scene: the confidence in the temporal continuity (in the relations) or the autonomy degree felt, on the one hand; the superiority or inferiority (physical, of resources or of capabilities), on the other. So, as in the previous subsections, self-confidence can be understood as the cognitive interpretation of the ability to prevent variable.

In this sense, it has been interpreted that the cognitive variables related to the attitude are attitude-voluntariness itself and the confidence as factor of degree of control felt: Degree of control felt because the situations felt under control make people to

¹Oxford Dictionaries
increase their self-confidence; and voluntariness due to the self-confidence level demonstrated when accepting, voluntarily, to face a risk. Both variables range from 0 to 1, implying 0 a complete opposition to the meaning of the magnitude and 1 a total concordance. In this sense, Voluntariness = 0 entails a forced actuation while degree of control = 1 means a total confidence on the own resources and capabilities.

The aggregation of both values is performed by the neural network, which has been trained using the data collected in Stage III. As can be observed in Figure 4.21, the output of the ANN balances the 'ability to prevent' value defined in the traditional approach (see subsection 4.2.4). This way, the safety systems available (estimated between 0 and 1) and the drone capabilities (i.e. autonomy, maximum speed, number of rotors), also ranged from 0 to 1, are included in the Self Confidence estimation, ranged from -0.5 to 2.5.

![Figure 4.21: Evolution of the minimum time to collision according to the situation.](image)

### 4.5.2 ANN training

Training a neural network model essentially means selecting one model for minimizing the cost function. These models are straightforward applications of optimization theory and statistical estimation that employ some form of gradient descent. Evolutionary methods, gene expression programming, simulated annealing, expectation-maximization, non-parametric methods and particle swarm optimization are some commonly used methods for training neural networks. In this sense, they can be grouped in three major learning paradigms, each one corresponding to a particular abstract learning task (335): reinforcement learning (RL) tries to establish the relationship among actions and costs, as well as discover a policy for selecting actions that minimizes the long-term cost (336). In this sense, data are usually not given but generated by the interactions with the environment: for each event (i.e. action performed), the environment generates an observation and an instantaneous cost, according to some dynamics. That is why RL is commonly applied in control problems and sequential decision-making tasks.
4. RISK COGNITION

Oppositely, unsupervised learning (UL) requires from both some data and the cost function to be minimized are given. The function form depends on the task and the \textit{a priori} assumptions (i.e. the implicit properties of the model, its parameters and the observed variables). The training process just adapt the constants for providing the best fitting for the data provided, being in this sense suitable for general estimation problems (e.g. clustering, the estimation of statistical distributions, compression and filtering).

Finally, in supervised learning (SL), the objective is finding a function that infers the model that relates inputs and outputs. In this sense, matching pairs are given and the cost function is related to the mismatch between the mapping and the data. The errors in the matching are iteratively propagated back through the system, adjusting and refining the connections weights controlling the network. This way, supervised learning is useful in pattern recognition (i.e. classification), regression (i.e. function approximation) and sequential data analysis tasks.

The three main ANNs (RK, RA and SC) have been trained using this SL paradigm. The matching pairs for feeding the training have been the one obtained on the results of the experiment described in subsection 4.4.5. Among all the situation (384 trials x 10 variables), only 250 have been used per variable (the most significant ones), obtaining a 0.82, 1.02e-05 and 2.13e-05 MSE on the respective on-data tests. Besides, a supervised ANN has been also implemented in order to integrate the results of the individual outputs, by using the perceptual architecture described in subsection 4.5.1. The general net integrates the results according to the logarithmic risk perception model described by Kahneman (337). Figure 4.22 presents the evolution of the training for RK (a) figure, representing the linear training of RK, RA and SC) and the general network (b) logarithmic).

4.5.3 Results and validation

The system has been proved by using 6 different videos and situations from the UAVRF’s dataset \footnote{UAVRF: http://controls.ae.gatech.edu/wiki/UAV\textunderscore Research\textunderscore Facility} \footnote{UAVRF videos: http://uav.ae.gatech.edu/videos/}. As can be observed in Table 4.10, the ANN-based cognitive cognitive system is capable to evaluate, individually, each one of the elements provided according to their characteristics. According to that, the system generates a complete danger map, what is produced by overlying each one of the individual perception. Moreover, as it is described Section 5.3, this maps is results from the overlying of each one of the individual perception.

In order to validate the accuracy and performance of the system, an additional cognitive experiment has been carried out: 12 subjects (Average age: 33 years; SD: ±11 years) have watched the videos analyzed. After the visualization, they have been
asked to rate, from 1 to 10, the risk that the elements in the videos would suppose in a potential navigation mission. As Table 4.11 presents, these data have been statistically analyzed and compared with the one provided by the cognitive system (CRAS). As can be observed, a 5.87% (9.38% absolute) mean error has been obtained. Besides, the Z-test that has been carried out gas showed a significant inclusion of the CRAS values in the human distribution.

As it is possible to appreciate in Figures 4.23, all the RPL values generated estimated by CRAS (in red) correspond to the human RPL normal distribution (in blue). Besides, all the confidence margins (grey shadow) resulting from the Z-test include the median values of the distributions and are contained within the distributions themselves. This validates that the CRAS emulates the actual human risk understanding and cognition.

4.6 Discussion

As important as perceiving the environment is being able to evaluate it correctly. Detecting specific opportunities, threads or risk is performed by human beings. Nevertheless, this assessment involves multitude of processes and requires from the evaluation of many different intangible variables: social prejudices, mind sets, psychological limitations or past experiences are intermingled, providing with really complex judgements basing on small pieces of incomplete information.

The work presented in this chapter has tried to reproduce this biological assessment system, focusing on the hazard/risk evaluation. In this sense, the global and univocal
4. RISK COGNITION

<table>
<thead>
<tr>
<th>Original image</th>
<th>Elements recognized</th>
<th>Risk map</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="72x581" alt="Image" /></td>
<td><img src="72x467" alt="Image" /></td>
<td><img src="72x353" alt="Image" /></td>
</tr>
<tr>
<td><img src="72x239" alt="Image" /></td>
<td><img src="72x125" alt="Image" /></td>
<td><img src="72x732" alt="Image" /></td>
</tr>
</tbody>
</table>

**Table 4.10:** Examples of danger map generation.

The leftmost images present the RGB image captured. The central ones depict the identification performed of the elements in the scene, while the rightmost ones presents the danger map generated (where a darker color implies less risk and a brighter level a higher potential hazards).
4.6 Discussion

a) Ground risk analysis

b) Static elements

c) Flying friendly elements

d) Flying elements

Figure 4.23: Statistical analysis of the human risk estimation (in blue) compared with the CRAS automatic evaluation (in red).

variables that balance the risk perception have been studied and analyzed. In this regard, a multidisciplinary experiment has been carried out, in order to estimate the relevance of each one of the variables on the global risk perception figure. As a result of this experiment, a relationship among the parameters has been defined, establishing an equation that determines the potential changes in the risk perception. Table 4.12 presents the variables, together with their contribution to the risk perception level, their theoretical support and their equivalence in the visual metrics.

By using this equation and the data extracted from the experiment, a set of artificial neural networks has been trained. As a whole, it evaluates the variables provided by
4. RISK COGNITION

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Ground</td>
<td>2.31</td>
<td>1.625</td>
<td>0.232</td>
<td>6.85%</td>
<td>0.238</td>
</tr>
<tr>
<td>Static elements</td>
<td>5.60</td>
<td>3.83</td>
<td>0.878</td>
<td>17.6%</td>
<td>0.142</td>
</tr>
<tr>
<td>Flying friendly elements</td>
<td>3.02</td>
<td>2.41</td>
<td>0.81</td>
<td>6.03%</td>
<td>0.502</td>
</tr>
<tr>
<td>Flying elements</td>
<td>6.34</td>
<td>7.05</td>
<td>0.469</td>
<td>-7.05%</td>
<td>0.299</td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td>5.87%</td>
<td>0.292</td>
</tr>
</tbody>
</table>

Table 4.11: Automatic risk evaluation vs. human subjective evaluation.

<table>
<thead>
<tr>
<th>Cognitive variable</th>
<th>Relevance</th>
<th>Theoretical support</th>
<th>System variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Damage distribution</td>
<td>35%</td>
<td>CP, PP</td>
<td>Size, FuzzyAquitance</td>
</tr>
<tr>
<td>Benefit perception</td>
<td>-76%</td>
<td>CC, PP, CD, SARF</td>
<td>%MissionAccomplished, missionPriority, distance2NextWP</td>
</tr>
<tr>
<td>Uncertainty</td>
<td>32%</td>
<td>.</td>
<td>DimVar, SpaVar</td>
</tr>
<tr>
<td>Delay Effect</td>
<td>-12%</td>
<td>CP</td>
<td>Tau, distEstimated</td>
</tr>
<tr>
<td>Observability (LO)</td>
<td>53%</td>
<td>PP</td>
<td>distEstimated, vel, visibility, size</td>
</tr>
<tr>
<td>Confidence</td>
<td>-53%</td>
<td>CTR, CC, PP</td>
<td>FuzzyAquitance, Reactivity, Guards</td>
</tr>
<tr>
<td>Risk knowledge (LO)</td>
<td>29%</td>
<td>PP, SARF, rH, aaH, CTR</td>
<td>FuzzyAquitance, confidenceFuzzyAquitance</td>
</tr>
<tr>
<td>Feeling evocation</td>
<td>±29%</td>
<td>aH, CP, MPF</td>
<td>Databased knowledge as f(Tau, Error yaw, height, battery,distance estimated)</td>
</tr>
<tr>
<td>Voluntariness (LO)</td>
<td>78%</td>
<td>CTR, CC</td>
<td>MissionPriority</td>
</tr>
<tr>
<td>Familiarity</td>
<td>±56%</td>
<td>PP</td>
<td>numIterations, elementsObserved</td>
</tr>
</tbody>
</table>

Table 4.12: Relationship among the variables to evaluate and the psychological, sociological or anthropological theory that originates them.

the perception module as a human being, pulling out the potential hazards and the estimation of their risk. This approach has been analyzed, proved and validated through several tests, ratifying its performance and similarity to the human cognitive system.
“The risk of a wrong decision is preferable to the terror of indecision”

— Maimonides

“The essence of risk management is to avoid high risks, manage medium risks, and live with low risks, “

— Anonymous
4. RISK COGNITION
Chapter 5

Risk avoidance

5.1 Introduction

Once the risky elements in the environment have been identified and their potential damage assessed the last step in any Risk Management Architecture should be to try to avoid them. However, as stated in section 1.3.1, the complete elimination of hazards is impossible. So, the goal of any Risk Reduction (RR) system, procedure or behaviour should try to minimize the effect of the risk as much as possible.

This is applicable to the engineering processes and human beings: both try to reduce the potential damage while maximizing the rewards or the goal achievement. Nevertheless, while persons do it dynamically, RR methodologies base their strategies in static evaluations, consequently providing stationary solutions. This approach is actually useful when analyzing the internal hazards (see subsection 5.2.1, since the inertia of these problems is much bigger. Being studied in subsection 5.2.1, the elimination-reduction-minimization procedure defined in the regulation is enough to mitigate the potential effects of breakdowns or environmental conditions. Nevertheless, they are clearly not enough for dealing with external (i.e. unpredictable, uncontrollable) risks.

Only sense & avoidance techniques, presented in subsection 5.2.2, provide an on-line RR methodology. In spite of this, they do not consider risks but the obstacles in the trajectory. So, without analyzing the implications they have, the solutions provided are structural and coercive (i.e. changes in speed, acceleration or attitude) instead of behavioural: observing the human reactions -as has been done in section 5.3-, these are based on altering the priorities and goals of mind sets. In this sense, instead of altering the behaviour in a direct way, human beings change the mental state that originate the reaction. It makes the human responses more context-adaptative and suitable: smooth and subtle when required, energetic and strong when needed.
5. RISK AVOIDANCE

The work presented in this section has tried to reproduce this context-adaptative behaviour in the field of aerial robotics. The incentives, principles, sources and modifiers of human reactions in risk avoidance situations have been studied. Then, these have been reproduced in an active behavioural rule-set called PWDP. This algorithm uses the cognitive risk perception level provided by the previous stage (see chapter 4) in order to alter the priorities of the system in terms of target and best way to achieve it.

5.2 Formal risk reduction strategies

As previously stated, Risk Reduction (RR) methodologies try to reduce the severity/likelihood of the potential loss. All the methods base on the evaluation performed during the assessment stage, focusing on not-acceptable risk situations. Thus, RR procedures define the strategy to follow and the steps to execute in order to suit that level.

As the risk estimation is performed globally and statically, the potential reduction mechanisms and alternatives are static too. Despite this limitation, the techniques are partially adaptable since they consider the nature of the risks, their main source and potential effects. Thus, it has to be distinguished between internal and external risks:

5.2.1 Internal hazards

As explained in section 2.4.2, internal risks are those derived from one or more procedures/elements associated to the application. In this regard, reaction is indentified to guarantee the Performance Level estimated during the risk assessment phase: according to ISO 12100-1:2003, there are three different levels and three different metrics to interact with the system in order to reduce the internal risk (39):

**Metrics:** They establish a relationship among the quality of the elements/processes and the level of safety guarantee. In this sense, the fuzzy Performance Level grade (i.e. the measure of safeness) is related to the Mean Time To Failure (MTTF) value, the Diagnostic Coverage (DC) figure and the type of controller: the first factor expresses the mean time when the first failure occurs either in a design or component -i.e. it determines the quality required for the components--; oppositely, the DC refers to the ratio between the number of dangerous failures detected and the occasions when the failure mode has been activated. Finally, the type of controller is defined by its category (Cat.). It determines -in case of existing a controller- the control architecture required for guaranteeing an adequate safety level. Figure 5.1 define this interrelations, defining which combinations of MTFF, DC and Cat are required in order to guarantee a predefined PL.
5.2 Formal risk reduction strategies

Stage I. Risk elimination in the design process: MTTF and DC adjustment are framed within the first level/stage defined in the ISO 12100-1:2003: elimination of the hazard by using an inherent safe design or selection of components (Chapter 4, of the ISO normative). Risk reduction in the design process or the requirement definition is a critical phase in which an inappropriate development may lead to the presence of risks and problems in the following stages.

Simulation, prototyping and test-bed are the safety mechanisms to be used in this stage. Basing on the component’s probability features, they allow to estimate the location and source of recurrent errors.

Stage II. Risk reduction by using complementary methods: If an optimal minimization is not possible in spite of an adequate design, the second level tries to reduce the risk by implementing complementary methods. These ones are intended to protect/prevent the system from failures and foreseeable misuse, or minimizing the harmful effects in case of breakdown (Chapter 5). Is in this stage where sensing systems, active controllers and mechanical guards are defined.

Regarding to the first two ones, they are framed within the control system, and therefore associated to its Category: as previously established, Cat. establishes the control architecture required (if needed - Cat. B do not require any type of controller), according to the ISO 13849-1:2008. As it is possible to appreciate in Figure 5.2,
5. RISK AVOIDANCE

Cat. I, II and III require from a closed-loop control scheme. Nevertheless, while for Cat. I this scheme is enough, Cat. II requires from a supervisor (S) that provides with an estimation of the error made by the controller. It allows to auto-detect errors or failures in-the-loop. Finally, going even further, last categories (III and IV), substitutes this supervisor by another parallel controller (L), defining a redundant scheme that allows no only to detect but also manage failures in the own control system.

Figure 5.2: Control architectures derived from the risk analysis. Categories I, II and III/IV, respectively.

These structures should be applied when considering: i) protective devices (e.g., control devices, sensing systems, locking devices, etc.), ii) control units (e.g., a logic block, data processing units, etc.) and iii) control elements (e.g., relays, safety switches, valves, etc.). Nevertheless, the inclusion of these schemes should be not the unique measure included. Additional redundancy structures, hardware supervisors, watchdogs, or ruggedization methods clearly improve on the fail-tolerance of the system, as well as the inclusion of diminished flight control mechanisms.

Stage III. Risk containment by establishing safety procedures: When the application of protective techniques or preventive measures do not reduce the risk adequately (Section 5.5 of ISO normative), risk have to be contained by establishing safety procedural rules (49, 338). Considering the procedures affecting only to the individual/internal system, they are indented to guarantee a minimum safety level during the flight.

Described the most common air regulations (see section 2.3), all the safety procedures are related to prevention. In this regard, they can be divided among pre-flight, on-flight and post-flight protocols, according to the nature of the risk they prevent:

1Cat.IV adds a direct feedback from the output while Cat.III employs the input value
5.2 Formal risk reduction strategies

among the first ones, the most important procedure is the system verification process (i.e. checking batteries, scanning frequencies in order to avoid interferences, measure wind speed, etc.). Focused on the system relation with the environment, all this processes are individually performed. Likewise, signaling - an on-flight procedure - protocols are based on the scenario-system connection. Nevertheless, in this case, protocol calls for altering the environment (by using lights or sounds) in order to decrease the exposition to the danger or reduce its effects.

Finally, after the mission, a flight report should be filled out, in order to have a temporal register of the events. This is useful for the maintenance process, making possible to obtained experimental data about motors functions, battery use, and other equipment on-board. Maintenance plays a fundamental role for the global safeness. Some of the activities that maintenance involve are: cleanliness, reparations, replacement, adjustment, calibration and verification.

5.2.2 External hazards

As it has been stated in subsection 2.4.2, external risks are those not connected to the system and therefore not controllable. In this sense, being not possible to act over them, two potential options arise to deal with them: on the one hand, if the elements have communication capabilities, it is possible to set a common policy -both in advance or in the loop- for avoiding the risk. The aviation regulations (339), the road/maritime traffic normative or even the social conventions (340, 341) are good examples of . Thar is why their application in form of air rules (342) or peer-negotiation (based on game theory, for example (343)) to the risk avoidance problems provide with valid solutions.

Nevertheless, these solutions are only applicable to communicable and adaptative systems: If considering reactive-but-not-adaptative elements (e.g. birds, kites, RC systems) or viceversa (e.g. buildings, trees, or even planes due to their big inertia), defining common solutions is not possible. Thus, this kind of scenarios require from an individual, non-deliberative resolution/approach to the RR. Among them, two different categories can be found: as for the internal risks, both risk elimination and reduction strategies (active and passive procedures, respectively):

5.2.2.1 Active risk avoidance systems

Many systems or methods can be considered active methods for risk avoidance. Nevertheless, the almost all can be included within the “sense and avoidance” name. As it was described in the introduction (see 1), these algorithms analyze the environment in their trajectory analyzing potential elements blocking their path (344). This perception is mainly performed -as described in section 3.2- by employing the data acquired by range sensors (e.g. laser, stereo pairs or radars). These data is analyzed in order
5. RISK AVOIDANCE

to extract movement patterns, relative velocities, overlapped trajectories or potential collision points.

The most simplistic -and extended approach- estimate the collision point and increase its volume -according to the drone size- in order to guarantee its safety (79). The volume define the no-entry spaces, providing in some approaches with a curve trajectory over the sphere (10, 345) or with some repulsive vectors (346).

As it is presented in section 5.4, the repulsive effect can be found in several sense and avoidance applications based on potential maps (347, 348). Nevertheless, due to its intensive computational requirements, local methods have been developed basing on PCA (Point of Closest Approach) or geometrical analysis (i.e. trajectory overlap) (349, 350). This kind of intermediate approaches provide with simple but accurate approaches: apart from potential fields, the most employed ones employ curve trajectories and statistical estimations: the first ones combine the collision points with curvilinear paths (351) -based on splines or Bezier curves (99)-. On the other hand, the probabilistic estimations mainly project the drone volume (as an sphere) though the space checking potential collisions (352, 353), constructing dynamic 3D roadmap.

Although almost all these techniques have successfully been extrapolated to multi-uav scenarios (354, 355, 356), almost no one of them have gone further: all the outputs are defined in terms of of variations in the attitude/velocity or by changing the waypoints (WPs). Nevertheless, they do not alter the awareness of the system neither modify its base behaviour further than the problematic point. Besides, despite being dynamic, they do not manage intangible parameters -except for uncertainty (357)-. It implies that algorithms are not flexible enough to deal with unexpected/unknown elements. Passive RR methods (see following subsection, 5.2.2.2) are thought to manage to potential effects of these unexpected.

5.2.2.2 Passive risk reduction methods

Passive RR systems are those elements not included in the core of the system, but added in order to provide an additional protection layer. Also know as guards, they are in charge of limiting the damage of the drone’s elements, and also to third party agents. They are conceived as physical -both passive and active- sentinels, capable of absorbing kinematic energy or limiting the movement of the vehicles. Examples of these kinds of elements are propeller protections, landing legs, parachute, airbags or protection nets.

5.3 Fundamentals of human reactions

As described above, traditional RR systems manage obstacles mathematically and logically, altering the attitude or the trajectory. Conversely, people not only manage risk
5.3 Fundamentals of human reactions

instead of obstacles, but also settle them in modifying directly the behaviour: Once a situation has been understood/interpreted and the risks around evaluated, last step involves the information assimilation and the corresponding reaction (if required). As it is possible to appreciate in Figure 5.3, when no reaction is required (i.e. no presence of risk) or when it is compelling (i.e. to urgent/risky to be deliberated), mental short-cuts are employed to minimize the opportunity cost and time: in the first case, predefined procedures are employed getting the target; in the second one, reactions arise, bypassing the deliberative side of the nervous system (358). It allows avoiding hazards in extreme situations, even at the expense of forgetting goals or fears. Anyhow, in both situations not reasoning is required.

![Diagram describing how to actions are intended](image)

**Figure 5.3:** Diagram describing how to actions are intended

On the contrary, if the risk levels are high enough but not too high, people tent to formulate intents according to the goals to achieve rather than moving immediately into action (359): not compelling situations allow people evaluating different alternatives, obtaining in most of the cases better results. Several authors have studied how human beings discriminate the urgency and the relevancy of the situations, focusing specially on how the potential behaviours are chosen:

5.3.1 The Theory of Affordances

Going further with the Ecological approach -presented in Subsection 3.3-, it provides a frame not only for perception but also for the cause-effect relation: The term ‘affor-
dance’ refers to a quality of an object or an environment to provide individuals the opportunity to perform an action (i.e. a disposition or potential to act, or an ability to discern possibilities for action within the environment). According to that, the Theory of Affordances -proposed by J.J.Gibson in 1979 (360)- tries to explain how inherent values and meanings of things in the environment can be directly perceived, and how this information can be linked to the action possibilities offered to the element by the environment (361).

Several interpretations have been done of this, depending on the interpretation of how the affordance is placed, how it emerges and how it links the agent and environment: Turvey understood affordances as dispositional properties of the environment that the agent could make effective (362). Stoffregen proposed them as properties that emerge from the object-environment relation, being not inherent in either the environment or the object independently (363). Finally, Chemero’s formalization defines them as relations between the capacities or abilities of the elements and features of the environment (364).

Nevertheless, more relevant that the affordance definition is its view according to where it is placed: it must be also taken into account the perspective of the action. Integrating all the theories presented above, it could be understood that the environment always offers the possibility of action (a service offered, in a C++ analogy), the agent/object perceives an opportunity to perform this action (to require or use the service) and the observer realizes the potential connection between the environment and the agent (a supervisor that monitors the process).

Rationalizing this, it could be understood that the environment, once perceived, provides to the object with a set of properties, alternatives or affordances. The agent, according to its criteria, evaluates the alternatives and selects the most suitable one. In this sense, it has been applied in diverse fields, from neuroscience to Human-Computer Interaction (HCI). It has been also used in robotics, mainly in relation to learning algorithms and techniques -i.e. perceptual learning-. Most of the works have used a element-environment equity relation, proofing it is a comprehensive and efficient method to associate consequences to a certain action or behaviours in a given situation (365, 366). Oppositely, some authors claim to the greater relevance of the element’s internal status over the changes in the environment. Anyhow, they all agree in the relation between learning of invariant properties of environments and the consequences of applying an action.

5.3.2 Rational Choice Theory - Utility theorem

Also known as Rational Actor Model (RAM) or Rational Actor Paradigm (RAP), the Rational Choice Theory (RCT) is a framework that tries to understand and model the human behaviour. Developed by Becker in 1976, it attempts to explain social
phenomena in terms of how self-interested individuals make choices under the influence of their preferences (367). Assuming that human beings base their behaviour on rational calculations and act rationally when making choices, RCT treats social interactions as economic exchanges. The system results from the combination of individual choices that all parties made trying to maximize their advantage or gain, and to minimize their disadvantage or loss.

It matches with the Von Neumann-Morgenstern’s utility theorem, that attempts to remove psychological assumptions from the theory of decision making (368). According to their research -basically an application of Game Theory to human behaviour analysis-, individuals having enough information about the consequences of their actions and sufficient time to weigh alternatives always take forward looking decisions.

Mainstream economic trends and behavioural psychology are based on these assumption. In this sense, by combining both approaches, it can be established that individuals always tend to make prudent and logical decisions that provide them with the greatest benefit -that are in their highest self-interest-. Likewise, people choose the options that minimize the risk level (369).

5.3.3 Cognitive dissonance

The feeling of uncomfortable tension which comes from simultaneously holding two or more conflicting thoughts in the mind was named Cognitive dissonance by Festinger in the 1950s. His team studied the inconsistency among ideas, believes, values or emotional reactions as a human motivator, resulting in one of the most influential theories in modern social psychology (370, 371).

They found that individuals tent to to reduce the dissonance and achieve consistency, trying in addition to avoid situations and information which would likely increase the inconsistencies (if they are present) (372). It often leads people to change the state of at least one of the conflicting beliefs or actions. It implies that, to release the cognitive tension, one of the following actions is taken:

- Change the behavior.
- Justify the behavior by changing the conflicting cognition.
- Justify the behavior by adding new cognitions.

On the other hand, the experiments Festinger conducted in a cult showed that if the dissonance is not reduced properly, it can result in restoring consonance through misperception, rejection or refutation of the information. Oppositely, increments of the commitment and conviction of own ideas were also observed.

In the case of an UAV, the thoughts in conflict would be the objective to reach and the risks to avoid.
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5.3.4 Hyperbolic discounting

The hyperbolic discounting theory postulates a time-inconsistent model of discounting for the preferences, choices and evaluations. Officially postulated by Frederick (373) regarding to economical trends, it had been previously observed in behavioral studies (both in humans and animals) (374, 375, 376). According to all of them, it is tended to increasingly choose a smaller-sooner reward over a larger-later one.

In fact, given a choice, people prefer a small benefit in the short term over a larger benefit in the longer term. However, if all choices appear to be in the longer term, larger benefits are chosen, even if these appear even later than the smaller benefit (377). This matches with the Richard Herrnstein’s ”matching law”, which states that when dividing the time/effort between two different rewards, most people allocate it proportionally to the size of each reward, and in inverse proportion to their delays (378).

Analyzing the relationship between the size of the reward and the time to get it, the change in preferences for short and long-terms gives a hyperbolic shape over time. It implies that people’s assessment is inversely proportional to delay of the reward/risk, matching with the non-linear human perception of time.

5.3.5 Intertemporal consumption

Also known as the Discount Utility Theory, it is a economical hypothesis that tries to explain how the human elections/preferences evolve along the time (379). Besides, it analyzes how the option availability is modified according to the decisions taken. In this sense, it posits that individual’s current decisions affect what options become available in the future (i.e. Theoretically, by not consuming today, consumption levels could increases significantly in the future, and viceversa) (380).

Its social approach is named Behavioural Life Cycle (BLCT): Proposed by Shefrin in 1988, it ports this approach to the social iterations and the human decision making system (381). According to his studies, people mentally divide their assets into non-fungible mental accounts - current benefit (income), status (assets) and future benefit. The decisions adopted result from the combination of these parameters, maximizing the relation status-future benefit-lost.

By considering three different economical scenarios (i.e. regular consumption, superannuation and windfall gains experiments), Shefrin’s performed an econometric analysis of the variables previously defined. The results showed that people prefer maintaining the status than risking the actual benefit for a greater one in the future (i.e. to spend greater for current income and least for future income). Even more, people tend to dismiss the risk when it is not too evident (overconsumption), becoming
cautious linearly as soon as the hazard get closer (both in time or distance). Nevertheless, if the maintenance of this behaviour does not provide with the expected results (i.e. unexpected risks, bad estimations, etc.), people usually change completely their behavioural pattern, reacting unexpectedly/irrationally in many cases. Besides, it was also found that reactions to unexpected risks are managed according to the magnitude of those events: reduced risks (windfall gains) are treated as long term risk, while big ones are taken care immediately (382).

5.3.6 Risk compensation theory

The Risk Compensation Theory (RCT) tries to define the behaviour of people in potentially hazardous activities. In other words, it analyzes how people change their behaviour in response to physical/procedural mitigation. Also known as “behavioral adaptation”, it has its origin in several traffic studies where compensatory behaviours were studied in response to safety measures (383). In this sense, it was observed that motorists drove faster when wearing seatbelts and closer to the vehicle in front when the vehicles are fitted with anti-lock brakes.

The analysis of these results suggested that people typically adjust their behavior in response to the perceived level of risk: people become more careful when the risk perceived is big and less careful when they feel safer. Although this effect is small -compared to the risk perceived level- clearly balances the reaction, being this way a behavioral modifier (384, 385) - this is one of the reasons why mitigations are seldom as effective as they are predicted to be.-

In this regard, Dulisse defined the relationship among safety and other goods (386). Although this metric is based on the comparison between the RLP with the own capabilities, it should not be confused with the risk perception balance described in Chapter 4. In this case, not the RPL but the reaction is modified according to the connection.

5.3.7 General considerations

Analyzing carefully the theories described in the sections above, it is possible to appreciate an interconnection among the proposals: more than overlapping their proposals, it arises as a behavioural workflow that integrates (387): Firstly, both the Theory of Affordances and the Feature Integration Theory (presented in subsection 3.3.2) agree that risky stimulus are processed independently for every instant of time. Thus, the general danger picture is defined by combining, in parallel, the individual impressions and considering the final objective. This integration is made -according to CD- in such a way that inconsistencies are avoided: that less risky elements are discarded when compared to higher risks. As well, temporal disruptions are discarded in consonance to the physical (i.e. both temporal and positional) contiguity restrictions.
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Once integrated all the stimulus and generated the danger map, evaluation is performed by assessing the benefit-lost account of the individual options: Considering benefit as the maximization of the closeness to the objective and lost as the potential damage to be suffered, RCT postulates that people choose the option that minimize this metric. So, the options are initially looked for around the goal, in order to maximize the chances to obtain the higher benefit. If no option is found, the range of the search is increased, looking for less optimal alternatives (see the hyperbolic discounting theory). Finally, if no result is found (i.e. no options available within a range), IC postulates that people change radically the scope, looking for potential options in a completely different approach/location.

This behavioural workflow matches with the rest of theories, such as Prospect theory, Expected Utility hypothesis, Optimal/Information Foraging Learning-to-Time (LeT) or Scalar Expectancy Theory. Thus, this methodology has been applied in order to define the algorithm to deal with the risks.

5.4 Risk avoidance method implementation

As it has been presented in the previous section, human decision bases on the reactions observed in the environment -en reference to their previous actions-. This builds up corresponding mental models that give them good decision guidance (388). Nevertheless, obtaining such feedback is not always possible in complex situations. According to Bakken, this omission cannot compensated by education or training, but by intuition (388, 389). In this sense, the intuition-like algorithms capable to fulfil de conditions specified in subsection 5.3.7 have been studied (390).

Only on-line, adaptative and on-board runnable algorithms have been considered. In other words, heavy and deliberative navigation methods have been discarded in favour of light and reactive ones, such us Dynamic Expanding Zones (391), Probabilistic Velocity Obstacle (392, 393) or Oriented Visibility Graphs (394). Nevertheless, the most used ones are the following:

**Nearness Diagram Navigation** - Framed under the situated-activity paradigm (SAP) of design, the Nearness Diagram Navigation (ND) is a geometry-based reactive navigation method: It uses the measurements (mainly proximity of obstacles and areas of free space) of a $360^\text{deg}$ sensor to generate a polar histogram modelling the environment. Then, using that information, the situation is identified by comparing the it with predefined diagrams. Finally, as far as each situation is associated -according to SAP- to specific actions or behaviours, laws of motion (i.e. actions) are applied to navigate safely (395).
5.4 Risk avoidance method implementation

In this sense, since the environmental structure is considered globally, ND avoids local traps situations (396). Besides, it provides with an oscillation-free motion. Nevertheless, on the other hand, cannot guarantee global convergence to the goal location, because they use a local fraction of the information available (sensory information). Furthermore, it only considers circular shapes and static elements, being its escalation really difficult.

**Wavefront propagation** - Wavefront propagation is a breadth-first navigation algorithm based on assigning to each point a value of it cost. This figure represents the time, distance or outlay (in terms of deviation form the objective, for example) that supposes to the robot reaching that point (397): as in a wave movement, each place gets the value of the time/distance when the wave crest arrived there first time. In case of being the area occupied by an obstacle, the wavefront simply flows around it (398).

Navigation naturally emerges when following the gradient of lower cost. Likewise, obstacle avoidance emerges by considering new elements in the picture. This can be achieved by updating the map dynamically or by estimating statistically the movement of the obstacle (399, 400). Nevertheless, due to its natural blindness, it is computational wasteful (401). Even discretizing the area into a 3D grid, wavefront propagation continues being really CPU consuming. Besides, the discretization makes de algorithm to overvalued the progress in certain directions (402).

**Potential fields** - Potential Fields (PF) is an on-line method for navigating avoiding obstacles (403). It is based in the behaviour of many natural species, whose consider food/refuge as attractors and predators/exposed places as repellents. By reproducing this behaviour, a path-planning methodology was developed by Borenstein and Koren (404) basing on the Khatib’s PF idea (403): similar to the influence maps, potential maps present goals as attractive poles and the obstacles ans negative ones. By degrading their respective effects according to the distance, navigation emerge (It arises as the process of following the gradient to towards the maximum benefit - in general minimum potential) (405, 406).

PF have been broadly applied to robotics following different approaches, being Elastic Bands (EB), Dynamic Windows (DW) Vector Field Histograms (VFH) and Virtual Force Fields (VFF) the most popular ones (407). As in the case of the animals, they all process stimuli eliciting not weak attraction but rather strong repulsion. In this sense, their behaviour provides with fast and adjusted measures responses (408). Focusing on VFH, since it computes the gradient locally, it also makes the method really CPU-consuming efficient (equally, animal reflexes operate over a close range and might not detect a threatening stimulus at a safe distance) (409). Nevertheless, this advantage is in turn a problem: local minima traps in many occasion the evolution of
5. RISK AVOIDANCE

the algorithm. Besides, the own nature of the method implies big oscillations in narrow passages or in presence de obstacles (410).

5.4.1 Potential wavefront dynamic propagation (PWDP)

As it can be appreciated above, no one of the actual navigation paradigms perfectly matches the human behaviour. Nevertheless, several approaches can partially fit some of the requirements. So, their strengths have been combined, integrated and redefined in order to give shape to an algorithm capable to reproduce the human behaviour described in subsection 5.3.7.

Named Potential Wavefront Dynamic Propagation (PWDP), it has been designed and implemented to integrate both the kinaesthetic and the vestibular human senses. In this sense, it combines both the local proficiency and simplicity of the potential fields and the global approach of the wavefront propagation techniques: the main idea underlying PWDP has been based on successive local searches that try to find regions guaranteeing a safe UAV movement.

In this sense, as it is possible to appreciate in algorithm 3), the design has tried to establish a relationship between the WP and the safe paths paths: the first step consists on localizing the direction of the next WP and set it as the present goal (or Motion Target, MT). This direction is computed by using i) the error in the Yaw/ψ angle and ii) the difference between the actual altitude and targeted one (ξh). The relationship between these values and the Field of View (FoV) projects the MT as a 2D point in the frontal view image (line 3). In case of having an angle divergence ξψ greater than the FoV (i.e. the next WP cannot be seen by the camera), the drone is commanded to correct the ψ error and aim the WP (lines 4 and 27, respectively).

Once MT is visible, the risk in its trajectory is projected over the image. This projection considers the minimum volume -centered in MT- that guarantees enough space for the drone’s movement towards the goal. The result of this process defines an ares over the image -named AreaMT-, that represents the area required for moving forward safely. It is employed in the potential field evaluation as the local frame, being its gradient understood as the tendency of the risk (line 7) In this sense, if the potential of the area is considered Free (i.e. its dangerousness is less than a minimum previously set), the drone moves forward towards the WP following the shortest (i.e. straight) path line 22).

On the other hand, if the potential of the area is greater than the threshold established, it is understood that this area is dangerous and therefore risky to go thought. Thus, an alternative path has to be looked for according to the psychological theories described in Section 5.3.7: This new behaviour should minimize the deviation from the original route, updating the MT according to the evaluation of the AreaMT surroundings. The direction of the search follows the direction fo the gradient previously
5.4 Risk avoidance method implementation

**Procedure 3** Potential Wavefront Dynamic Propagation algorithm

**Require:** Risk map && Target point

**Ensure:** Movement vector

```plaintext
1: while nextWP is not reached do
2:  Counter ← 0
3:  Update MT (MT ← WP direction \( f(ξ_ψ,ξ_h) \))
4:  if MT ∈ FoV then
5:     repeat
6:         Increase Counter
7:         if \( P(Area_{MT}) \leq MIN \) then
8:             \( S(Area_{MT}) \leftarrow \text{Free} \)
9:         else
10:             if \( P(Area_{MT}) \) has a movement vector then
11:                 Update MT (MT += Potential)
12:             else
13:                 MT = MT + rand() \( P(Image) \)
14:                 \( S(Area_{MT}) \leftarrow \text{Free} \)
15:         end if
16:     end if
17:     if Counter ≥ MAX\(^1\) \_ITER then
18:         MT + rand()
19:     end if
20: until Area\(_{MT} \neq \text{Free} \&\& Counter \leq MAX\(^2\) \_ITER
21: if Counter ≤ MAX\(^2\) \_ITER then
22:     Linear movement towards MT
23: else
24:     Predefined maneuver
25: end if
26: else
27:     Command \( ψ \rightarrow ξ_ψ^0 \)
28: end if
29: end while
```
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calculated (since it is though that the declining direction points to areas with lower risk levels) (line 11). If the potential is uniform -due to a saturation or a equal distribution of the risk-, an adjacent random $Area_{MT}$ is selected, according to the global potential of the scenario (line 13). It search continues until a free a trajectory (i.e. $Area_{MT}$) is found, or until a maximum number of iterations $MAX_{ITER}$ are reached (line 20). When it happens, it is understood that no solution is going to be found around the original MT. So, a change of scope is required: a random MT is generated, and the process starts again (line 18). This scope-change is repeated as many times as the $MAX_{ITER}/MAX_{ITER}$ specifies. If a solution is found -through any of the possible branches-, the drone is headed towards the last MT/solution (line 22). If not, it is considered that the situation has no a direct solution, so a predefined context-dependant maneuver is carried out (stop or moving backwards, according to the global risk level).

![Isometric view of the PWDP search](image1)

![Frontal view of the PWDP search](image2)

\(a)\) Isometric view of the PWDP search  
\(b)\) Frontal view of the PWDP search

**Figure 5.4:** Evolution of the PWDP in a random search.

The colour scale and the $Z$ axis represent the risk perceived, being the red color the maximum risk and the green one the completely lack of hazards.

Figure 5.4 presents an example of the search task. As it is possible to appreciate, the search is initiated in the center of the scene, where the MT is located. Since that location is risky (i.e. high $Z$ value - red colour), the search is continued to the right, following the potential gradient. Same happens in the next iteration, although the value of the risk is lower (orange, lower $Z$). This process continues until the risk is reduced to an acceptable value, depicted in green.

Likewise, Figure 5.5 presents three different potential scenarios to be found. The first one depicts a situation where the solution has been found close to the MT. In the second one, the search has been longer, although a solution has been found after
5.4 Risk avoidance method implementation

several interactions. Finally, last situation has not found any possible solution in a continuous search. So, after $MAX_{ITER}$ iterations the scope has been changed, looking for alternatives in another area and finding a feasible solution.

5.4.2 Experimental evaluation

In order to evaluate the PWDP performance before experimenting with the real system, a simulation framework has been used: it has resulted from a combination between Gazebo\textsuperscript{1} -to simulate the physics- and the Darmstadt’s Hector Quadrotor stack\textsuperscript{2} -to reproduce the dynamics and control of the UAV. In this sense, by using both frameworks, it has been defined a set of potential situations to be found in an outdoor scenario (111).

This collection of experiments result from combining the CRAS-controlled drone with the obstacles and risks that have been considered in subsection 3.4.4.2: trees, buildings, high voltage pylons, drones from the fleet, kites and other UAVs (helicopters). On the one hand, the drone has been modeled considering the Asceding Technologies’ Pelican quadrotor \textsuperscript{3}: 1.65 Kg of total mass (no payload), 0.7 m radius, maximum speed limited to 3 m/s and inertia $i_{xx}=0.01152$, $i_{yy}=0.01152$, $i_{zz}=0.0218$.

On the other obstacles have been defined as follows:

- Tree (10x):1.5 m radius, 6.5 m height.
- Helicopter: 7.5 m radius (blades), 2 m side (cabin) , 1.5 m height (Model: EC175).
- mUAV: 0.7 m radius (Model: Astec’s Pelican).
- Building: 15x10x0.5 m (wall), 10x8x4 m (house).
- High voltage pylon: 5 m side, 18 m height.
- Kite: 1 m height, 0.8 m width

Besides, different capabilities and behaviours have been established for these elements. They include different speeds (from 0.5 m/s to 3 m/s), variability/oscillation levels (from 0 to 2 Hz in all the axis; maximum 2m amplitude) and relative altitudes, both initial and final (from 1 m to 5 m). By combining all the factors and type, 5 different types of situations have been proposed, including 13 different type of trials:

1. Situations with static elements. Different layouts and configurations

2. Situations with a single dynamic element. Different types of objects and movements

\textsuperscript{1}http://gazebosim.org/
\textsuperscript{2}http://wiki.ros.org/hector_quadrotor
\textsuperscript{3}http://www.asctec.de/en/uav-uas-drone-products/asctec-pelican/
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a) Near solution: The solution is found after three iterations.

b) Far solution: The solution is found after eight iterations.

c) Not continuous solution: The solution is not found after eight iterations due to local recurrent minimum. A random position is evaluated after the last iteration, finding a free path.

Figure 5.5: PWDP search in different scenarios
3. Situations with static elements and an unique flying object

4. Situations with several dynamic elements. Different trajectories and configurations

5. General situation with multiple elements of different types.

The following subsections present the performance of CRAS along the experiments. For each of them, it has been presented a 3D reproduction of the situation plus different views of the trajectories covered by the drone (red line) and the obstacles (blue line)\(^1\). Besides, all have been analyzed: Firstly, a quantitatively analysis has been carried out, where several persons have performed a subjective evaluation of the kindness/riskiness of the situation. Secondly, all the scenarios have been analyzed qualitatively considering the deviation suffered from the optimum trajectory. Finally, the most representative scenarios have been presented to several human pilots, who have carried out the same mission. This has allowed to compare the performance of the system developed with the one expected from a human being, using the distance to the risk focus as the main metric.

**Static situations** Static situations refer to those scenarios where the only moving element is the controlled drone. Three different situations have been proposed, defined and tested. The design of the scenario have tried to analyze the behaviour when facing concentrated obstacles (Experiment 1a), disperse (Experiment 1b) ones and surrounding ones (Experiment 1c).

As can be observed in Figure 5.6, during the first one, CRAS has understood that the straight path is not navigable. So, it has surrounded from the very beginning the area full of the trees. Likewise, in situation 1b, the drone has detected the building almost after start moving, so CRAS has commanded a displacement to the right. As it is possible to appreciate in Figure 5.7, at least two different attempts to recover the ideal path have been done. Nevertheless, since a risk has been still perceived, the deviation has continued until it has disappeared.

Finally, Figure 5.8 present the results from experiment 1c. As it can be appreciated, CRAS has detected a navigable path among the trees. It has been selected as the most sub-optimum trajectory and, therefore, commanded. It can be also observed that the path has been readjusted once the trees have been overpassed. Likewise, it can be observed that no oscillation or doubt have been recognized in the trajectory, verifying this way the soft-control of CRAS.

\(^1\)The drone’s trajectory is always depicted from the bottom of the graph (lowest latitude) to the top of \(t\) (maximum latitude). The obstacles’ one is presented always in the other way round.
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Figure 5.6: Experiment scenario 1a - Leafy forest
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a) 3D Scenario render view.

b) Top view.

c) Isometric view.

d) Lateral view.

Figure 5.7: Experiment scenario 1b - House and high voltage pylon
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a) 3D Scenario render view.

b) Top view.

c) Isometric view.

d) Lateral view.

Figure 5.8: Experiment scenario 1c - Corridor in the forest
5.4 Risk avoidance method implementation

**Dynamic situations**  Dynamic situations refer to those scenarios where the controlled drone has to face other moving element. Considering this, four different situations have been designed and tested: they all have tried to sum up the different conditions that may be found: in the first scenario (experiment 2a), the drone has been faced to an helicopter that moves toward it. The main goal has been evaluating how CRAS reacts regarding to mobile elements. In this sense, as it is possible to observe in Figure 5.16, after having detected the helicopter, it has been commanded a left turn to avoid it. However, this movement makes more visible the propellers, making necessary to increase the height in order to avoid the collision. Finally, when the risk is over, the trajectory focusing the goal has been recovered.

**Experiment 2a: Helicopter**

**Obstacle 1**
Origin: Lat 40, Long -30, height 1.2 m.
Target: Lat -40, Long -30, h = 1.2 m
Speed: 2 m/s. No oscillation. Starting time: 0 s.

Contrarily, during the experiment 2b, the drone has been confronted to another mUAV of the fleet (i.e. capable to send communications). In this regard, the goal of the experiment has been evaluating the impact of the knowledge/confidence in the CRAS behaviour: as it is possible to observe in Figure 5.10, the reaction has been softer and the deviation and distance taken smaller. This is due to increment of CRAS's the confidence on the other mUAV behaviour (i.e. the communications received confirm the maintenance of the mUAV trajectory, increasing therefore the certainty).

**Experiment 2b: mUAV from the same fleet**

**Obstacle 1**
Origin: Lat 30, Long -30, height 5 m.
Target: Lat -30, Long -30, h = 9 m
Speed: 2 m/s. No oscillation. Starting time: 0 s.

Finally, the last two experiments refers to an obstacle that moves around a certain location: Firstly, scenario 2c present a situation where the oscillation has been really small (< 0.5m) and centered in the X axis. On the contrary, in experiment 2d, the obstacle has been placed in the same location but the oscillation has been increased (< 3m in all both X and Y axis, < 0.5m in height). By comparing the CRAS behaviour, it can be observed (see Figures 5.11 and 5.12, respectively), the response in the first case is soft -just enough for avoid the obstacle- and the deviation taken small. On the other hand, the reaction in the second case has been more aggressive due to the incertitude.
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derived from the bigger oscillation. In this sense, these experiments has validated the correct adaptability of CRAS to the incertitude/lack of confidence perceived in the obstacle.

**Experiments 2c and 2d**: Oscillating kite

**Obstacle 1**
Origin: Lat 0, Long 0, height 5 m.
Target: Lat 0, Long 0, h = 5 m
Speed: 0 m/s. Oscillation < 0.5 m, 0.5 Hz (2c); < 2 m, 1 Hz (2d). Starting time: 0 s.

**Static-dynamic situations** Static-dynamic scenario are those resulting from the combination of both situations above -i.e. presenting both static and mobile elements-: Experiment 3a has combined both the scenario from experiment 1c (see Figure 5.8) and the UAV presented in the experiment 2a (see Figure 5.10). As can be observed Figure 5.13, the behaviour executed by the CRAS-controlled drone has been similar to the one shown in the same scenario. Nevertheless, a significant difference can be perceived when the other mUAV has been detected: as no side movements are possible, a soft ascension has been commanded to avoid the collision. It has been proportional to the size of the risk, and has lasted only until the obstacle has been overcome. Besides, after that, a proportional descend has been executed to head the target.

**Experiment 3a**: mUAV moving among the trees

**Obstacle 1**
Origin: Lat 30, Long 0, height 2 m.
Target: Lat -30, Long 0, h = 2 m
Speed: 1.5 m/s. Oscillation < 0.5 m, 1 Hz. Starting time: 0 s.

On the other hand, experiment 2b (see Figure 5.14) has reemployed the scenario from experiment 1b: Besides the house and the high voltage pylon, an oscillating helicopter -the one from experiment 2b- has been added. It smoothly oscillates in the middle of the trajectory the drone performed during the experiment 1b (in order to allow to quantify the deviation from the previous route). As it can be observed, in this experiment, the drone has surrounded the obstacle: as a lateral side has been possible, the circumscription has been promoted instead of resorting to ascendant/descendant movements.

**Experiment 3b**: Oscillating helicopter between a house and a high voltage pylon

**Obstacle 1**
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![3D Scenario Render View](image)

- a) 3d scenario render view.

![Top View](image)

- b) Top view.

![Lateral View](image)

- c) Lateral view.

![Isometric View](image)

- d) Isometric view.

- e) Isometric view.

**Figure 5.9:** Experiment scenario 2a - An helicopter approaching
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a) 3d scenario render view.

b) Top view.

c) Lateral view.

d) Isometric view.

e) Isometric view.

Figure 5.10: Experiment scenario 2b - A quadrotor approaching
5.4 Risk avoidance method implementation

Figure 5.11: Experiment scenario 2c - An static kite
5. RISK AVOIDANCE

![Image of kite scenario views]

Figure 5.12: Experiment scenario 2d - A kite blown by the wind
5.4 Risk avoidance method implementation

Origin: Lat 8, Long 15, height 4 m.
Target: Lat 8, Long 15, h = 3 m
Speed: 0 m/s. Oscillation < 0.5 m, 1 Hz. Starting time: 0 s.

**Dynamic-dynamic situations** The dynamic-dynamic situations are those having more than one mobile element in the scene. In this thesis, three different situations have been evaluated considering different layouts resulted from combining the movement of two helicopters: in the first situation (experiment 4a), both helicopters move forward, in parallel, though the drone. They have been separated 12m in the X axis and 2m in the height, and moved with different speeds. Taking that differential into account, the goal of this experiment has been analyzing if the CRAS recovers the shorts route has soon has the risk disappeared. In this regard, as it is possible to observe in Figure 5.15, after avoiding the first helicopter (going up right), the drone the drone has focused again in the goal. This has changed again when the second obstacle has been detected (which was avoided turning left and going down).

**Experiment 4a**: Two separated helicopters in parallel

**Obstacle 1**
Origin: Lat 30, Long -30, height 5 m.
Target: Lat -30, Long -30, h = 5 m
Speed: 1 m/s. No oscillation. Starting time: 0 s.

**Obstacle 2**
Origin: Lat -30, Long -42, height 3 m.
Target: Lat -30, Long -42, h = 3 m.
Speed: 2 m/s. No oscillation. Starting time: 0 s.

Likewise, experiment 4b has reproduced a situation where the obstacles move in parallel. Nevertheless, in this case, since they have been placed really close (6m between them), the scenario does not allow the drone to directly focus the goal in any moment. Thus, as it can be appreciated in in Figure 5.16, CRAS has commanded a detour around both helicopters

**Experiment 4b**: Two helicopters in parallel

**Obstacle 1**
Origin: Lat 30, Long -35, height 5 m.
Target: Lat -30, Long -35, h = 5 m
Speed: 1 m/s. No oscillation. Starting time: 0 s.

**Obstacle 2**
5. RISK AVOIDANCE

Figure 5.13: Experiment scenario 3a - A moving obstacle in the forest
5.4 Risk avoidance method implementation

a) 3D Scenario render view.

b) Top view.

c) Lateral view.

d) Isometric view.

e) Isometric view.

Figure 5.14: Experiment scenario 3b - House, high voltage pylon and helicopter in hovering
5. RISK AVOIDANCE

Finally, experiment 4c has set out a scenario where both helicopters cross their trajectories phased out (5 sec.). The composition of both the perpendicular and longitudinal movements define a complex scenario for the drone: as it is possible to appreciate in Figure 5.17, the first obstacle that has been spotted is the Helicopter 1. Thus, the drone maneuvers turning to the left (looking to the obstacle) in order to avoid it. Nevertheless, after this movement, Helicopter 2 has been shown. A right displacement has been then commanded to avoid this second object. Nevertheless, this second avoidance has made the drone to face again the first helicopter, that has been displaced in the meanwhile. Therefore, in order to avoid the collision, a fast ascend has been executed over Helicopter 1, going back to the route as soon as possible.

In this experiment, it has been indented to i) challenge the capabilities of the system, and ii) verify the priority of the lateral movements over the deviations in height. Both topics have been granted, verifying as well the capability to perceive and manage independent elements with different behaviours.

**Experiment 4c: Two helicopters crossing**

**Obstacle 1**
Origin: Lat 30, Long -30, height 5.5 m.  
Target: Lat -30, Long -30, h = 5.5 m  
Speed: 1 m/s. No oscillation. Starting time: 0 s.  
No oscillation

**Obstacle 2**
Origin: Lat -9, Long -45, height 5 m.  
Target: Lat -9, Long -10, h = 5 m.  
Speed: 1 m/s. No oscillation. Starting time: 5 s.

**General** The last experiment has combined all the element shown in the rest of the scenarios (i.e. multiple static elements plus several moving obstacles). As this general experiment has been designed to verify the system in the hardest conditions, the most difficult scenarios have been overlapped: the crossing helicopters of experiment 4c have been added to the irregular house and high voltage pylon of experiment 1b. This has defined a challenged scenario with multiple simultaneous to-be-considered at the same time. Nevertheless, as can be observed in Figure 5.18, the performance of CRAS has been outstanding: after avoiding the house turning right, the drone has detected the
5.4 Risk avoidance method implementation

Figure 5.15: Experiment scenario 4a - Two helicopters approaching
5. RISK AVOIDANCE

Figure 5.16: Experiment scenario 4b - Two helicopters approaching together
5.4 Risk avoidance method implementation

![a) 3D Scenario render view.](image1)

![b) Top view.](image2)

![c) Lateral view.](image3)

![d) Isometric view.](image4)

![e) Isometric view.](image5)

**Figure 5.17:** Experiment scenario 4c - Two helicopters crossing
5. RISK AVOIDANCE

Helicopter 2 \(^1\) and has surrounded it by displacing up-left. Then, after recovering the trajectory towards the goal, the Helicopter 1 has been been avoided by turning left again and descending a bit. In all the cases, the maneuvers have been carried out smoothly, guaranteeing always a safe distance to all the obstacles (X min). In this sense, it has been validated the capability to manage multiple disorganized elements at the same time.

**Experiment 5: General**

**Drone**

Origin: Lat -30, Long 0, height 3 m.
Target: Lat -30, Long -30, h = 4.5 m

**Obstacle 1**

Origin: Lat 30, Long -30, height 5.5 m.
Target: Lat -30, Long -30, h = 5.5 m
Speed: 1 m/s. No oscillation. Starting time: 0 s.

**Obstacle 2**

Origin: Lat -9, Long -45, height 5 m.
Target: Lat -9, Long -10, h = 5 m.
Speed: 1 m/s. No oscillation. Starting time: 10 s.

5.4.2.1 Results and validation

Apart from the number of successful avoidances (79% during the first round. 100% in the last round, after fixing and adapting the corresponding ranges), the deviation has been used to assess the performance of the system: mean distances covered in each one the situations have been compared to minimum distance joining starting and ending point. Since this comparison is not real (it would imply to go through the obstacles), it has been also compared with the minimum theoretical distance capable to avoid the obstacles. These optimum paths have been defined using the visibility graphs method (412), adding the radius of the UAV (0.7m) as the safety perimeter.

As can be observed in Table 5.1, the mean deviation from the optimum path is 8.1m, what supposes a 10.1 % difference of the distance covered. It supposes an small deviation from the theoretical optimum. Nevertheless, although this value reflexes the performance of the system, it does not provide with any information about its closeness to the human behaviour.

So, as previously mentioned, besides the quantitative comparison, a qualitative one has been also performed: a couple of pilots have run the most representative situations

\(^{1}\text{In this scenario, compared to experiment 4b, Helicopter 2 has been detected firstly due to the modification of the angle provoked by the avoidance of the house.}\)
5.4 Risk avoidance method implementation

Figure 5.18: Experiment scenario 5 - Combined scenario
5. RISK AVOIDANCE

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
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<td>61.55</td>
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<tr>
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</tr>
<tr>
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<tr>
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<td>54.29</td>
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<td>57.31</td>
<td>58.36</td>
<td>8.11</td>
<td>10.12</td>
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</tbody>
</table>

Table 5.1: Comparison of distances. 'Real distance' refers that has been covered by the drone navigated by the CRAS. 'Straight distance' refers to the distance from the first point to the last one, while 'Optimum distance' is the minimum distance to avoid the obstacles, according to the Visibility Graph theory. 'Real-Opt difference' refers to the absolute difference between the real distance and the optimum ones. 'Real-Opt relat. diff' refers to the relative value (%) of the previous data. All the values are expressed in meters.

previously simulated (1a, 1b, 2a, 3b, 4a, 4b), reproducing the same mission the system set. They have used a joystick to navigate and the quadrotor’s on-board camera image to observe the environment.

Figures 5.19, 5.20, 5.21, 5.22, 5.23 and 5.24 compares the CRAS performance (in red) with the ones that have been showed by the human pilots (magenta, in dotted and continuous line).\footnote{In Figures 5.23 and 5.24 the color for the second pilot is depicted in green in order to maximize the distinction}

Table 5.2 presents the numerical results obtained from the CRAS-Human pilot comparison. As can be observed, the distance to the risk has been employed as the metric to compare the behaviours. In this sense, it has been evaluated both the minimum and the mean distances to the risk performed by each one of the navigation (CRAS and human).

Results show a 4.5m (min.), 4m (mean) difference between the human performance
5.4 Risk avoidance method implementation

b) Top view.

c) Lateral view.

d) Isometric view.

e) Isometric view.

Figure 5.19: Verification static situation 1a
5. RISK AVOIDANCE

b) Top view.

c) Lateral view.

d) Isometric view.

e) Isometric view.

Figure 5.20: Verification static situation 1b
5.4 Risk avoidance method implementation

Figure 5.21: Verification dynamic situation 2a
5. RISK AVOIDANCE

Figure 5.22: Verification static dynamic situation 3b
5.4 Risk avoidance method implementation

![Figures 5.23: Verification dynamic dynamic situation 4a](image)

- a) Top view.
- b) Lateral view.
- c) Isometric view.
- d) Isometric view.
Figure 5.24: Verification dynamic dynamic situation 4b
and the CRAS one, in a 60m trajectory. It represents a 7.5% (min.), 6.6% (mean) relative difference. Besides, it can be also observed to different behaviours in the pilots.

Since the training provided in Chapter 4 has been conservative -both due to safety reason and the inclusion of the traditional metrics-, it has been additional compared to the most moderated one. In this approach, the difference has been reduced to 1.5m (2.5%), being possible to say that the system behaves as a conservative person.

<table>
<thead>
<tr>
<th>Situation</th>
<th>CRAS</th>
<th>Pilot 1</th>
<th>Pilot 2</th>
<th>Difference</th>
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<td></td>
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<td>Mean</td>
<td>Min.</td>
<td>Mean</td>
</tr>
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<td>2.34</td>
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<td>1.80</td>
<td>13.71</td>
<td>3.37</td>
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<tr>
<td>3b</td>
<td>8.58</td>
<td>23.423</td>
<td>5.24</td>
<td>24.12</td>
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<tr>
<td>4a</td>
<td>7.11</td>
<td>19.66</td>
<td>0.95</td>
<td>13.58</td>
</tr>
<tr>
<td>4b</td>
<td>16.00</td>
<td>23.05</td>
<td>3.90</td>
<td>16.49</td>
</tr>
<tr>
<td>Average</td>
<td>7.64</td>
<td>17.96</td>
<td>2.85</td>
<td>16.13</td>
</tr>
</tbody>
</table>

Table 5.2: Distance to risk evaluation.

For each one of the situations, the columns show the behaviour observed on the CRAS and the human pilots, as well as the difference among them. The metrics are 'Min' for the minimum distance to the closest risk, and 'Mean' for the mean distance to the closest risk (both measured in meters).

This is also noticeable in Figure 5.25, which compares the mean distance to the risk computed for each flight. As it is possible to appreciate, the CRAS responses are shown in advance (2.1 seconds before, aprox.) and the magnitude of the reaction is slightly smaller (<10%). It has confirmed the cautious attitude of CRAS, validating at the same time its nature when observing the similarities between its behaviour and the actual human one.

5.5 Discussion

To be able to perceive and analyze risk is meaningless if then that knowledge is not used to avoid/limit it: reaction, as the last stage of risk management, is where knowledge is applied and where perception and action get connected. In this sense, traditional approaches establish this link either theoretically or generically. This implies that formal risk reduction strategies perform successfully in specific situations, but not in generic scenarios. Besides, their nature is usually more focused on limiting the damage than on preventing the risk.
5. RISK AVOIDANCE

Figure 5.25: Comparison of distance to the risk between the CRAS and the human pilots. In red, the distance performed by the CRAS. In magenta, the ones obtained by the human pilots (one in dotted line, the other one in straight).
Completely opposed, human reactions are context-adaptative and prevention-focused: Human beings update the perception-reaction link constantly, according to the circumstances and the observations made about previous reactions. This makes the reactions fitted and the people flexible. Nevertheless, in order to guarantee a behavioural stability, the updates only balance few common precepts, all of them based on two key principles:

- Risk are processed independently and in parallel, and reactions derive from their individual intensity.
- Actions are motivated by the risk/benefit perceived relationship.

According to that, responses mainly react to the strongest stimuli and usually try to minimize the deviation from the original plan -because it entails a benefit loss (i.e. displeasure or loss of optimality)-. Likewise, changes of scope are performed when the risk/benefit ratio is impossible to be balanced under certain conditions.

As no one of the current methods or techniques follow these precepts, a new algorithm has been designed considering all above: PWDP reproduces this human behaviour by considering the main principles mentioned. This emulation has been analyzed and validated during the experiments, obtaining a small deviation respect to the human behaviour. Besides, both the magnitude and the time of the reaction are aligned with the ones observed in the actual human pilots, verifying this way the suitability of the approach.
“In literature and in life we ultimately pursue, not conclusions, but beginnings.”
— Sam Tanenhaus. *Literature Unbound*

“O most lame and impotent conclusion!.”
— William Shakespeare. *Othello*

“It’s the job that’s never started as takes longest to finish.”
— J.R.R. Tolkien.
Chapter 6

Conclusions and future work

6.1 Conclusions

The goals of this Thesis have been summarized in Section 1.4 in five different points. Thus, the conclusions extracted refer to those set objectives.

The first goal regards to the analysis and emulation of the human perception using computer vision techniques. In this sense, the study of the main perceptual theories has allowed to establish a model of human perception workflow in what concerns visual processing. Besides, its understanding has allowed to emulate this perception by adapting and designing new visual algorithms to reproduce these processes —which includes several new algorithms of visual intelligence—. The processing emulated provides a success rate higher than > 90% (> 80% average confidence in the estimation), being also the computing time required aligned with the human mental processing lag. (∼ 300ms). Therefore, it can be concluded that the human visual perception has been successfully emulated in terms of performance and robustness. Nevertheless, the restrictions imposed to the perceptive module imply that this emulation is only valid within the scope defined and with the elements considered. The complete reproduction of the HVS would require a higher adaptability, which implies a learning process.

Regarding the second and third goals: sociological, anthropological and psychological theories related to risk understanding and assessment have been studied and interpreted. From them, the underlying principles, procedures and mechanisms have been extracted and compared to the traditional risk evaluation methodologies. The selection of these parameters has been carried out theoretically -based on knowledge obtained from bibliography-, so their suitability could only be verified in a theoretical manner. Nevertheless, assuming them as the most suitable ones, their relevance in the risk cognition process have been assessed unambiguously: the collection of experiments carried out has allowed to correlate the individual contribution of each of one
6. CONCLUSIONS AND FUTURE WORK

the variables selected to the global risk estimation. Besides, the results obtained from these experiments have been validated by carrying out an additional cognitive test. In it, the human cognition and estimation provided to the module have been verified by evaluating a series of situations displayed in video sequences. This analysis has showed a < 6% difference between both evaluations, validating therefore the suitability of the system.

Finally, the fourth goal concerns the reproduction of the avoidance behaviour. In this sense, the traditional avoidance mechanisms and methodologies have been studied. In the rest of the modules, they have been correlated with the human motivators and behaviours related to risk avoidance. Their synergies have been analysed, emulating the result by combining well-known methodologies in a structured procedure. This resulting algorithm -original and custom-designed- reproduces the main behaviour observed in human beings when facing risks. Its performance has been verified by using a simulator and comparing the results with both the mathematical approaches and the decisions taken by actual human pilots. On the one hand, the first verification has proved a < 11% difference between the optimum path and the one performed by the autonomous system. On the other hand, this difference is even smaller (∼ 4%) when the avoidance trajectories and the ones performed by the human pilots have been compared. So, it can be concluded that the developed system’s behaviour is similar to the human one, also proving that both systems behave in a way that closely matches the optimum one.

The final conclusion extracted from this research refers to the human-inspired methodology. Along the research, it has been proved the high adaptability and suitability degree of the human mental processes. That is why multitude of AI algorithms and methodologies have tried to reproduce them. Nevertheless, in most of the cases, these techniques have only considered specific principles. This limitation has been originated by the huge number of parameters and cross-correlations used by brain -which is computationally unmanageable-. However, it has been found out in this work that the most relevant variables and factors employed in many human processes can be reduced and summed up: it is possible to determine the most significant ones by carrying out psychophysical and neurological experiments. In this work, only the inclusion of the obtained knowledge has allowed to overcome the traditional limitations, Only the integration of holistic and global cognition has provided with real adaptability and flexibility to the system. So, as a conclusion of the research carried out, only by means of multidisciplinarity and integration possible to obtain the most suitable approaches and solutions.

6.1.1 Main contributions

A doctoral dissertation must provide with relevant contributions to the state of the art in the corresponding matter. In this sense, beyond the conclusions presented above,
6.1 Conclusions

the main contributions of this thesis can be summed up as follows:

- The main contributions of Chapter 1 are related, on the one hand, to the bibliographical analysis and comparison of the most relevant Risk Management architectures. This study has revealed weaknesses and strengths, allowing to propose the most suitable RMAs for mUAVs missions. Besides, on the other hand, the mental processes related to human being’s risk management have been also studied. So, as a second contribution, the brain’s processes and information flow have been defined in an engineering architecture. Finally, the most relevant contribution of this chapter is the one related to the integration of both architectures in a combined workflow. This proposal supposes the integration of cognitive reasoning into the traditional RMAs, opening a new way to deal with risks.

- The main contributions of Chapter 2 are, firstly, the study, categorization and synopsis of the legislation applied to air systems. This holistic analysis provides a summary of the requirements derived from air legislation and common applying normative. Secondly, the application and customization of these protocols in a real mUAV outdoor mission supposes a practical contribution: the breakdown and evaluation of internal and external hazard sources provides generic and constructive information for any outdoor UAV mission.

- The main contributions of Chapter 3 are related to the analysis and the human perception workflow establishment. In this sense, first main contribution is the study of the people’s brain processes and their organization as connected subsystems that transform and share information. Furthermore, the adaptation and design of new methods to reproduce these processes -which includes several new algorithms of visual intelligence- is also a relevant contribution from this chapter. Both the global approach and the individual methods developed are significant milestones.

- Chapter 4 contains the core novelty of this thesis. The approach proposed is innovative itself, since it integrates sociology, anthropology and psychology in an robotic area where cognitive sciences has not been employed before in combination. Moreover, the innovative integration between the neuroscientific and the engineering methodologies results into several independent contributions: i) the analysis of both neurophysiological and socio-antropological factors related to risk perception and the extraction of their common underlying variables; ii) the association between these variables and the visual characteristics perceived; iii) the analysis of the relevance of each variable (by conducting different psychophysical experiments); and iv) the integration of the results in an intelligent algorithm capable to evaluate the risk of real scenarios.
6. CONCLUSIONS AND FUTURE WORK

• Main contributions of Chapter 5 are related to the analysis of the human conduct and its translation into reactive algorithms. In this sense, the extraction and abstraction of the motivators that define the human reactions have been the first milestone. Basing on that, two different contributions should be considered: firstly, the combination of the hazards to generate a dynamic danger map is a remarkable landmark. Secondly, the integration of well-known techniques in a behavioural architecture in order to reproduce the human behaviour is also noteworthy contribution (specially considering the extensive verification process carried out).

• Finally, the most relevant contribution of this research is the approach performed itself. The idea of changing the obstacle avoidance paradigm by the risk avoidance one has been not addressed yet (< 0.2% according to the papers published in this topic). Furthermore, although cognitive robotics is one of the main trends on AI and robotics, human inspiration had not been applied in risk-evasion algorithms yet. Moreover, the cognitive approaches applied had been inspired by individual and independent principles, while in this thesis the perspective is global, holistic and integrative. Therefore, the whole approach proposed in this research is innovative and supposes an step forward for the AI applied in robotics.

6.2 Future work

Time is always the strictest limitation in the development of any kind of system. So, despite the work done, there are still many things unclear, undefined or not addressed yet. Among the issues to be improved, it is clear that familiarity and delay effect should be characterized more carefully. Their evolution, saturation and dynamics have to be defined properly by doing individual experiments. Equally, the effect of incertitude should be characterised properly, studying which the features that provoke uncertainty and how the work. Finally, it has been assumed (according to the literature) that rewards have an equivalent physiological effect to risks (magnitude, opposite sign). This seems reasonable, but should be clearly experienced.

Also the relation among the visual moment and the dynamics/weight of the objects should be studied deeper. In fact, all the experiments done in chapter 5 should be enlarged: although many situations have been considered, a proper study of all of them (i.e. parametric variations of the locations, relative speeds, etc.) would be of the utmost interest. Besides, these results should be compared with some other sense-and-avoidance methodologies to be able to assess the performance of PWDP. Besides, regarding to the issues still opened, the frustration/saturation effect should has been studied. The validation of the hypothesis relies on people’s capability to perceived. So,
the effects of mental overload should have been also characterized in order to have a complete definition of the risk perception.

It should be also mentioned that the quantitative comparison between the system proposed and the the working sense\&avoidance systems remains as a pending issue. This comparison has been addressed as one of the goals of the thesis. Nevertheless, the time limitations and the difficulty of implementing and customizing many of them have made physically intractable their comparison within this work.

Finally, regarding to the actual future work, there are also a lot of things to be done: Firstly, it would be really interesting to design an automatic learning mechanism to update the feeling evocation parameters dynamically. It would allow to maximize the adaptability of the system to the scenario it is working on. That it is also applicable to the perceptive algorithm: developing its learning capabilities would make the algorithm flexible and adaptive enough to be context-independent. Besides, it could be also interesting to analyze how is risks are perceived by using other senses. And even more, it should be studied how the rest of senses (i.e. audition, smell) influence the vision perception. However, the most relevant future work is, undoubtedly, the implementation of CRAS in a real system. Although it will surely require a great integration effort, the verification under real physical conditions is required. It is an indispensable condition to validate the performance of the human-inspired approach.

### 6.3 Potential applications

The whole human inspired approach has been designed in order to provide with a higher degree of autonomy to robotic systems. In this sense, the applications where CRAS is suitable to be applied are those requiring from high levels of autonomy. Besides, it can be also really useful in system that require to navigate/move in high complexity environments with dynamic and unstructured elements.

In this regard, autonomous vehicles are, of course, the main and most straightforward potential application. Autonomous pilots in boats or planes would increase their safety by implementing a human-inspired avoidance system. Nevertheless, the most promising application regards to autonomous car driving: the developed system bases its obstacle avoidance capabilities on the environmental understanding. Thus, by adapting CRAS, it would be possible not only to safely navigate but also to do it fully autonomous and optimally.

In fact, CRAS perception has already been used in service robotics in the ROCKIN competition. The same concept can be applied to wheelchairs: paraplegics would be able get along more autonomously, relaying in a system that will guarantee their safe navigation. Equally, blind people would clearly increase their autonomy by wearing a device (e.g. smart glasses, Google glass-like) capable to describe them the environment
(as in the case of the autonomous cars, it would only imply adjusting the perceptive system to the environment to evaluate).
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Declaration

I herewith declare that I have produced this paper without the prohibited assistance of third parties and without making use of aids other than those specified; notions taken over directly or indirectly from other sources have been identified as such. This paper has not previously been presented in identical or similar form to any other Spanish or foreign examination board.

The thesis work was conducted from 2010 to 2015 under the supervision of Prof. Antonio Barrientos Cruz and Jaime del Cerro Giner, both at Universidad Politecnica de Madrid.

Madrid, May 14th, 2015