UNIVERSIDAD POLITÉCNICA DE MADRID

**ESCUELA TÉCNICA SUPERIOR DE INGENIEROS DE
TELECOMUNICACIÓN**

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**PROPUESTA DE UNA INTERFAZ COGNITIVA PARA
LA EXPLORACIÓN DISTANTE DE ENTORNOS
VIRTUALES COMO AYUDA A LAS PERSONAS
CIEGAS DURANTE LA CREACIÓN DE MAPAS
COGNITIVOS.**

Antonio Cobo Sánchez de Rojas
Ingeniero de Telecomunicación
Máster en Telemedicina y Bioingeniería
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**DEPARTAMENTO DE TECNOLOGÍA FOTÓNICA Y
BIOINGENIERÍA**

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2018

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**PROPOSAL OF A COGNITIVE INTERFACE FOR
DISTANT EXPLORATION IN VIRTUAL
ENVIRONMENTS AS A COGNITIVE MAPPING AID
FOR BLIND PEOPLE.**

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To Paco, in Memoriam.

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Resumen

El desempleo entre las personas ciegas y con deficiencia visual es muy alto (70%). Estas cifras no son más altas gracias al esfuerzo de organizaciones como la ONCE, que provee gran cantidad de servicios para la inclusión en el mercado laboral ordinario, además de impulsar el mercado laboral protegido, a través de sus filiales. Las exigencias del propio entorno, ya sea en el lugar de trabajo o durante el trayecto al mismo, están catalogadas como una de las principales barreras para las personas ciegas a la hora de conseguir un trabajo o mantenerlo. En concreto, las actividades basadas en habilidades de orientación y movilidad (O&M) (es decir cartografía cognitiva, wayfinding, y navegación) son particularmente difíciles para ellos. La disponibilidad de tecnologías y ayudas adaptadas está catalogada como una de las 3 mejores soluciones a estos retos. La evidencia científica apoya la idea de que la cognición espacial es compatible con la ceguera. Además, la prevalencia de la experiencia de la visión entre las personas ciegas y con discapacidad visual se puede considerar alta. A nivel simbólico, hay tres tipos de conocimiento espacial, siendo el conocimiento de configuraciones (del inglés *survey knowledge*) el más completo y poderoso de entre los tres. La representación mental de una determinada región en dicho formato se conoce como mapa cognitivo. La cartografía cognitiva (del inglés *cognitive mapping*) es el proceso de adquisición de conocimiento espacial. Se puede realizar mediante dos métodos diferentes: el aprendizaje basado en rutas (es decir, explorar físicamente un entorno para aprender su trazado) y el aprendizaje basado en configuraciones (es decir, el aprendizaje de un entorno sin la necesidad de la locomoción). Las habitaciones son por lo general espacios de pequeño tamaño que pueden ser inspeccionados en su totalidad sin necesidad de moverse. Tales espacios de pequeño tamaño se denominan espacios de vista (del inglés *vista spaces*). Sin embargo, las personas ciegas se ven forzadas a utilizar el aprendizaje basado en rutas incluso en espacios de vista. Tanto las personas videntes como las personas ciegas, pueden adquirir conocimiento espacial en un entorno virtual y aplicarlo en el espacio físico equivalente. Por lo tanto, se ha propuesto utilizar visitas a simulaciones de espacios reales en realidad virtual como un medio para que las personas ciegas aprendan la disposición de los obstáculos dentro de una estancia, antes de visitarlos presencialmente. Esos entornos virtuales se exploran de acuerdo con un enfoque de proximidad (es decir, hacer que un avatar replique en el mundo virtual el aprendizaje basado en rutas que la persona ciega haría en el mundo físico). Dentro de la presente disertación, se presenta una herramienta de cartografía cognitiva basada en un enfoque de exploración a distancia. Un enfoque de exploración a distancia permite a las personas ciegas explorar una habitación entera desde un único punto de observación. Dicha herramienta consta de dos interfaces complementarias. Por un lado, una interfaz cognitiva, que es el foco de la presente disertación, conocido como el foco de atención, que permite que las personas ciegas controlen dónde quieren dirigir su atención; y por otro lado, una interfaz sensitiva, responsable de proporcionar retroalimentación. Esta herramienta de cartografía cognitiva se ha implementado en forma de videojuego de realidad virtual para smartphone. Se formuló la hipótesis de que la exploración distante mejora la eficacia y eficiencia del proceso de exploración sin un impacto perjudicial en la calidad y utilidad de los mapas cognitivos resultantes.

Los mapas cognitivos no se pueden observar directamente, para evaluarlos es necesario que las personas construyan una representación externa de los mismos, como un dibujo, una maqueta, o una descripción verbal; el resultado de esta exteriorización se conoce como producto espacial. Se ha empleado una técnica configuracional que proporciona un conjunto de puntos bidimensionales que describen la distribución de obstáculos en el mapa cognitivo. Una regresión bidimensional es capaz de dar cuenta de los niveles de similitud entre dos conjuntos de puntos bidimensionales, sin embargo, no soporta la fuga de datos (del inglés *missing data*). Por lo tanto, se definió un índice novedoso para la evaluación de la calidad de los mapas cognitivos. Dicho índice de calidad se conoce como el Spatial Understanding Quality Index (SUQI). Se define como la distancia de Mahalanobis entre dos vectores de cuatro dimensiones que representan un producto espacial y la escena original, respectivamente. Al estar basado en el uso de la distancia de Mahalanobis, se requiere una estimación de una matriz de covarianza calculada a partir de los elementos de un conjunto representativo de productos espaciales. Se formuló la hipótesis de que un conjunto de productos espaciales de una habitación en particular, es válido para evaluar correctamente la calidad de productos espaciales que representan habitaciones diferentes de aquella. Se llevó a cabo un estudio transversal entre-sujetos (estudio e-Glance), en el que diecinueve personas con ceguera total exploraron tres espacios virtuales de complejidad similar. Los participantes exploraron individualmente cada espacio virtual con un tipo diferente de configuración del foco de atención, esto es, exploración de proximidad (noFoA), foco esférico (sFoA), y foco plano (fFoA). Además, tres evaluadores independientes clasificaron los cincuenta y cuatro productos espaciales del conjunto de datos del estudio e-Glance en función de su similitud con su escena original correspondiente. La evidencia corrobora la hipótesis de que la eficacia mejora debido a la exploración distante ($p\text{-value} = 0,0006$). La configuración distante fFoA conlleva una reducción del 53% en el tiempo de descubrimiento ($p\text{-value} = 0,0027$). Se observa una tendencia que supone una reducción del 38% en la duración total de la etapa de exploración para una configuración de foco plano ($p\text{-value} = 0,067$). La efectividad a la hora de detectar las paredes altera la duración de la exploración ($p\text{-value} = 0,012$). Las mejoras en la eficacia y el tiempo de descubrimiento están asociadas a un menor tiempo total de exploración. La duración de la exploración después del tiempo de descubrimiento depende de la eficacia a la hora de detectar las paredes. Los beneficios de una configuración de exploración a distancia no son suficientes para construir mejores mapas cognitivos. En comparación con la evaluación humana, la fiabilidad entre evaluadores (IRR) del SUQI es excelente: $ICC(A, 1) = 0,999$, IC del 95% (0,997, 0,999); La IRR de la distancia euclídea es de moderada a buena: $ICC(A, 1) = 0,794$, IC del 95% (0,669, 0,875); y la IRR de la colocación de puntos de referencia es moderada: $ICC(A, 1) = 0,720$, IC del 95% (0,561, 0,828). La IRR entre las diferentes estimaciones de la matriz de covarianza es de buena a excelente: $ICC(A, 1) = 0,886$, IC del 95% (0,825, 0,929). Los resultados de la evaluación de los productos espaciales con el SUQI son, por lo tanto, equivalentes a los obtenidos por evaluadores humanos; y esto es así porque, a diferencia de la distancia euclídea, el SUQI tiene en cuenta las diferencias de variabilidad entre las diferentes características representativas de los mapas cognitivos. El mapa cognitivo de una escena se puede evaluar con una matriz de covarianza basada en una escena diferente.

Abstract

Unemployment among blind and visually impaired people is very high (70%). These figures are not higher thanks to the effort of organizations such as ONCE, which provides a great number of services for blind people inclusion into the ordinary labour market, in addition to driving the protected labour market, via its subsidiary organizations. The demands from the environment itself, either at the workplace or during commute, were identified to be a major barrier for blind people to get or maintain a job. In particular, activities based on orientation and mobility (O&M) skills (i.e., cognitive mapping, wayfinding, and navigation) are particularly challenging for them. The availability of adapted technologies and aids was identified as one of the top 3 solutions to said challenge. Scientific evidence supports the idea of spatial thought being compatible with blindness. In addition, the prevalence of vision experience among blind and visually impaired people can be presumed to be high. At a symbolic level, there are three types of spatial knowledge, being survey knowledge the most complete and powerful among all three of them. The mental representation of a given piece of survey knowledge is referred to as a cognitive map. Cognitive mapping is the process of acquiring spatial knowledge. There are two cognitive mapping methods: route-based learning (i.e., physically explore an environment to learn its layout) and survey-based learning (i.e., learning an environment without the need of locomotion). Rooms are usually small-scale spaces that can be inspected in their entirety with no need of locomotion. Such small-scale spaces are referred to as vista spaces. However, blind people are compelled to use route-based learning even in vista spaces. Both sighted and blind people can acquire spatial knowledge in a virtual environment and apply it in the corresponding physical space. Thus, visits to simulations of real spaces in virtual reality have been proposed as a means for blind people to gain spatial knowledge regarding the disposition of obstacles in a place before they actually visit its physical location. Those virtual environments are explored according to a proximity approach (i.e., making an avatar to mimic route-based learning). Within the present thesis dissertation, a cognitive mapping tool based on a distant exploration approach is presented. A distant exploration approach allows blind people for exploring an entire room from a single observation point. Said tool consists of two complementary interfaces. On the one hand, a cognitive interface, which is the focus of the present thesis dissertation, referred to as the spotlight, for blind people to control where they want to direct their attention; and on the other hand, a sensitive interface, responsible for providing feedback. This cognitive mapping tool is implemented in the form of a virtual reality video-game for smartphones. It was hypothesised that distant exploration improves efficacy and efficiency of the exploration process without a detrimental impact on the quality or usefulness of the resulting cognitive maps. Cognitive maps are not directly observable, in order to assess their quality, people must build an external representation of them, such as a drawing, a model, or a verbal description; the resulting outcome is referred to as a spatial product. A configurational technique was used; thus, it was possible to produce a set of two-dimensional points describing the spatial layout in the cognitive map. Bidimensional regression is able to account for similarity levels between two planar points-layouts; however, it does not deal well with missing data. Thus, a novel index for the assessment of cognitive-map quality was defined as well. Said quality index is referred to as the Spatial Understanding Quality Index (SUQI).

It was defined as the Mahalanobis distance between two four-dimensional vectors representing a spatial product and the original scene, respectively. Being based on the use of the Mahalanobis distance, it is required an estimation of a covariance matrix computed from the elements of a representative set of spatial products. It was hypothesised that a set of spatial products of a single particular room is valid to correctly assess the quality of spatial products representing different rooms. A within-subjects cross-sectional study, where nineteen totally blind people explored three virtual spaces of similar complexity, was conducted. Participants individually explored each virtual space with a different type of spotlight configuration, namely, proximity exploration (noFoA), spherical spotlight (sFoA), and flat spotlight (fFoA). In addition, three independent evaluators ranked all fifty-four spatial products in the eGlance-study dataset according to their similarity to their corresponding original scene. Evidence supports effectiveness improvements due to distant exploration (p-value=0.0006). The fFoA distant-configuration entails a 53% reduction in discovery time (p-value= 0.0027). A trend is observed entailing a 38% reduction in the duration of the overall exploration stage for a flat spotlight configuration (p-value=0.067). Wall-detection effectiveness alters exploration duration (p-value = 0.012). Improvements in effectiveness and discovery time are associated with shorter overall exploration time. Exploration duration after discovery time depends on wall-detection effectiveness. Benefits from a distant exploration configuration are not enough to build better cognitive maps. Compared to human assessment, inter-rater reliability (IRR) of the SUQI was excellent: $ICC(A, 1) = 0.999$, 95% CI (0.997, 0.999); IRR of the Euclidean distance was moderate to good: $ICC(A, 1) = 0.794$, 95% CI (0.669, 0.875); and IRR of landmark placement was moderate: $ICC(A, 1) = 0.720$, 95% CI (0.561, 0.828). IRR between different estimations of the covariance matrix was good to excellent: $ICC(A, 1) = 0.886$, 95% CI (0.825, 0.929). Thus, the results from spatial-product assessment with the SUQI are equivalent to those obtained from human assessment; and that is so because, conversely to Euclidean distance, the SUQI accounts for variability differences across cognitive-map features. The cognitive map of a scene can be assessed with a covariance matrix based on a different scene.

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1. INTRODUCTION

The present thesis dissertation was the first one to be developed within the CTB's research line on typhlotechnology. The Royal Spanish Academy Dictionary of the Spanish Language defines the meaning of the voice typhlotechnology as the study of the adaptation of procedures and techniques for its use by the blind (ASALE, 2014). The purpose of the CTB's research line on typhlotechnology is to develop technological solutions reducing the gap between sighted and blind people's ability to make daily decisions, which is indeed a wide gap for eighty percent of the information required for people's daily life comes from vision (ONCE, 2018). In particular, the CTB's typhotechnological research line currently focuses on the gap related to decisions requiring the use of orientation and mobility (O&M) skills.

Travelling from one place to another is, for instance, a typical situation where O&M skills are required to make effective and efficient decisions. When sighted people go into a room, they rely on visual inputs to identify and locate a target item. They keep relying on visual inputs to build a travel plan and follow a route leading to the corresponding target location. They can do so because rooms are usually small-scale spaces that can be inspected in their entirety with no need of locomotion. Such small-scale spaces are referred to as vista spaces; on the other hand, large-scale spaces where locomotion is necessary are referred to as navigation spaces (Golledge, Dougherty, & Bell, 1995; Montello, 1993; Shelton & McNamara, 2004; Wolbers & Wiener, 2014). Even within navigation spaces, where the destination is not in sight, sighted people are still able to reach said destination. The ability to trace a travel plan between an origin and a destination, particularly when the destination is out of sight, is referred to as wayfinding (Allen, 1999). It is believed to rely on a form of spatial knowledge known as cognitive map (Tolman, 1948) and requires people to previously learn the spatial relationship between the original location and the target destination. Such a learning process is known as cognitive mapping (Kitchin, 2001). Finally, the ability to implement a given travel plan is referred to as navigation, and it requires the traveller to track his position along the route (Golledge, 1999). Figure 1 illustrates the differences between these three stages of travel.

Figure 1. Differences between stages of travel.

For blind people, even small-scale vista spaces, such as a room, act as navigation spaces; hence, they must walk around vista spaces in order to learn their spatial layout instead of learning it from a single observation point (Picinali, Afonso, Denis, & Katz, 2014). The present thesis dissertation presents a cognitive mapping tool for blind people to carry out such a form of distant exploration. Said tool consists of two complementary interfaces. On the one hand, a cognitive interface, which is the focus of the present thesis, for blind people to control where they want to direct their attention; and on the other hand, a sensitive interface, responsible for providing feedback. This cognitive mapping tool is implemented in the form a virtual reality video-game for smartphones.

This introductory section consists of two inner sections, namely ‘Background’ and ‘Hypothesis and objectives’. The background section covers four different topics. First, a review about whether blind people are capable of understanding and manipulating spatial concepts. Then, current theories on the mental representation of spatial knowledge are explained, together with an analysis of the particularities concerning blind people. In the third place, a review about the cognitive mapping process is presented together with an analysis of cognitive mapping aids for blind people. Finally, a review of methods and techniques to assess cognitive-map quality is presented. The title of the ‘Hypothesis and objectives’ section

is self-explanatory. The remainder of the document is structured as follows: section two describes the methodology used to collect data and test the hypotheses; section three summarizes the results; section four explores their significance; section five presents the main conclusions of the work; finally, section six explores further possibilities to expand the present research line.

1.1. Background

1.1.1. Blindness and spatial cognition

Key Points

- Scientific evidence supports the idea of spatial thought being compatible with blindness.
- The question remains whether blind people are capable of optimal spatial thought.
- However, the fact is that the prevalence of vision experience among blind and visually impaired people can be presumed to be high.

Spatial cognition has attracted attention from multiple branches of psychology. Allen (1999) highlights the contributions of the psychometric tradition, the information-processing tradition, the developmental tradition, and the neuropsychology tradition. Figure 2 summarises the main spatial abilities identified by either approach.

1. The psychometric tradition aims at characterising the operational mode of the mind by objectively measuring human behaviour (Furr & Bacharach, 2013).
2. The information-processing tradition models the brain as a computing machine. According to this approach, people develop their abilities as a consequence of processing stimuli as part of a training process (Lachman, Lachman, & Butterfield, 2015).
3. The developmental tradition models human development as a biological process consisting of different stages depending on the age of an individual. The weight of nature and nurture contributions to human development are studied within this approach (Butterworth, 2014).
4. The neuropsychology tradition studies how mental processes and human behaviour relates to neural processes and activation patterns (Goldstein & McNeil, 2004).

Figure 2. Spatial abilities identified by different psychological approaches.

Regardless of the particular approach, each of these abilities might contribute to solve problems and perform tasks in at least one of three situations (Allen, 1999).

1. Interactions between a stationary observer and an object. Particularly, objects of small size relative to the observer's size.
2. Interactions between observers and mobile objects.
3. Interactions between mobile individuals travelling around an environment containing large, immobile objects. These are the kind of tasks requiring O&M skills.

The sense of sight is the primary source of spatial inputs (Golledge, Klatzky, & Loomis 1996; Rieser, Guth & Hill, 1982) hence, blind people's ability to understand and manipulate spatial concepts has been a topic of discussion within the scientific community. There have

been three traditional branches of thought known as deficiency, inefficiency, and difference theories (Andrews, 1983) as shown in Figure 3.

Figure 3. Theories of spatial thought in the absence of sight.

Deficiency theory rejects any possibility of developing spatial thought in the absence of visual experience. Thus, congenitally blind people would be unable to perform spatial reasoning due to a lack of the required perceptual processes. On the other hand, both inefficiency and difference theories suggest that, despite their constraints, blind people are capable of spatial thought. The difference between these two theories relies on whether or not blind people are capable of performing optimal spatial thought. While inefficiency theory argues that blind people are intrinsically handicapped by constrained perceptual processes; difference theory argues that they merely lack a continuous flow of information, being otherwise as capable of spatial thought as sighted people (Kitchin, Blades & Golledge, 1997).

Evidence found in scientific literature nullifies the deficiency hypothesis. Despite differences found between blind and sighted people, all three groups of congenitally, early, and late blind people have shown to be able to apply spatial mental abilities to solve problems of different nature and complexity. Blind people were observed using spatial mental-processes for pictorial tasks like mentally clustering objects according to their shape (Aleman, van Lee, Mantione, Verkoijen, & de Haan, 2001) mental changes of perspective in indoor scenes (Rieser, Guth, & Hill, 1986) mental manipulation of items locations (Aleman, van Lee, Mantione, Verkoijen, & de Haan, 2001; Gaunet & Thinus-Blanc, 1996; Lessard, Paré, Lepore, & Lassonde, 1998; Rieser, Guth, & Hill, 1986; Vanlierde & Wanet-Defalque, 2004; Zwiers, Opstal, & Cruysberg, 2001) and applying visual imagery to mental rotation and transformation problems (Carpenter & Eisenberg, 1978; Marmor & Zaback, 1976; Ungar, Blades, & Spencer, 1995; Vecchi, Tinti, & Cornoldi, 2004) among other manipulatory tasks (Cornoldi, Cortesi, & Preti, 1991; Klatzky, Golledge, Loomis, Cicinelli, & Pellegrino, 1995).

Blind people's ability to solve problems that require the use of spatial imagery suggest that inputs from different sensing modalities result in a common internal representation (Aleman, van Lee, Mantione, Verkoijen, & de Haan, 2001). Such an idea can be traced back to Barsalou (1999) and his perceptual symbol systems. The concept is nowadays referred to as spatial image; and there are three hypotheses regarding its nature, namely, multimodal, supramodal, and amodal (Struiksmā, Noordzij, & Postma, 2009). The multimodal hypothesis states that all modalities contribute to the formation of spatial images but, instead of resulting in a common representation, each modality produces a different image. The supramodal hypothesis states that different modalities contribute to building the same spatial image, but the said image is the result of modality-specific pieces of information. Finally, the amodal hypothesis states that, for a given piece of spatial knowledge, and regardless the input modality, inputs from any of the three spatial senses, language, and long-term memory would retrieve and produce the very same spatial image. The discussion is not yet settled, but it revolves around the dispute between the amodal hypothesis (Loomis, Klatzky, & Giudice, 2013; Noordzij, Neggers, Ramsey, & Postma, 2008) and the supramodal one (Bonino et al., 2015; Struiksmā, Noordzij, & Postma, 2009). A recent fMRI study detected activation of common brain areas for both visual and non-visual spatial perception as predicted by both amodal and supramodal hypotheses; however, differences between the activation patterns of blind and sighted participants points at a supramodal representation of spatial images (Bonino et al., 2015).

Being the deficiency theory rejected, the focus of the discussion nowadays falls on whether blind people are capable of optimal spatial thought. Postma, Zuidhoek, Noordzij, & Kappers (2007) argue that the role of visual experience is not homogeneous across different spatial abilities and, thus, its impact varies from task to task. Besides, Cattaneo et al. (2008) argue that the type of vision impairment acts as an additional variable. Those conclusions might explain some contradictory results found in scientific literature. Congenitally blind people seem to find it hard to simultaneously manipulate spatial attributes from multiple items (Cattaneo et al., 2008; Cornoldi, Cortesi, & Preti, 1991; Ruggiero, Ruotolo, & Iachini, 2009; Vecchi, Tinti, & Cornoldi, 2004); nevertheless, they are able to form and manipulate (e.g. rotate) mental images of simple items (Aleman, van Lee, Mantione, Verkoijen, & de Haan, 2001; Gaunet & Thinus-Blanc, 1996; Lessard, Paré, Lepore, & Lassonde, 1998; Rieser, Guth, & Hill, 1986; Vanlierde & Wanet-Defalque, 2004; Zwiers, Opstal, & Cruysberg, 2001). In the latter case, differences of performance, compared to sighted people, are attributed to differences in the mental strategies used to form mental images (Bonino et al., 2015; Vanlierde & Wanet-Defalque, 2004). On the other hand, difficulties in simultaneous manipulation of multiple items are attributed to the fact that blind people's sensing inputs operate sequentially only, in contrast to the parallel capability of vision (Cattaneo et al., 2008; Cornoldi, Cortesi, & Preti, 1991; Ruggiero, Ruotolo, & Iachini, 2009; Vecchi, Tinti, & Cornoldi, 2004). Another example comes from memorising locations: while Gaunet, Martinez, & Thinus-Blanc (1997) and Gaunet & Thinus-Blanc (1996) argue that the use of systematic exploration patterns has more influence than the role of vision, Loomis et al. (1993) and Rieser, Guth, & Hill (1986) argue that navigational tasks are indeed influenced by visual experience. From a neural perspective, visual experience seems to be necessary for the

maturation of multisensory neurons (Pasqualotto & Proulx, 2012).

In conclusion, visual experience is not a mandatory requirement to understand and manipulate spatial concepts, but it seems to be required to achieve optimal levels of spatial thought. The fact, however, is that visual experience is prevalent among the blind and visually impaired population. According to the last statistical report published by the National Organization for Spanish Blind People (ONCE, in its Spanish acronym) only 1.17% of its members are early blind or visually impaired children between zero and five years of age (ONCE, 2017). If a more restrictive criterion were applied and the age threshold were raised to sixteen years of age, the proportion of blind and visually impaired people would grow to 5.16% of the ONCE members. Blindness is defined as the absolute absence of vision or the vague perception of light (i.e., being able to tell the difference between absolute darkness and the presence of a light source) on the other hand, vision impairment involves a visual rest of functional use for daily life (travelling, housework, etc.). According to these definitions, the proportion of early blind people is even smaller: only 19% of children between zero and five are blind while the proportion of blind children between five and sixteen rises to 49%. Hence, the proportion of visually inexperienced people would fall down to 2.18% of ONCE members. Regardless, even sticking to the figures in the most restrictive case, 89.95% of the target population would have gone blind or visually impaired after their sixteen years of age and, thus, can be considered to be visually experienced (see Figure 4).

Figure 4. Distribution of ONCE members by age according to (ONCE, 2017).

1.1.2. Mental representation of spatial knowledge

Key Points

- At a symbolic level, there are three types of spatial knowledge: landmark, route, and survey knowledge.
- There is a hierarchical relationship between them; being survey knowledge the most complete and powerful among all three of them.
- The mental representation of a given piece of survey knowledge is referred to as a cognitive map.
- A labelled graph is the representation format better accounting for the sketchy and distorted properties of cognitive maps.
- Spatial knowledge may be represented relative to an egocentric, an allocentric, or an intrinsic frame of reference.
- Blind people find it hard to produce allocentric spatial representations unless learning an environment from a stable body position.
- At a neuropsychological level, the hippocampus has been identified to have a vital role in the mental representation of spatial knowledge.

The mental representation of spatial knowledge is an internal phenomenon that, by definition, is not directly observable. It has attracted attention from several disciplines like cognitive science (Wen, Ishikawa, & Sato, 2013), psychology (Jacobson, 1998), cartography (Kitchin, 1994), neuropsychology (Bonino et al., 2015), and artificial intelligence (Chown & Yeap, 2015). Models of spatial knowledge representation in the human mind have been developed at a symbolic level, by explaining the nature, properties, and relationships of spatial concepts (Golledge, 1999; McNamara, 1986; Remolina & Kuipers, 2004; Tversky, 1992) and at a neuropsychological level, by observing the activation patterns of neural structures (Jeffery, 2015; Jeffery & Burgess, 2006; Nadel, 1999; O’Keefe & Nadel, 1978). These approaches have even guided the development of computational cognitive models of spatial memory in the fields of artificial intelligence and robotics (Madl, Chen, Montaldi, & Trapp, 2015; Manning, Lew, Li, Sekuler, & Kahana, 2014).

Tolman (1948) coined the term *cognitive map* to refer to a mental representation of spatial knowledge. It was based on the observation of rats being able to implement detours and shortcuts to build optimal routes between two locations. Said rats had no previous experience of the optimal routes they were following; thus, it looked like they were reading a planar map of the area. The notion of a mental map has been somehow controversial, many alternative terms have been proposed (Kitchin, 1994). While many authors understand the term as an actual mental construct storing spatial information; some others think it represents just a convenient but fictional convention (Kitchin, 1994). Critics to the cognitive map hypothesis highlight the fact that it was born from behavioural observations only and argue that the ability to use shortcuts might be explained as a product of heuristics with no need of mental maps (Chow & Yeap, 2015). Also, not everybody shows the ability to infer new routes, but Weisberg, Schinazi, Newcombe, Shipley, & Epstein (2014) argue that the

phenomenon might be explained by accounting for individual differences in sense of direction (SOD). Significant correlations have been observed between different levels of SOD and the ability to develop such kind of spatial knowledge (Weisberg, Schinazi, Newcombe, Shipley, & Epstein, 2014; Wen, Ishikawa, & Sato, 2011, 2013). Besides, a region within the brain, known as the hippocampus, was identified to play a vital role in the understanding of space and the storage of spatial memories (Nadel, 1999; O’Keefe & Nadel, 1978). Place cells within the hippocampus are believed to be the neural support of cognitive maps for they show a stable pattern of activation for a given location regardless heading direction (Madl, Chen, Montaldi, & Trapp, 2015). Wolbers & Wiener (2014) argued that the role of the hippocampus could have been misinterpreted by inappropriate acknowledgement of the scale of space in spatial cognition studies. They argued that results from vista space were being taken as valid results for navigation space. They conducted a review that confirmed the participation of the hippocampus in the mental representation of space both for vista and navigation scales. Their review found just some minor differences depending on the frame of reference (please check the next paragraph for an explanation about frames of reference and other related concepts). The hippocampus has also been observed to intervene in non-spatial processes, and it is argued that its actual role is to organise personal experiences within memory (McNamara, Shelton, & Shelton, 2003). Cognitive maps would then encompass different domains of memory and organise their information according to spatiotemporal relations useful for achieving different goals (Schiller et al., 2015). As a final remark about the neural organization of spatial knowledge in the brain, information regarding obstacles in vista space has been observed to be split and encoded in two separate systems known as the “what” and the “where” systems (Amorim, 1999). This concept has been successfully tested for cognitive mapping applications in the field of robotics (Chown, 1999).

Spatial knowledge has been observed to be encoded relative to different types of frames of reference. Traditionally, spatial knowledge was considered to be encoded relative to either an egocentric or an allocentric frame of reference (Iachini, Ruggiero, & Ruotolo, 2014; Manning, Lew, Li, Sekuler, & Kahana, 2014; Serino et al., 2015) in addition, Mou & McNamara (2002) proposed an additional type: the intrinsic frame of reference. For an egocentric frame of reference, the conceptual north is selected relative to one’s body itself; thus, landmark locations are described in a self-to-object manner, to further complicate things, multiple egocentric frames of reference may coexist each of them anchored to a different body part (Wolbers & Wiener, 2014). On the other hand, for an allocentric frame of reference, the conceptual north is selected relative to an external object. Landmark locations are described in an object-to-object manner. As for an intrinsic frame of reference, the conceptual north is selected according to the specific configuration of the particular spatial layout to be remembered. Yamamoto & Philbeck (2013) identified previous evidence for the following criteria as guides for the selection of an intrinsic frame of reference: “... egocentric orientations of observers in an environment (Shelton & McNamara, 1997, 2001), allocentric features of the surroundings (such as a floor mat and room walls; McNamara, Rump, & Werner, 2003; Shelton & McNamara, 2001), geometric structures of the spatial layout (Mou & McNamara, 2002), and the interaction among them (Kelly & McNamara, 2008; Mou, Zhao, & McNamara, 2007; Shelton & McNamara, 2001).” (p. 448). The existence of both

egocentric and allocentric representations is supported by neurological observations that identified the entorhinal complex in the hippocampus as the location of allocentric representations and the precuneus as its homologous for egocentric representations (Madl, Chen, Montaldi, & Trapp, 2015). It has been suggested that allocentric representations are related to long-term memory while egocentric ones relate to short-term memory, acting as a buffer for the egocentric-like sensory inputs (Byrne & Becker, 2007). It has been suggested that wayfinding tasks (i.e., route planning) rely mostly on allocentric information while navigation tasks (e.g., route following) rely mostly on egocentric information (Meilinger, Frankenstein, & Bühlhoff, 2013; Wolbers & Wiener, 2014). A bidirectional relationship between these two types of representations has been observed to be mediated by the posterior parietal and retrosplenial areas of the brain (Byrne, Becker, & Burgess, 2007) and to support people's orientation while navigating across a given environment; in fact, emphasising egocentric heading information within an egocentric representation of said environment facilitated navigation more than a more detailed planar map representation (Serino et al., 2015). An additional property of spatial knowledge is the orientation in which the frame of reference is stored. When there is a preferred orientation to access a given piece of spatial knowledge, it is said to be orientation-dependent, otherwise (i.e., all directions show the same delays and number of errors when accessed) the accessed cognitive map is said to be orientation-free (Meilinger, Frankenstein, & Bühlhoff, 2013). The relationship between the type of frame of reference and the orientation is not clear (Manning, Lew, Li, Sekuler, & Kahana, 2014; Iachini, Ruotolo, & Ruggiero, 2009). Though, according to Serino et al. (2015) the CA3 region in the hippocampus has been observed by Behrendt (2013) to process allocentric information in a viewpoint-dependent manner and later feed that information to the CA1 region, where it is encoded as allocentric viewpoint-independent knowledge.

At a symbolic level, spatial knowledge in navigation space is described as a hierarchy of different types of knowledge (Siegel & White, 1975; Tussyadiah & Zach, 2012; Weisberg, Schinazi, Newcombe, Shipley, & Epstein, 2014). Three different forms of spatial knowledge have been described in scientific literature, namely, landmark knowledge, route knowledge, and survey knowledge (Siegel & White, 1975; Wen, Ishikawa, & Sato, 2011, 2013). Each of them explains a subset of abilities and behaviours. Landmark knowledge explains people's ability to recognize locations in vista space. This recognition ability is based on the presence of remarkably meaningful elements, known as landmarks. For anything in vista space to become a landmark, it has to be particularly meaningful by either showing a remarkable feature or holding a personal meaning (Golledge, 1999). Landmarks act as checkpoints and decision points in wayfinding and navigation tasks (Golledge, 1999). A number of attributes like visibility, salience, distinctiveness, relevance, reliability, and persistence (Ruddle, Volkova, Mohler, & Bühlhoff, 2011) have been described for landmarks, but specific selection criteria and mechanisms are not referred in the literature (Chown & Yeap, 2015). In fact, individual differences in these selection criteria might explain the variability between different people's cognitive mapping outcomes for the same place (Weisberg, Schinazi, Newcombe, Shipley, & Epstein, 2014). Route knowledge explains people's ability to find their way from a given origin to a particular destination via a previously learned route; and consists of an ordered sequence of place-action associations that link a collection of related

landmarks to one another (Chrastil & Warren, 2012; Farran, Courbois, Van Herwegen, & Blades, 2012; Rossano & Reardon, 1999; Siegel & White, 1975; Thorndyke & Hayes-Roth, 1982; Wen, Ishikawa, & Sato, 2013). Survey knowledge explains people's ability to take shortcuts and detours via novel routes when those people had not previously experienced them; and cannot be accounted for by route knowledge (Chrastil & Warren, 2012, 2013; McNamara, Shelton, & Shelton, 2003; Meilinger, Frankenstein, & Bühlhoff, 2013). Survey knowledge involves information regarding the relative location of landmarks and the paths connecting them to one another (Chrastil & Warren, 2012; Farran, Courbois, Van Herwegen, & Blades, 2012; Golledge, 1999; Rossano & Reardon, 1999; Siegel & White, 1975; Thorndyke & Hayes-Roth, 1982). The following three observations reinforce the notion of a hierarchical relationship between these three types of knowledge: 1) the computation of novel routes without previous experience of them (Chrastil & Warren, 2012, 2013; McNamara, Shelton, & Shelton, 2003; Meilinger, Frankenstein, & Bühlhoff, 2013; Tolman, 1948) 2) the emergence of survey knowledge from a collection of overlapping routes (Morganti, Carassa, & Geminiani, 2007) and 3) for survey knowledge to emerge from overlapping routes, the latter ones need to share common landmarks, otherwise information coming from plain path integration is not reliable enough to compute effective shortcuts which, in turn, reinforces the notion of landmarks acting as the building blocks of spatial knowledge and their crucial role in the organisation of recently acquired spatial knowledge (Foo, Warren, Duchon, & Tarr, 2005).

Many models have been proposed to explain survey knowledge, from isomorphic representations in the form of mental images (Nelson, 1996; Afonso et al., 2010) to graph-like representations (Chrastil & Warren, 2014; Kuipers, Tecuci, & Stankiewicz, 2003; Werner, Krieg-Brückner, & Herrmann, 2000) including hierarchical formats (McNamara, 1986). Isomorphic representations account for the linear relationship observed to link the distance between two objects and the time spent while mentally scanning the path that connects them together (Afonso et al., 2010). Nevertheless, isomorphism cannot account for observed distortions like asymmetries (Kuipers, 1982), overestimation of short distances (Lloyd & Heivly, 1987), size transformations, directional compression, and elongation (Gärling, 1999). The graph-like hierarchy proposed by Chrastil & Warren (2015) can reconcile these two views. According to them, survey knowledge is represented in the form of a graph where several levels of detail are possible. The simplest form is a topological graph where different pieces of landmark knowledge, in the form of vista spaces, are connected to one another forming a network with no metric information. The next form of spatial knowledge consists of a labelled graph. A labelled graph is a network of nodes linked to one another by topological relations where the edges are annotated with metric information (distances and angles) but, contrary to the isomorphic model, edges within a labelled graph may represent different distance values when travelled along different senses; and the sum of angles within triangles need not be consistent (Chrastil & Warren, 2014, 2015). Such a format is able to predict the computation of new routes, even based on a shortest-path metric, many forms of distortion, and even the existence of graph portions showing Euclidean properties (Chrastil & Warren, 2014, 2015). A complete form of survey knowledge is then a labelled graph where distances and angles are consistent with Euclidean geometry. Sketchy cognitive maps based

on graphs of vista spaces or scenes have been successfully implemented in AI and robotics applications that, otherwise, would have been expensive and inefficient regarding both storage and computational needs (Chown, 1999; Chown, Kaplan, & Kortenkamp, 1995; Kuipers, 1982). Finally, it should be noted that the idea of a single cognitive map summarising someone's spatial knowledge was dismissed in favor of multiple cognitive maps of different spaces (Kuipers, 1982; Wong, 1979).

Some particular considerations should be taken into account for the particular case of blind people. The main inconveniences for blind people as a consequence of the absence of vision are the sequential nature of their perception mechanisms, as opposed to the parallel nature of sight, and the lack of feedback regarding distant information (Cattaneo et al., 2008). Fortunately, spatial knowledge acquired from verbal descriptions has been observed to preserve metric properties in mental images; the same kind of delays have been observed while mentally scanning verbally and visually acquired cognitive maps, though both acquisition and scanning are less efficient in the former case (Afonso et al., 2010). It has also been observed that route descriptions are a better help for blind people than survey ones (Noordzij, Zuidhoek, and Postma, 2006) which is consistent with our observations in exploratory workshops with blind volunteers. Blind people might find difficulties to translate information in a given frame of reference into a different type of frame of reference (Coluccia, Mammarella, & Cornoldi, 2009; Coluccia, Mammarella, De Beni, Ittyerah, & Cornoldi, 2007). According to Ruggiero, Ruotolo, & Iachini (2012) congenitally and adventitiously blind people experience these difficulties differently. Congenitally blind people would experience these difficulties when processing near/far spatial relations, while adventitiously blind people will do so when processing left/right ones. In a subsequent publication, Iachini, Ruggiero, & Ruotolo (2014) report contradictory evidence regarding the differences in the "choice" of a frame of reference between people with different levels of visual experience. While some works show that early-blind (congenitally blind) people are prone to egocentric spatial representations in contrast to the allocentric representations of visually experienced people (Pasqualotto, Spiller, Jansari, Proulx, 2013; Cattaneo et al. 2008; Thinus-Blanc & Gaunet, 1997; Schmidt, Tinti, Fantino, Mammarella, & Cornoldi, 2013); some other works failed to observe such a difference (Hollns & Kelley, 1988; Coluccia, Mammarella, & Cornoldi, 2009; Ruggiero, Ruotolo, & Iachini, 2012; Tinti, Adenzato, Tamietto, & Cornoldi, 2006). Iachini, Ruggiero, & Ruotolo (2014) observed that said disagreement could be explained by accounting for the scale of the mapped space. As such, congenitally and early-blind subjects find it more challenging to develop allocentric representations in large-spaces (those that require both haptic and locomotor exploration) than in small-spaces (those requiring haptic exploration only). Actually, they argue that as long as blind people are empowered to map the environment from a stable body position, they might be able to effectively translate between those two frames of reference. Further research would be necessary to explore whether blind people are able to build proper allocentric survey representations should they be provided with distant information while in a stable body location. Even intrinsic frames of reference have been observed to emerge from sequential access to information, e.g., haptic input modalities (Yamamoto & Philbeck, 2013) and verbal descriptions (Mou, Zhang, & McNamara, 2004).

1.1.3. Cognitive mapping

Key Points

- Cognitive mapping is the process of acquiring spatial knowledge.
- There are two cognitive mapping methods: route-based learning and survey-based learning.
- Blind people are compelled to use route-based learning even in vista spaces.
- Being in control of where and when attention is directed improves cognitive mapping outcomes.
- Both sighted and blind people can acquire spatial knowledge in a virtual environment and apply it in the corresponding physical space.
- Multimodal feedback improves cognitive mapping outcomes.

Cognitive mapping is the process of acquiring spatial knowledge (Kitchin, 2001). It can be carried out through two different methods, namely, route-based learning and survey-based learning. Either way, a cognitive map can result from directly experiencing the environment to be learnt or from checking secondary information sources like maps (Brunyé, Gardony, Mahoney, & Taylor, 2012; Golledge, 1999, Piccardi et al., 2011). Please, notice that both route-based learning and survey-based learning should not be mistaken for route knowledge or survey knowledge. While the former ones are methods for people to acquire information in order to produce spatial knowledge of a given environment, the latter ones, as described in section 1.1.2., are two types of cognitive mapping outcomes representing the said environment. Route-based learning involves sequential learning of different parts of the environment that cannot be perceived simultaneously; thus, it is usually related to navigation space (Golledge, Dougherty, & Bell, 1995; Madl, Chen, Montaldi, & Trappl, 2015; Shelton & McNamara, 2004; Wolbers & Wiener, 2014). Survey-based learning involves simultaneous learning of different landmarks and their connections to one another; it is usually related to the use of planar maps, but it is also suitable for learning small-scale environments in vista space (Golledge, Dougherty, & Bell, 1995; Montello, 1993; Shelton & McNamara, 2004; Wolbers & Wiener, 2014).

Route-based learning can result in both route and survey knowledge. The ordered sequences of place-action associations that are involved in route knowledge (Chrastil & Warren, 2012; Farran, Courbois, Van Herwegen, & Blades, 2012; Rossano & Reardon, 1999; Siegel & White, 1975; Thorndyke & Hayes-Roth, 1982; Wen, Ishikawa, & Sato, 2013) come straightforward as a natural outcome of the sequential exploration of different vista spaces. Objects within any given vista space are more likely to become landmarks if a route decision is required to be made based on them (Wolbers & Wiener, 2014). However, according to Lingwood, Blades, Farran, Courbois, & Matthews (2015) in the absence of landmarks, routes

can also be learnt as a sequence of junctions on the basis of a directional strategy. As explained in section 1.1.2., survey knowledge may emerge from a set of multiple overlapping routes where common landmarks can be found (Foo, Warren, Duchon, & Tarr, 2005; Morganti, Carassa, & Geminiani, 2007). The hierarchical relationship between different types of knowledge is the basis of a theory about knowledge acquisition known as spatial cognitive microgenesis (Siegel & White, 1975). According to said theory, cognitive mapping follows a sequential model where the development of landmark knowledge precedes the development of route knowledge, which, in turn, precedes the development of survey knowledge. However, subsequent evidence showed that survey knowledge may emerge directly on its own, with no need of previous development of route knowledge (Ishikawa & Montello, 2006; Weisberg, Schinazi, Newcombe, Shipley, & Epstein, 2014). Also, Wen, Ishikawa, and Sato (2011, 2013) argue that contradictory results about survey knowledge directly emerging from route-based learning can be explained by individual differences in sense of direction (SOD). They observed “... that people with a good SOD encoded and integrated knowledge about landmarks and routes into egocentric survey knowledge in verbal and spatial working memory, which is then transformed into allocentric survey knowledge with the support of all three components, distances being processed in verbal and spatial working memory and directions in visual and spatial working memory. In contrast, people with a poor SOD relied on verbal working memory and lacked spatial processing, thus failing to acquire accurate survey knowledge.” (Wen, Ishikawa, & Sato, 2013, p. 176). Spatial knowledge from cognitive maps is consolidated in neural structures during sleep and states of quiet wakefulness, as supported by the observation of firings of the same sequences of place cells in the hippocampus both while planning novel routes within previously known areas, and during sleep (Pfeiffer & Foster, 2013; Schmidt & Redish, 2013; Sutherland & McNaughton, 2000).

It has been suggested that specific properties of mental representations of spatial knowledge depend on the learning method in use. For instance, performance in judgement of relative direction (JRD) and scene- and orientation-dependent pointing (SOP) have been observed to behave as a function of the learning method (Zhang, Zherdeva, & Ekstrom, 2014) and survey-based learning has been observed to lead to earlier development of survey knowledge than route-based learning (Brunyé, Gardony, Mahoney, & Taylor, 2012). In fact, these authors even argue that the learning method is strongly related to the frame of reference resulting from the cognitive mapping activity (egocentric vs. allocentric) and to the scale of space required for a given wayfinding task, with route-based learning better fitting short-range planning and survey-based learning better fitting long-range distances.

Active learning has been observed to be more effective than passive learning (Chrastil & Warren, 2012, 2013, 2015; Picinali, Afonso, Denis, & Katz, 2014). While passive learning has been observed to rely on visual information only, six additional components have been identified as possibly acting as contributors to active learning, namely: 1) efferent motor commands, 2) proprioceptive information, 3) vestibular information, 4) cognitive decision making, 5) allocation of attention, and 6) mental manipulation of spatial information (Chrastil & Warren, 2013). Being in control of where and when attention is directed in a grid of objects

improves cognitive mapping outcomes (Voss, Gonsalves, Federmeier, Tranel, & Cohen, 2011). These authors even suggest that the hippocampus is actively involved in deciding what additional information is needed to optimise exploration. When actively acquiring survey knowledge in place, learning metric information (i.e., distances and angles) has been observed to be facilitated mainly by podokinetic¹ information with cognitive decisions about the direction of travel having no influence at all (Chrastil & Warren, 2013). On the other hand, acquiring topological and route knowledge via route-based learning has been observed to be facilitated mainly by cognitive decision making about the direction of travel as long as idiothetic² information is also present; together they facilitate the early acquisition of survey knowledge in the form of a labelled graph (Chrastil & Warren, 2015). Ruddle et al. (2011) argue that depending on the scale of space, idiothetic information contribute to learning distances (small spaces) or both distances and directions (large spaces). Chrastil & Warren (2013) and Piccardi et al. (2011) reported mixed results for gender differences from previous literature. Differences were indeed observed in their respective studies, but with somewhat different implications. While Chrastil & Warren (2013) observed men outperforming women without accounting for the causes of said difference; Piccardi et al. (2011) observed performance differences in cognitive mapping when learning from secondary sources but not from route-based learning. Also, those differences diminished with exposure to the environment to be learnt, so men learnt spatial relations more easily than women, but performance converges as a function of experience. Woollett & Maguire (2010) observed another curious phenomenon related to navigation skill and experience. They observed that skillful taxi drivers from London learnt novel environments more easily than inexperienced people; but, on the other hand, they experienced more difficulties when adding new pieces of spatial knowledge to very familiar spaces.

This observation agrees with the inter-representational network (IRN) framework that Haken and Portugali (1996) applied as a general pattern-learning and pattern-recognition framework for cognitive mapping tasks. This framework describes the cognitive mapping process, from a symbolic level, as an iterative competition between preconceived internal representations of prototypical spaces and the external representations coming from the environment to be learnt (Portugali, 1999). At each iteration, external stimuli interact with preconceived internal representations until no additional value is obtained from each iteration (i.e., until the cognitive map reaches a stable status). Such added value need not be measured in terms of metric accuracy, but it may very well be measured in terms of goal-specific usefulness.

Some particular considerations should be taken into account for the particular case of blind people. First, cognitive maps do not remain in memory forever. Manning, Lew, Li,

1 Chrastil & Warren (2013) refer to Weber, Fletcher, Gordon, Melvill Jones, & Block (1998) to define podokinetic information as the combined information from "... (a) efferent motor commands that determine the path of locomotion, (b) proprioceptive information about displacement with respect to the substrate..." (p. 1520)

2 Podokinetic information together with vestibular information about head movement in an inertial frame (Chrastil & Warren, 2013).

Sekuler, & Kahana (2014) were able to predict taxi driver's behaviour by controlling for two parameters, namely, vision (V) and memory (M) where the M parameter establishes a limit to the amount of time that a particular piece of information remains stored in the system cognitive-map. Without the continuous flow of information that vision provides, it is very tough to build and maintain cognitive maps (Rieser, Guth, & Hill, 1982; Golledge, Klatzky, & Loomis, 1996). Nonetheless, studies from both cognition and robotics proved that concepts developed in spatial cognition are sound enough to be valid regardless input modalities (Chown & Yeap, 2015). Yamamoto & Philbeck (2013) highlight that complex spatial relations have been successfully encoded within intrinsic frames of reference from sequential input modalities and even from spatial language.

The primary orientation and mobility (O&M) aids for blind people in real spaces are the long cane and the dog guide (Balan, Moldoveanu, & Moldoveanu, 2015a; Brock & Kristensson, 2013; Kirner, Gonçalves Kirner, Wataya, & Valente, 2012; Lahav, Schloerb, & Srinivasan, 2015). In the absence of any additional aid, blind people need to physically explore the environment by means of locomotion in order to acquire spatial knowledge at either scale of space (i.e., vista space and navigation space) (Picinali, Afonso, Denis, & Katz, 2014). Lahav, Schloerb, & Srinivasan (2015) divide O&M aids into two groups, namely, in-situ aids and preplanning aids. They base this classification on the ability of a given aid to help blind people to build a cognitive map before arriving at a given environment. They highlight the following examples of preplanning aids: verbal descriptions, tactile maps, physical models, digital audio and tactile screens, and sound and haptic-based VE systems. This classification is somewhat coarse and, in fact, it has been suggested that it could be more useful to describe O&M aids according to the O&M stage they are able to support. Yatani, Banovic, & Truong (2012) for instance, classify O&M aids as either 1) interfaces for map exploration, or 2) interfaces for navigation and wayfinding. Their classification mixes generic O&M stages with particular means for fulfilling them. Map exploration, for instance, is a particular method to carry out cognitive mapping, but additional methods are possible. In addition, navigation and wayfinding are different stages of the O&M process (Allen, 1999; Golledge, 1999). So, within the present thesis, a variation is proposed in the form of a capability description consisting of three categories, namely, cognitive mapping, wayfinding, and navigation. As shown in Figure 5: 1) cognitive mapping aids are those helping blind people to identify landmarks, identify topological relationships between landmarks, identify values for their metric attributes, and even identify hierarchical relationships between landmarks; 2) wayfinding aids are those helping blind people to identify possible routes, identify optimal routes, identify values for dynamic attributes of routes, such as temporarily unavailable ones, during the travel planning stage, and eventually select a particular route; finally, 3) navigation aids are those helping blind people to recognise landmarks, select a course and keep said course, e.g., avoiding obstacles. A given O&M aid may be of application for several of these categories. In fact, the ideal aid should support all tasks in the O&M process.

Figure 5. O&M stages and associated tasks.

Navigation aids have attracted most of the attention, from simple ultrasound devices that report the presence of obstacles as they approach, to sophisticated systems based on a combination of GPS, GIS and Web cybercartography (Bartyna et al., 2005; Punwilai, Noji, & Kitamura, 2009; Wang, Li, & Li, 2012; de Almeida & Tsuji, 2005; Sanchez, Aguayo, & Hassler, 2007); advances in the field of robotic navigation have also been tested as navigation aids for blind people (Knight, 2012; Kaiser & Lawo, 2012). There are two main groups of navigation aids. On the one hand, those that do not require equipping the environment with additional hardware. An example of this kind of navigation aid is the portable device described by Chebat, Maidenbaum, & Amedi (2015). Their device is based on infrared sensors that report distance to obstacles in the direction at which the subject points. It has no landmark recognition capabilities. Additional examples include wearable systems based on stereo vision (Brock & Kristensson, 2013; Kirner, Gonçalves Kirner, Wataya, & Valente, 2012). These systems are too bulky to gain user acceptance. On the other hand, there are navigation aids that do require equipping the environment with additional hardware. Nakajima & Haruyama (2013, 2012) describe an indoors navigation system that updates blind people location within a map as they pass under light bulbs with visible light communication capabilities. These light bulbs communicate with blind people's smartphones that use their information to reset their own gyroscope readings. Attenuation patterns of electromagnetic waves (e.g., Wi-Fi, RFID) have also been proposed as a means to update people's location within a map (Alghamdi, Schyndel, & Alahmadi, 2013).

Besides verbal descriptions, maps and virtual reality have been identified to support cognitive mapping without physically navigating the environment; tactile maps present contents in relief, their main limitations include their production cost, the limited area of coverage, and their lack of flexibility to accommodate updated information (Lahav, Schloerb,

& Srinivasan, 2015; Yatani, Banovic, & Truong, 2012). Interactive maps aimed at enhancing the effectiveness and usability of simple tactile maps. Brock, Truillet, Oriola, Picard, & Jouffrais (2015) identified 1) tactile maps enhanced with interactive zones with audio and voice feedback, 2) tactile maps based on a dynamic matrix of pins (this type of interactive maps are expensive) 3) touch screens that do not provide tactile feedback but vibrations and auditory feedback.

Virtual reality (VR) attracted much attention from the field of spatial cognition as a tool to explore spatial cognition concepts (Dijkstra, de Vries, & Jessurun, 2014; Morganti, Carassa, & Geminiani, 2007). It has also attracted attention as a cognitive mapping aid for blind people. Visits to virtual reality simulations of real spaces have been proposed as a means for blind people to: 1) train their O&M skills as part of an O&M rehabilitation programme, 2) learn the spatial layout of remote places before visiting their actual physical location 3) as an O&M diagnostic tool (Lahav, Schloerb, & Srinivasan, 2015; Sánchez, 2012; Seki & Sato, 2011). Within a virtual environment, the user is represented by an avatar. The avatar's movements within the environment determine the pieces of information that are reported back to the subject at any given instant. Prior experiences with blind people exploring virtual environments are based on a proximity approach (Connors, Chrastil, Sánchez, and Merabet, 2014; Lahav & Mioduser, 2004, 2008a, 2008b; Lahav, Schloerb, Kumar, & Srinivasan, 2008, 2012; Lahav, Schloerb, & Srinivasan, 2015; Merabet, Connors, Halko, and Sánchez, 2012; Picinali, Afonso, Denis, & Katz, 2014; Sánchez, 2012). A proximity approach allows blind people to control an avatar and explore a virtual scene mimicking the exploration techniques they would use in a physical space, i.e., navigating with the aid of a cane; and, despite the lack of idiothetic feedback (see section 1.1.3.) Chebat, Maidenbaum, & Amedi (2015) argue "... that the transfer of knowledge between real and virtual environments and vice versa is indeed possible [52–55]" (p. 14). Lahav and Mioduser (2008b) observed that blind people acquired better spatial knowledge when making use of such virtual environments and that they also performed better than non-users in physical-world tasks. Picinali, Afonso, Denis, and Katz (2014) observed that direct control over the avatar's movements results in better spatial knowledge than passive exploration. Finally, gamification has been observed to provide blind people with a richer set of alternative routes and shortcuts than explicitly instructing them to learn the scene layout (Connors, Chrastil, Sánchez, and Merabet, 2014; Merabet, Connors, Halko, and Sánchez, 2012).

1.1.4. Cognitive maps assessment

Key Points

- Cognitive maps are not directly observable. They must be externalised into spatial products.
- There are two types of externalization techniques: route-based techniques and configurational techniques.

- Distance estimation, direction estimation, counting correctly positioned miniatures of landmarks, and bidimensional regression are the currently available methods to assess the quality of spatial products.
- Distance estimation, direction estimation, and counting landmarks fail to provide a combined measurement of these three landmark properties.
- Bidimensional regression is able to account for similarity levels between two planar points-layouts; however, it does not deal well with missing data.

Researchers working on cognitive mapping aids for blind people need tools able to let them assess which ones result in cognitive maps of higher quality. Cognitive maps, as mental representations of spatial knowledge are internal phenomena that, by definition, are not directly observable. They must be externalised and indirectly assessed based on features from the resulting spatial products (Golledge, 1999). Kitchin & Jacobson (1997) reviewed cognitive map externalisation methods for blind and visually impaired people as shown in Figure 6.

Figure 6. Methods and techniques for the externalization of cognitive maps; according to Kitchin and Jacobson (1997).

Configurational-based techniques represent the layout of a given area into a single spatial model while route-based techniques consist of a collection of values each describing the relationship between two specific locations in a given area. Regardless, spatial models may emerge from route-based outcomes by applying uni-to-multidimensional techniques; for instance, a collection of distance and direction estimations may be translated into a two-dimensional spatial model of landmark coordinates (Kitchin & Jacobson, 1997). In addition, verbal descriptions in the form of both closed questionnaires (Iachini, Ruggiero, & Ruotolo, 2014; Ruggiero, Ruotolo, & Iachini, 2012; Schmidt, Tinti, Fantino, Mammarella, & Cornoldi, 2013) and open interviews (Lahav & Mioduser, 2004, 2008a, 2008b; Lahav, Schloerb, Kumar, & Srinivasan, 2008, 2012; Lahav, Schloerb, & Srinivasan, 2015) have also been used to externalise, at least in part, cognitive-maps contents. These works assessed quality by computing the sum of correct answers. There is no standardisation, so each research team uses a different number and set of questions. In addition, Lahav & Mioduser (2004, 2008a, 2008b); Lahav, Schloerb, Kumar, & Srinivasan (2008, 2012); and Lahav, Schloerb, & Srinivasan (2015) used open interviews to externalise indoors spatial knowledge but did not

provide a metric for quality assessment.

Route-based techniques are useful to externalise knowledge about the relationship of two specific locations within a given environment. i) Both, retracing and inferring a route, are useful to directly assess the usefulness of a particular piece of spatial knowledge. These methods test how well said piece of spatial knowledge supports specific wayfinding and navigation tasks. Retracing a route is related to the assessment of route-knowledge while, inferring a route, is by design, related to the assessment of survey-knowledge. Merabet et al. (2012) used success of task completion, path length, and completion time as quality metrics. These techniques have been used in experiments designed for sighted people as well. These works use different variables to assess quality, Morganti, Carassa, & Geminiani (2007) scored each task from zero to four depending on the distance between the destination actual location and the subject's estimation. Labate, Pazzaglia, & Hegarty (2014) used shortcut length as quality metric but failed to provide a score for the overall cognitive map. Chrastil & Warren (2014) used this technique to assess multiple pairs of objects and used the proportion of correct estimations of target locations as a quality measure. This approach requires access to the actual physical environment to be remembered, though virtual reality could be used as a surrogate. It is time-consuming, with the amount of required time highly dependent on the scale of space and the number of origin-destination pairs to be assessed (besides the dependence on the ability of the specific participant). Also, during the execution of physical world tasks, spatial knowledge gets updated by the act of walking around the physical space; thus, performance level need not necessarily reflect the quality of the subject's cognitive-mapping outcome. ii) Distance estimation consists of asking subjects to estimate the distance between one or multiple pairs of landmarks (Tinti, Adenzato, Tamietto, & Cornoldi, 2006). On the other hand, direction estimation consists of asking subjects to point at the direction of one or multiple landmarks from a given location (Fortin et al., 2008). The two of them may be found together even without providing a combined score (Schinazi, Nardi, Newcombe, Shipley, & Epstein, 2013; Tinti, Adenzato, Tamietto, & Cornoldi, 2006). Pointing quality is quantified in the form of a pointing error (i.e., as the angle between the actual and the estimated directions) (Schinazi, Nardi, Newcombe, Shipley, & Epstein, 2013; Morganti, Carassa, & Geminiani, 2007; Labate, Pazzaglia, & Hegarty, 2014). Sometimes, errors from multiple landmark-pairs are averaged to produce an overall quality score for a subject's cognitive map (Pasqualotto, Spiller, Jansari, & Proulx, 2013; Weisberg, Schinazi, Newcombe, Shipley, & Epstein, 2014). In the case of sighted people, pointing onsite favours access to egocentric knowledge, while doing so offsite favours access to allocentric knowledge (Schinazi, Nardi, Newcombe, Shipley, & Epstein, 2013).

Configurational-based techniques result in spatial products of the survey-knowledge type. It has been argued, however, that those very same spatial products could emerge from a sequential depiction of route knowledge (Schinazi, Nardi, Newcombe, Shipley, & Epstein, 2013). i) Graphic tests require blind participants to draw a sketch of a previously learnt space. Drawing is a particularly challenging task for blind people; however, Jacobson (1992) claims that, despite their initial rejection, blind people managed to produce this kind of spatial products via a particular variation of the procedure known as normal sketch mapping. There

are also systems designed to help blind people with such a task. The TDraw system does so by means of a heating stylus applied on swell paper (Kurze, 1996). An additional drawback underlying the use of sketches as an externalization method is the difficulty in distinguishing between distortions coming from actual cognitive map content and those resulting from subject's drawing abilities (Morganti, Carassa, & Geminiani, 2007). ii) Partially graphic and reconstruction tests do not require drawing skills. Thus, they qualify better as externalization methods for blind people. They involve building a replica of the original space with a given modelling kit. Magnetic bars are well suited to assess route knowledge (Yatani, Banovic, & Truong, 2012). Other types of spatial knowledge are tested by asking subjects to place miniatures of landmarks and other elements on a scaled model of the original space (Lahav & Mioduser, 2004, 2008a, 2008b; Lahav, Schloerb, Kumar, & Srinivasan, 2008, 2012; Schmidt, Tinti, Fantino, Mammarella, & Cornoldi, 2013). iii) Uni-to-multidimensional tests are a way to produce bidimensional spatial products from a collection of distance and direction estimations. Once obtained, these bidimensional spatial products are assessed similarly to all other configurational-based forms of spatial products. iv) Recognition tests assess the ability of a particular piece of spatial knowledge to help someone to identify a physical model that represents the correct spatial layout. The usual metric for quality assessment involves labelling the recognition task as either successful or failed.

Both subjective assessment techniques (Jacobson, 1998; Morganti, Carassa, & Geminiani, 2007) and objective assessment ones (Labate, Pazzaglia, & Hegarty, 2014; Giraudo & Pailhous, 1994; Schinazi, Nardi, Newcombe, Shipley, & Epstein, 2013; Schmidt, Tinti, Fantino, Mammarella, & Cornoldi, 2013; Weisberg, Schinazi, Newcome, Shipley, & Epstein, 2014; Wen, Ishikawa, & Sato, 2011) have been used to assess the quality of spatial models. Subjective assessment involves having a spatial model, or a set of spatial models, assessed according to the criteria of one or multiple human raters (Jacobson, 1998; Morganti, Carassa, & Geminiani, 2007). Raters' criteria are internal and implicit; there is no need for them to state which features led them to make one decision or the other. On the other hand, the most cited objective techniques are the assessment of landmark placement; either as the proportion of correct placements (Labate, Pazzaglia, & Hegarty, 2014; Wen, Ishikawa, & Sato, 2011) or as the average metric error (Schmidt, Tinti, Fantino, Mammarella, & Cornoldi, 2013) and bidimensional regression (Giraudo & Pailhous, 1994; Schinazi, Nardi, Newcombe, Shipley, & Epstein, 2013; Weisberg, Schinazi, Newcombe, Shipley, & Epstein, 2014). "Bidimensional regression is a method for comparing the degree of resemblance between 2 planar configurations of points and, more generally, for assessing the nature of the geometry (Euclidean and non-Euclidean) between 2-dimensional independent and dependent variables." (Friedman & Kohler, 2003, p. 468). Since its very inception, cognitive-map assessment was an intended application (Friedman & Kohler, 2003; Tobler, 1994).

Objective techniques are powerful tools for assessing the geometric similarity between two datasets of planar coordinates. Nevertheless, cognitive maps have been proven to be sketchy, incomplete, and distorted, even violating Euclidean-geometry postulates, and yet be useful in wayfinding and navigation tasks (Chown, 1999; Chown, Kaplan, & Kortenkamp, 1995; Chrastil & Warren, 2014, 2015; Gärling, 1999; Kuipers, 1982; Lloyd & Heivly, 1987) meaning that cognitive maps are more than mere stores for the structural information in a

physical space; they are the result of a process of spatial comprehension that might include the understanding of semantic and functional meanings of physical obstacles and their layouts. Thus, since the subjective assessment of spatial models relies, by definition, on the very properties of cognitive maps, it is more likely to grasp the level of spatial understanding in someone's cognitive map than objective techniques; which, in fact, fail to predict human-based similarity assessment outcomes; as will be proven in the following sections. Bidimensional regression, in particular, does not deal well with missing data (Friedman & Kohler, 2003). It is based on the assumption that all the elements in the original scene have their counterpart within the corresponding spatial model. Friedman & Kohler (2003) were only able to identify a couple of suboptimal workarounds: either remove cases with missing data, which leads to limited statistical power, or use statistical algorithms to fill in the blanks, which eliminates the ability to account for the effect of forgotten landmarks. Subjective assessment also comes with some drawbacks. Deciding which of two spatial models are more similar to a given scene is easy, but replicability and consistency of numeric scores are hard to achieve.

1.2. Hypotheses and objectives

The present thesis dissertation is part of the e-Glance project scientific outcomes. The present section begins with a brief description of the project rationale and its objectives. After that, the hypothesis that motivates the research presented herein is stated. Finally, the particular objectives concerning the present thesis are presented.

1.2.1. The e-Glance project

Key Points

- Unemployment among blind and visually impaired people is very high (70%).
- The e-Glance project aims at preventing them from getting expelled from the labour market.
- Its objective is to develop a piece of technology for blind people to build their own cognitive maps of indoor spaces without being compelled to physically explore them.
- It is based on the use of virtual reality and introduces a novel distant exploration approach to overcome the limitations of the traditional proximity approach.
- It was awarded the 'La Razón' Innovation and Technology Prize in the category of Social Innovation.

The e-Glance project aims at boosting blind people's autonomy and independence so they do not get expelled from the labour market. It was funded by the Cátedra Indra-

Fundación Addeco and counted with the support of ONCE and Fundación ONCE, which acted as external advisers during the development stage and helped with contacting volunteers for the study, during the recruitment stage. The project was awarded the 'La Razón' Innovation and Technology Prize in the category of Social Innovation (Ruiz, 2017).

Autonomy during adulthood is, to a great extent, linked to having a job. Jobs provide financial support which allows people for building their own life project. Besides, jobs boost self-esteem and self-efficiency, and act as a source of social interactions and activities (Pallero & González, 2003). Vision loss is associated to a limiting effect that interferes with people's daily performance for, as stated before, vision accounts for eighty percent of the information required for people's daily life (ONCE, 2018). Unemployment among blind and visually impaired people is very high as a direct consequence of this high dependence on visual input. It is estimated that, in developed countries, only 30% of them have a job, compared to 70%-80% of the entire workforce (La Grow & Daye, 2005). In the particular case of Spain, the National Organization for Spanish Blind people (ONCE, in its Spanish acronym) reported that 33.5% of their working-age members had a job back in 2011; 67.4% of them selling tickets for the ONCE daily lottery and 32.6% working at external companies or at companies related to either ONCE itself or its Foundation (ONCE, 2011). In fact, according to Cazallas (2008) only 26.3% of their working-age members worked at the ordinary market, i.e., competing with non-disabled people. Those figures are possible thanks to the employment support services offered by organizations like ONCE itself (see Figure 7).

Figure 7. ONCE employment support services as described by ONCE (2011).

In addition, Gillies, Knight, & Baglioni Jr (1998) observed low satisfaction levels with career development among blind and visually impaired people and La Grow & Daye (2005) observed that 79% of blind and visually impaired people report “... barriers to gaining employment, retaining employment and/or gaining advancement in their careers.” (p. 178). Two issues have been identified as main barriers for blind people to get a job. On the one hand, employers’ attitude, either discrimination or ignorance (La Grow & Daye, 2005; McDonnall & Crudden, 2015; McDonnall, Zhou, & Crudden, 2013). On the other hand, the demands from the environment itself, either at the workplace or during commute, with the availability of adapted technologies and aids among the top 3 solutions (La Grow & Daye, 2005). In particular, activities based on O&M skills are particularly challenging for blind people (Alghamdi, Schyndel, & Alahmadi, 2013; Connors, Chrastil, Sánchez, & Merabet, 2014; Lahav, Schloerb, & Srinivasan, 2015; Yatani, Banovic, & Truong, 2012). Spanish laws offer subsidies and economic benefits for companies employing blind people as long as they keep these workers for at least three years. For instance, subsidies include up to 900 € to accommodate the workplace (ONCE, 2011).

When people become blind, they must start an adjustment process and adapt to their

visual deficit. The said process gets to be facilitated or obstructed by personal attitudes, aptitudes, and perceptions in combination with social perceptions and attitudes, e.g., overprotective relatives interfere with an optimal adjustment (Pallero & González, 2003). Blind people are at risk of oversizing said limiting effect beyond its actual impact, as a consequence, they might voluntarily refuse to try some activities, afraid or baselessly persuaded of their inability to succeed (Pallero & González, 2003). These kinds of thoughts may undermine their self-esteem and self-confidence making them adopt passive or aggressive profiles rather than assertive ones, especially when those thoughts become recurrent in nature; and may even lead them to anxiety and depression (Pallero & González, 2003).

The e-Glance project objective is to develop a piece of technology for blind people to build their own cognitive maps of indoor spaces without being compelled to physically explore them. Such a technology would allow blind people for making efficient decisions at situations where knowing the status of distant locations and events is a determinant factor. In addition, it would decrease the extra effort (both physical and mental) that blind people experience when making daily decisions. As noted above, the intended application of this technology is to help blind people at work and prevent them from being expelled from the labour market, but the concept also applies to public spaces such as hotels, malls, railway stations, etc. e-Glance is based on virtual reality as a technological approach, and it aims at overcoming the limitations found for the previously used proximity exploration approach by substituting it for a distant exploration approach. In a first stage, blind people can explore off-site the virtual representation of a place, prior to visiting its actual location. In a second stage, the technology is being expanded to support on-site real-time visits. Within the e-Glance project, human-computer interaction is split into two interaction concepts, namely, the cognitive interface and the sensitive interface. On the one hand, the concept of cognitive interface, which is the focus of the present thesis dissertation, refers to the method or interface subjects use to direct their attention to a particular region in the world. In particular, the cognitive interface is designed to allow blind people for directing their attention to distant regions (beyond the reach of the hand and the cane) of previously virtualised rooms. Said cognitive interface is implemented in the form of a software entity, referred to as the spotlight, embedded in a virtual reality video game that follows the user's commands to move through a virtual representation of a given room. The spotlight may be controlled by interacting with a smartphone app via rotating the device, tapping, and sliding a finger on the device touch screen. On the other hand, the concept of sensitive interface refers to the method or interface by which subjects receive feedback from the system. Additional details may be found in section 2.1.

1.2.2. Hypotheses

Key Points

Main hypothesis:

- It is possible to create a model of the act of glancing down at a scene and replicate it in situations in which the observer lacks vision. Therefore, it is possible for blind people to use an implementation of the said model to learn a room layout from a single observation point.

Secondary hypothesis:

- It is possible to predict the outcomes of human assessment of spatial models by characterising those spatial models according to the fundamental properties of cognitive maps and not just the geometrical properties of their landmarks.

The first and main hypothesis above is based on the following facts in the background section. In the first place, spatial thought is compatible with blindness; so blind people are capable of understanding and manipulating spatial concepts (Aleman, van Lee, Mantione, Verkoijen, & de Haan, 2001; Carpenter & Eisenberg, 1978; Cornoldi, Cortesi, & Preti, 1991; Gaunet & Thinus-Blanc, 1996; Kowler, Anderson, Doshier, & Blaser, 1995; Lessard, Paré, Lepore, & Lassonde, 1998; Marmor & Zaback, 1976; Rieser, Guth, & Hill, 1986; Ungar, Blades, & Spencer, 1995; Vanlierde & Wanet-Defalque, 2004; Vecchi, Tinti, & Cornoldi, 2004; Zwiers, Opstal, & Cruysberg, 2001). Even congenitally blind people, who lack any kind of visual experience, are able to produce the same spatial images than sighted people (Bonino et al., 2015; Loomis, Klatzky, & Giudice, 2013; Noordzij, Neggers, Ramsey, & Postma, 2008; Struiksmā, Noordzij, & Postma, 2009). However, the fact is that the vast majority of blind people do indeed have visual experience (ONCE, 2017). Secondly, besides motor inputs, which are used while physically walking around a room, blind people are able to acquire spatial knowledge from language and verbal descriptions with no need of changing their physical location (Afonso et al., 2010). In fact, and despite their ability to acquire spatial knowledge of the survey type, blind people find it hard to produce allocentric spatial representations unless learning an environment from a stable body position (Iachini, Ruggiero, & Ruotolo, 2014). In the third place, blind people acquire better spatial knowledge when they are empowered to exert active control over when and where they direct their attention, just like sighted people do when they glance down at a scene; conversely, guided routes in a room or predefined scene descriptions result in low-quality outcomes (Chrastil & Warren, 2012, 2013, 2015; Picinali, Afonso, Denis, & Katz, 2014; Voss, Gonsalves, Federmeier, Tranel, & Cohen, 2011).

The main limitations of blind people's most informative sensing modalities come from their short range, their discontinuous information flow, and their sequential nature (Cattaneo et al., 2008; Golledge, Klatzky, & Loomis, 1996; Rieser, Guth, & Hill, 1982). The latter one is hard to address. On the other hand, the first one (short range) can be addressed by providing blind people with access to a record of obstacles and their locations; and the impact of the second one (discontinuous information flow) might decrease by allowing blind people to access that information on demand. Virtual worlds, for instance, support those two functionalities and the transference of spatial knowledge between physical and virtual worlds has been observed to be feasible for blind people (Chebat, Maidenbaum, & Amedi, 2015;

Connors, Chrastil, Sánchez, & Merabet, 2014; Lahav & Mioduser, 2008b; Merabet, Connors, Halko, & Sánchez, 2012; Picinali, Afonso, Denis, & Katz, 2014).

On the other hand, the secondary hypothesis is based on the following facts in the background section. Objective techniques are powerful tools for assessing the geometric similarity between two datasets of planar coordinates. Nevertheless, cognitive maps have been proven to be sketchy, incomplete, and distorted, even violating Euclidean-geometry postulates, and yet be useful in wayfinding and navigation tasks (Chown, 1999; Chown, Kaplan, & Kortenkamp, 1995; Chrastil & Warren, 2014, 2015; Gärling, 1999; Kuipers, 1982; Lloyd & Heivly, 1987). Thus, subjective assessment of spatial models is more closely based on the properties of cognitive maps than objective techniques, which, in fact, fail to predict human-based similarity assessment outcomes; as will be proven throughout the present thesis dissertation. Subjective assessment, however, also comes with some drawbacks. Deciding which of two spatial models are more similar to a given scene is easy, but replicability and consistency of numeric scores are hard to achieve.

1.2.3. Objectives for the present thesis

Key Points

Particular objectives for the present thesis:

- Finding a novel model for spatial exploration able to narrow the effort gap between blind and sighted people without a detrimental impact on cognitive-map quality.
- Finding a novel model for cognitive-map characterization able to account for incorrectly identified landmarks.
- Finding a model for cognitive-map quality assessment able to mimic human assessment outcomes.

Blind people spend disproportionate amounts of time and effort to learn vista-space scenes compared to sighted people because vision is the primary source of perceptual updating (Golledge, Klatzky, & Loomis, 1996; ONCE, 2018; Rieser, Guth & Hill, 1982). Even if a blind person is decided to carry out a comprehensive exploration in a room, there will be multiple details beyond his reach. The proximity exploration approach in virtual environments is not an exception. It prevents blind people from suffering physical injury and allows them to learn the spatial layout before visiting the actual physical location but adds little value in an on-site real-time scenario and it is still time-consuming. In conclusion, the proximity-exploration approach in virtual environments is a suboptimal solution. In order to narrow the gap between blind and sighted people, a distant-exploration approach is proposed. Distant exploration must allow blind people for inspecting an entire vista-space from a single observation point. While it may seem obvious that removing the need of locomotion will decrease exploration time, the sequential nature of their sensing modalities might obstruct the

rapid assessment of relative locations between objects; besides, the lack of idiothetic information might interfere with distance assessment. A distant-exploration approach seamlessly fits in with an on-site real-time scenario and, complemented with the appropriate location and interaction technologies, could be the basis of blind-friendly physical environments that would foster blind people's independent behaviour and would empower them to abandon passive attitudes.

In addition to reducing the effort gap between blind and sighted people, the quality of the resulting cognitive maps should not decrease. Currently available methods to assess cognitive map quality (distance estimation, direction estimation, counting correctly positioned miniatures of landmarks, and bidimensional regression) fail to capture all relevant features in a scene into a single score. Even bidimensional regression, which is specifically designed for measuring similarity levels between two planar layouts, can not account for incorrectly identified landmarks because it does not deal well with missing data. Bidimensional regression requires every point in both of the two datasets (the original scene and the spatial product) to have one-to-one correspondence with a point in the other dataset. Friedman and Kohler (2003) were only able to identify a couple of suboptimal workarounds: either remove cases with missing data, which leads to limited statistical power, or use statistical algorithms to fill in the blanks, but that eliminates the ability to account for the effect of forgotten landmarks. As a consequence, assessment outcomes resulting from applying these methods are suboptimal. They are still useful, but they provide extraneous results when compared to human assessment. A novel measurement model could be very useful to assess blind people's progress along a training programme and compare different cognitive-mapping aids according to blind people performance.

2. METHODOLOGY

2.1. General Method

2.1.1. Cognitive interface for distant exploration

Key Points

- A software entity, known as the spotlight, was modelled based on the active learning principle (controlling the region of the room in which they wanted to focus their attention).
- The spotlight always remains along the line of sight of said avatar and attention can be directed to a particular region by controlling the direction of the line of sight and by selecting how far the spotlight should go to look for obstacles along said direction.
- When the spotlight hits an obstacle, the sensitive interface reports its identity and how far away from the blind person's avatar it is.
- The spotlight cannot remain stationary in thin air; it jumps instantly from one obstacle to the next one.
- Two spotlight configurations were modelled: the spherical spotlight (sFoA) and the flat spotlight (fFoA).
- The sFoA is represented by spherical coordinates. The fFoA is represented by polar coordinates.

Distant exploration in virtual environments has been an object of little study so far. A software entity, known as the spotlight, was modelled so that blind people could control the region of the room in which they wanted to focus their attention; even allowing them for exploring locations beyond the reach of the cane. When the spotlight hits an obstacle, the sensitive interface reports its identity and how far away from the blind person's avatar it is. The spotlight exploration model is a sequential type of survey-based learning. By using such a cognitive interface, blind people will still lack the parallel-perception feature of sight, but they will be able to explore an entire room from a single observation point without the need of locomotion. The spotlight is based on the active-learning principle, i.e. the general observation of active learning being more effective than passive learning (Chrastil & Warren, 2012, 2013, 2015; Picinali, Afonso, Denis, & Katz, 2014); and the particular observation of the fact that being in control of where and when attention is directed in a grid of objects improves cognitive mapping outcomes (Voss, Gonsalves, Federmeier, Tranel, & Cohen, 2011).

The location and heading of a given blind person are represented by the corresponding attributes of an avatar within the virtual environment. The spotlight always remains along the line of sight of said avatar and attention can be directed to a particular region by controlling the direction of the line of sight and by selecting how far the spotlight should go to look for obstacles along said direction. The selection of the exploration depth was modelled to mimic the eye behaviour, i.e., the spotlight cannot remain stationary at thin air but must be in contact with an obstacle. Blind people can control the exploration depth by instructing the spotlight to look for obstacles both ways along the line of sight. In such a case, the spotlight jumps instantly from one obstacle to the next one. Two options were taken into account for the line of sight control-model. The first option, referred to as the spherical spotlight (sFoA), involves the use of spherical coordinates (ρ , ϕ , θ) so the values of ϕ and θ determine the direction of the line of sight. The second option, referred to as the flat spotlight (fFoA), involves the use of polar coordinates (ρ , ϕ) so just the value of ϕ is necessary to determine the direction of the line of sight. Each of these two configurations shows the following specific features (see Figure 8):

1. The sFoA configuration is shaped in the form of a floating circle before the avatar, with a one-metre diameter, and perpendicular to the line of sight. This configuration is sensitive to changes in direction to the left, right, up and down.
2. The fFoA configuration is shaped in the form of a vertical plane before the avatar and perpendicular to its line of sight; it is as wide as the avatar's shoulders and spans along the entire distance between the floor and the ceiling. This configuration is sensitive to changes of direction to the left and right, but not up and down.

The fFoA was thought to make easier the detection of obstacles for it does not require precise aiming; it reports all obstacles in front of the avatar regardless of their size and vertical location.

Figure 8. Cognitive interface for distant exploration. sFoA (up) fFoA (down).

2.1.2. Quality index for cognitive-map assessment

Key Points

- Spatial products are represented by a four-dimensional vector where each element represents a different error-term; namely, identification error, location error for structures, absolute-location error for objects, and relative-location error for objects. The choice of vector features is based on the fundamental properties of cognitive maps.
- An error-free spatial product is represented by (0, 0, 0, 0); while the most dissimilar spatial product is represented by (1, 1, 1, 1).
- The SUQI measures the Mahalanobis distance between a given spatial product and the

error-free spatial product.

- The Mahalanobis distance accounts for those possible variability differences across vector features by scaling the coordinate axes of each feature by their corresponding variance value. The multidimensional generalization of the concept of variance is the covariance matrix, which, in the absence of a mathematical description of the corresponding probability distribution, must be computed from a sample of empirical observations.

A quality index was defined to quantify, into a single numeric value, the similarity between two different representations of the same indoors spatial layout. Said index was given the name of Spatial Understanding Quality Index (SUQI) and aimed to overcome the limitations of currently available cognitive-map assessment metrics, with a focus on the inability of bidimensional regression to deal with missing data. The graphical representation of a dartboard in Figure 9 was used to capture the concept behind the SUQI design. The objective in a cognitive mapping session is to replicate the original scene into a cognitive map, just as the objective in a dartboard game is to hit the target (i.e., the centre or origin -- point A in Figure 9). Being point A equivalent to the original scene and being dart-hits equivalent to cognitive maps externalizations (i.e., spatial products), the further away from point A a dart hits the board, the greater the dissimilarity level between the original scene and the corresponding spatial product (point B in Figure 9). Consequently, the dissimilarity level is equivalent to the distance between the target and the dart-hit (line b in Figure 9) i.e., the distance between point A, (0, 0) in its coordinate form and point B, (x_b , y_b) in its coordinates form. Thus, the lower the score, the better the quality. In conclusion, all that is required to assess the similarity between a cognitive map and its corresponding original scene is to describe said cognitive map (or its corresponding spatial product) as a numeric vector, and to find a proper metric able to assess the distance between two given vectors

Figure 9. Graphical representation of similarity between a spatial product (point B) and its corresponding original scene (point A) in a theoretical two-dimensional space. The longer line b gets, the lower the similarity between them.

The SUQI is actually defined as the Mahalanobis distance between a given spatial product and the corresponding original scene. The rationale behind this choice is that the variances in a sample of cognitive maps might be very different across different vector features. In such a case, the vector feature showing the greater variance will distort the resultant distance values in favour of said vector-feature readings. The Mahalanobis distance accounts for those possible differences by scaling the coordinate axes of each feature by their corresponding variance value. Figure 10 shows the original distribution of a random variable (left) where the ellipse represents the area within the range of its variance; the circle on the right represents the unitless outcome after axis scaling.

Figure 10. Mahalanobis scaling effect on a set of empirical observations in a two-dimensional random variable. Original distribution of the random variable (left) and unitless outcome after Mahalanobis scaling of the axes (right).

Each spatial product in the dataset is an instance of a multidimensional random variable. In order to perform the above-mentioned scaling operation, it is necessary to compute the variance of said random variable. The multidimensional generalization of the concept of variance is the covariance matrix, which, in the absence of a mathematical description of the corresponding probability distribution, must be computed from a sample of empirical observations. Meaning that a covariance matrix is an estimation of the expected variability in a population, computed from a set of previously observed instances. In the present case, spatial products in the e-Glance dataset fulfil the role of empirical observations. The mathematical expression for the computation of the Mahalanobis distance is shown in Figure 11, where $\vec{x}$ and $\vec{y}$ are the vectors representing a spatial model and its corresponding original scene, respectively; and S is the covariance matrix. Please note that the Euclidean distance is a particularization of the Mahalanobis distance when the covariance matrix equals an identity matrix.

$$d(\vec{x}, \vec{y}) = \sqrt{(\vec{x} - \vec{y})^T S^{-1} (\vec{x} - \vec{y})}$$

Figure 11. Mathematical expression for the computation of the Mahalanobis distance.

The choice of vector features is based on the fundamental properties of cognitive maps. First, the borders of an environment have been observed to trigger a characteristic neural response in a specific type of brain cells known as border cells (Madl, Chen, Montaldi, & Trappl, 2015); thus, the shape of the environment was identified as a relevant feature. Second, at a symbolic level, cognitive maps are collections of landmarks, in this case, obstacles in a room, which are related to each other by relationships of relative position; but cognitive maps may not comply with Euclidean geometry postulates such as the triangle angle sum theorem (Chrastil & Warren, 2014, 2015). Obstacle attributes are split and encoded in two separate brain systems: the “what” system and the “where” system (Amorim, 1999). These two systems explain situations where someone remembers an obstacle to be present in a scene but not its specific location and, vice versa, when someone remembers that there was something at a particular spot but does not remember what it was. Thus, two additional and

separate relevant features were identified: (i) the obstacles identity (“what”) and (ii) their location (“where”). Finally, location information was split into two terms, one for the absolute location of objects in relation to the shape of the room; and an additional one for the relative location of objects, regardless the borders of the room. The separation of location information into these two terms makes it possible to account for situations where landmark miniatures in a given spatial product, though misplaced, preserved the correct spatial relationship to one another.

Vector features were modelled as error-terms; hence, the original scene is equivalent to an error-free vector with all its elements set to zero, i.e. (0, 0, 0, 0). Please note that all four error terms are bounded between zero and one. Thus, the SUQI is bounded as well. In the case of the e-Glance study, the maximum score for the complete set of externalizations had a value of 9.79. The quantification criteria for each error term can be found below.

1. Identification error: it represents the error committed by a participant while remembering which obstacles were present in the scene during the exploration stage. Obstacles are modelled as a nominal variable with three levels, namely, correct identifications, omissions, and insertions. Correct identifications are obstacles present in the original scene and so identified; omissions are obstacles present in the scene but identified as not present, while insertions are obstacles not present in the scene but identified as present.

The more omissions and insertions the higher the value of the error term should get. On the other hand, correct identifications should not alter the value of the error term. Thus, the identification error was computed as the normalized sum of omissions and insertions, as shown in Equation 1.

$$\text{Equation 1. } \textit{identificationError} = \frac{\textit{totalOmissions} + \textit{totalInsertions}}{\textit{totalNumberOfObstacles}}$$

2. Location error for structures: it represents the error committed by a participant while identifying the empty room in the original scene. Participants were given three models of three different empty rooms and were asked to identify which one represented the original scene. The only possible outcome of that task is either success or failure, so the location error for structures was modelled as a dichotomous variable. An incorrect identification should increase the value of the error term, while a correct one should not alter its value. Thus, the location error for structures is quantified with a value of zero when a participant succeeds; otherwise, it is assigned a value of one. See Equation 2.

$$\text{Equation 2. } \textit{locationErrorForStructures} = \begin{cases} 0 \Leftrightarrow \textit{modelChoice} = \textit{success} \\ 1 \Leftrightarrow \textit{modelChoice} = \textit{failure} \end{cases}$$

3. Absolute-location error for objects: it represents the error committed by a participant

when placing, in a scaled model of the room, miniatures of correct identifications. Both polar coordinates (i.e., rho and phi) of miniatures within a spatial product were assessed. The two-dimensional nature of the disposition of objects in the model led to the definition of two auxiliary variables known as distance elements and angle elements. Distance elements were assigned a value of zero if the rho polar-coordinate of the corresponding miniature was error free, otherwise they were assigned a value of one, see Equation 3(a); analogously, angle elements were assigned a value of zero if the phi polar-coordinate of the corresponding miniature was error-free; otherwise they were assigned a value of one, see Equation 3(b).

$$\text{Equation 3(a). } distance_i = \begin{cases} 0 \Leftrightarrow modelRho_i = sceneRho_i \\ 1 \Leftrightarrow modelRho_i \neq sceneRho_i \end{cases}$$

$$\text{Equation 3(b). } angle_i = \begin{cases} 0 \Leftrightarrow modelPhi_i = scenePhi_i \\ 1 \Leftrightarrow modelPhi_i \neq scenePhi_i \end{cases}$$

The absolute-location error for objects was then computed as the sum of distance elements plus the sum of angle elements, all of it normalized by twice the number of correct identifications. See Equation 4.

$$\text{Equation 4. } absoluteLocationError = \frac{\sum distance_i + angle_i}{2 \times correctIdentifications}$$

The identification error term above accounts for the impact of omissions and insertions so there is no need for additional acknowledgement of them. In addition, it is not justified to evaluate the location of insertions because they can not be compared to any location of reference in the original scene. Analogously, omissions lack any location in the spatial product that could be compared with the corresponding location in the original scene.

4. Relative-location error for objects: as in the case of the absolute-location error for objects, only correctly identified miniatures were taken into account. All possible combinations of correct identifications taken in pairs were assessed. The value of this error term should grow only if the relative location between two objects in a given pair were incorrect. Thus, pair-scores were assigned a value of zero if the relative location of those two miniatures was equivalent to the relative position of the corresponding objects in the original scene; a value of one was otherwise assigned. See Equation 5.

$$\text{Equation 5. } pairScore_j = \begin{cases} 0 \Leftrightarrow modelRelativeLocation_j = sceneRelativeLocation_j \\ 1 \Leftrightarrow modelRelativeLocation_j \neq sceneRelativeLocation_j \end{cases}$$

The relative-location error for objects was then computed as the sum of pair-scores, normalized by the number of correct-identification pairs. See Equation 6.

$$\text{Equation 6. } \text{relativeLocationError} = \frac{\sum \text{pairScore}_j}{\text{correctIdentificationsPairs}}$$

2.1.3. The eGlance Study

Key Points

- A within-subjects cross-sectional study, where nineteen totally blind people explored three virtual spaces of similar complexity, was conducted.
- Participants individually explored each virtual space with a different type of spotlight configuration, namely, proximity exploration (noFoA), spherical spotlight (sFoA), and flat spotlight (fFoA).
- Participants explored all virtual rooms by interacting with a smartphone; which translated touch screen inputs and internal gyroscope readings into movements of an avatar within the virtual world.
- Cognitive-map spatial products were collected by means of a questionnaire and a scaled modelling kit. Exploration events were automatically recorded into a log file.
- Afterwards, participants completed three different tasks at the real equivalent of each original virtual scene.

The e-Glance study tested the use of virtual environments for blind people to explore unknown spaces before actually visiting them. Three configurations of a software entity known as the spotlight were compared to determine whether distant exploration, compared to proximity exploration, during a visit to a virtual room, results in better cognitive maps for blind people.

The study complied with the tenets of the Declaration of Helsinki. Informed consent was obtained from each participant.

2.1.1.1. Participants.

A within-subjects cross-sectional study was conducted. Eligible subjects were required to fulfil the following inclusion criteria: (i) be over eighteen years old, (ii) suffer total blindness, (iii) have become blind at least two years before the beginning of the study, and (iv) suffer no additional disabilities. Nineteen participants (m=50.63 years old, sd=15.17) were recruited among people affiliated to ONCE (National Organization for Spanish Blind people), workers of the ONCE Foundation, and from the support service for students with disabilities of the Technical University of Madrid. All participants became blind at least seven years before the beginning of the study (m=32.31, sd=19.76). Being this the research team's first

approximation to the topic, the duration of the experiment was limited. In order to choose a proper sample size, the order of magnitude identified in previous proximity-based studies was preserved; while taking into account the restrictions imposed by the availability of physical spaces and the size of the research team.

2.1.1.2. Apparatus.

A video game, implemented in Unity3D, was deployed on a smartphone (model BQ Aquaris E5) running Android 4.4.4 (KitKat). The device weighs 139 g, it is 143.15 mm long, 72.15 mm wide, and 8.7 mm deep. It counts with a 5" screen (16:9) with a resolution of 1280x720 (HD). The CPU is a Qualcomm® Snapdragon™ 410 Quad Core A53 (1.2 GHz) and the GPU is a Qualcomm® Adreno 306 (400 MHz). 16 GB of internal memory; and a LiPo battery (2850 mAh). Wi-Fi™ 802.11 b/g/n, Bluetooth 4.0, GPS + GLONASS, and 4G (LTE) FDD (800 / 1800 / 2600). The app requires a smartphone equipped with a gyroscope and a touch screen (see Figure 12).

Figure 12. Example of virtualized room.

The goal of the video game was for blind people to learn the layout of the three virtual scenes in Table 1 and Figure 13. Blind participants' actions in the physical world were collected by the smartphone touch screen and by its internal gyroscope readings; and were translated into movements of an avatar within the virtual world. The application shows the virtual representation of each room as a first-person view of the avatar's point of view. Despite the fact that visual information is irrelevant for blind people, it is useful for the development process and debugging purposes.

	Office	Pub	Bedroom

Structures	Walls (x4) Windows (x2) Columns (x1) Doors (x2)	Walls (x4) Windows (x2) Columns (x1) Doors (x3)	Walls (x4) Windows (x2) Columns (x1) Doors (x2)
Objects	Paper bin (x1) Drawer (x1) Chair (x1) Desk (x1) Bookshelves (x1) Thermostat (x1)	Doorstep (x1) Umbrella stand (x1) Stool (x1) Bar (x1) Dartboard (x1) Fire extinguisher (x1)	Magazine rack (x1) Trunk (x1) Bedside table (x1) Bed (x1) Closet (x1) Coat rack (x1)

Table 1. List of obstacles in each room.

Figure 13(a). Disposition of obstacles within the office scene.

Figure 13(b). Disposition of obstacles within the pub scene.

Figure 13(c). Disposition of obstacles within the bedroom scene.

2.1.1.3. Procedure.

Participants individually completed three experiences making use of a different type of spotlight each time. Each experience involved the exploration of one of the three virtual scenes in Figure 13 (office, pub, or bedroom). Such a within-subjects design entail the risk of carry-over effects, which means that the order in which the different scenes were to be experienced could bias the study outcomes. Besides, there is a risk of an additional carry-over effect: the study outcomes might get biased if each scene were explored with the same spotlight configuration by all participants. In order to minimize the impact of possible carry-

over effects, pairs of both room and FoA were randomized, together with the execution sequence, according to the latin square in Table 2.

Participant id	First experience	Second experience	Third experience
1	fFoA-office	noFoA-pub	sFoA-bedroom
2	noFoA-bedroom	sFoA-office	fFoA-pub
3	sFoA-pub	fFoA-bedroom	noFoA-office
4	sFoA-bedroom	noFoA-pub	fFoA-office
5	fFoA-pub	sFoA-office	noFoA-bedroom
6	noFoA-office	fFoA-bedroom	sFoA-pub

Table 2. Latin square.

Each participant completed the following six stages for each virtual scene:

1. Welcome: participants were told the rationale and procedures of the study, and they were instructed about the corresponding spotlight operative details.
2. Training: participants became familiar with the corresponding spotlight by exploring a simplified virtual scene for training. Said virtual scene consisted of two windows, two doors, a sofa and a paper bin. Participants were given no time constraints.
3. Exploration: participants explored one of the target scenes until they considered they had learnt its layout. As in the case of the training stage, they were given no time constraints. The initial location of the avatar within the virtual scene was always the same, i.e., next to one of the doors in the room and facing the opposite wall. Participants had direct control over the activation of the exploration screen. In order to do so, they were instructed to slide one of their fingers left or right on the smartphone touch screen. They remained stationary in the physical world and issued commands to the spotlight in two ways depending on the type of exploration, as described in section 2.2.2. Members of the research team were responsible for closing the exploration screen after participants notified completion. The application kept a log of obstacle detections, timestamps, participant interactions, and distances. This log file was automatically stored on a remote server when the researcher closed the exploration screen.
4. Questionnaire: participants reported the structures detected during the exploration stage. Answers were manually collected by a member of the research team.
5. Model: participants reproduced the layout of the original scene by means of a physical modelling kit. For each scene, the modelling kit consisted of three models of different empty rooms and twelve furniture miniatures, for each target scene. Six of the miniatures represented objects actually present in the original scene while the other six did not. Participants were asked to (i) identify the correct empty model of the target room; (ii) identify which miniatures represented objects actually present within

the original scene, and (iii) place those miniatures at their proper location within the empty model. The duration of the whole modelling stage was manually recorded, and a photograph of the final model-layout was taken (see Figure 14).

Figure 14. Photograph of particular spatial product.

6. Physical spaces: participants completed three different tasks in the physical equivalent of the original virtual scene (see Figure 15). They began their physical-world exploration at the same initial location as the avatar did in the virtual world. A member of the research team manually recorded completion status (success vs. failure).

Figure 15. Graphical depiction of three illustrative physical-world tasks.

2.2. Cognitive interface substudy

The proposed distant-based cognitive interface was compared to a traditional proximity-based approach. Data concerning blind people's performance and behaviour were collected. It was hypothesised that:

- distant exploration improves efficacy (i.e., a higher percentage of obstacles is detected during an exploration session) and efficiency of the exploration process (i.e., blind people need less time to detect obstacles for the first time).
- In addition, it was hypothesised that those changes have an impact on blind people's exploration-behaviour. In particular, it was hypothesised that higher efficiency would be associated with shorter duration of the overall exploration stage. However, alternative scenarios were taken into consideration, like exploration duration remaining unaltered as a consequence of greater effectiveness requiring the use of extra time to learn the disposition and relationships between a higher number of obstacles.

Noordzij, Zuidhoek & Postma (2006) suggest that both late and early blind people benefit more from a route description than from a survey description of spaces; and Pasqualotto, Spiller, Jansari & Proulx (2013) suggest that early blind people tend to produce egocentric representations of the space, while late-blind and sighted people tend to produce allocentric ones. However, according to Iachini, Ruggiero, & Ruotolo (2014) blind people might be able to produce allocentric spatial representations provided that they learn the environment from a stable body position, so:

- It was hypothesised that the adoption of distant exploration does not have a detrimental impact on quality or usefulness of the resulting cognitive maps.
- Finally, it was also hypothesised that a distant-exploration configuration with a greater scope and lesser degrees of freedom performs better than the reciprocal configuration. The former configuration is known as flat spotlight (fFoA) while the latter one is

known as the spherical spotlight (sFoA). Proximity exploration is referred to as noFoA.

Figure 16 below, summarises these hypotheses.

Figure 16. Hypotheses in the cognitive interface substudy.

Section 2.2.1. holds a description of the variables of the study. Section 2.2.2. holds a description of the system used to collect data. Finally, section 2.2.3. holds a description of the study design and protocol.

2.2.1 Variables

The variables in Figure 17 were assessed for three different exploration configurations (FoA): one configuration of proximity exploration (noFoA) and two different configurations of distant exploration (fFoA and sFoA).

Figure 17. Variables assessed in the cognitive interface substudy.

2.2.1.1 Exploration process

The effectiveness of the exploration process was defined as the total number of obstacles (both structures and objects) detected during the exploration of a virtual room. The greater the number of obstacles detected, the more effective the exploration process.

On the other hand, the efficiency of the exploration process was measured via the duration of the discovery stage (i.e., discovery time). Discovery time is the amount of time from which all the obstacles that are detected (both structures and objects) have already been previously detected during a given exploration session. Beware of the fact that this definition does not mean that all the obstacles in the scene were detected during the discovery stage, but just a maximum number of them, which can be lower than the total number of obstacles in the scene.

The duration of the exploration process is modelled as the total amount of time spent on exploring a virtual room.

Finally, extra time is the amount of time from the end of the discovery stage until the end of the overall exploration process.

2.2.1.2 Quality of cognitive maps

Quality of cognitive maps was assessed with two variables, namely, the SUQI score and fluency of the participants to remember their content.

The SUQI was described in section 2.1.2.

Finally, fluency to remember the content of cognitive maps was modelled as the time spent on building a model of the previously explored room. The lower the time spent, the more fluent the participant was.

2.2.1.3 Usefulness of cognitive maps

Participants were asked to complete three types of tasks in the real equivalent of the previously explored virtual room (see Figure 18).

1. Egocentric task: as an egocentric task, participants must walk from the initial exploration point to a target object; thus, such a task assesses the usefulness of absolute locations in the cognitive map.
2. Allocentric task: as an allocentric task, participants must walk from an object to another one; thus, the usefulness of relative locations in the cognitive map is assessed.
3. Orientation task: as an orientation task, participants must walk back to the starting point; thus, this task assesses participants' ability to update their cognitive maps while walking through a real room.

Figure 18. Graphical depiction of three illustrative physical-world tasks.

Usefulness of cognitive maps was modelled as a dichotomous variable for each type of task. A value of zero represents success, and a value of one represents failure.

2.2.2 Cognitive interfaces (FoA)

Key Points

- During distant exploration, participants can modify the direction of the line of sight by spinning around themselves with the smartphone screen facing towards themselves in both cases (either the sFoA and the fFoA), and, additionally, up and down in the case of the sFoA configuration.
- In addition, participants can explore the list of obstacles along the line of sight by sliding a finger up and down on the smartphone touch screen.
- The sensitive interface provides feedback via voice messages.
- The cognitive interface for proximity exploration (noFoA) was modelled as a volume

surrounding the avatar. Participants can control the direction of the line of sight, the avatar's walking status (stationary or walking), and the walking direction. It detects and reports the presence of obstacles within a one-meter range in front of the avatar and to the left and right of it.

- Participants may change the avatar's walking status by tapping the smartphone touch screen, and they may modify the direction of the line of sight by spinning around themselves with the smartphone screen facing toward themselves, either when the avatar is stationary or walking.
- The sensitive interface provides feedback via voice messages, and tactile and audio cues.

Two cognitive-interface configurations were described in section 2.1.1. for a distant exploration approach; namely, the spherical spotlight (sFoA) and the flat spotlight (fFoA).

1. The sFoA configuration was implemented as a beam along the avatar's line of sight. This beam is shaped as the projection of a sphere of one metre of diameter along the avatar's line of sight. On changes in the direction of the line-of-sight, the sFoA computes collisions between the beam and all the obstacles in the new direction. Type and distance of each detected obstacle are recorded, and information regarding the closest obstacle to the avatar is reported. Participants can sequentially check the complete set of detected obstacles by exploring the obstacle list either way along the current line of sight with the only limitation of reaching a wall, the ceiling or the floor. This configuration is sensitive to changes of direction to the left, right, up, and down while the avatar stays stationary at a fixed location.
2. The fFoA configuration behaves like the sFoA but (i) the beam is shaped as the projection of a vertical plane in front of the avatar and perpendicular to its line of sight; it is as wide as the avatar's shoulders and spans all along the space between the floor and the ceiling; and (ii) this configuration is sensitive to changes of direction to the left and right, but not up and down.

In both cases, participants can control the direction of the line of sight with the avatar always remaining stationary in its initial location. Participants can modify the direction of the line of sight by spinning around themselves with the smartphone screen facing towards themselves in both cases, and, additionally, up and down in the case of the sFoA configuration. Participants can explore the list of obstacles in the line of sight by sliding a finger up the smartphone touch screen to check the next obstacle away from the avatar; and by sliding a finger down the smartphone touch screen to check the previous obstacle towards the avatar. Obstacle reports consist of the type of obstacle and its distance to the avatar. This information was conveyed via a voice message over the speaker.

In order to compare the distant approach to the proximity approach, an additional

cognitive interface for proximity exploration (noFoA) was developed. Proximity exploration involves providing blind people with information at the reach of the cane. Thus, the noFoA configuration was modelled as a volume surrounding the avatar, which is able to provide information regarding the obstacles within a one-metre range in front of the avatar, a one-metre range to the left and right of the avatar, and all along the space between the floor and the ceiling. The noFoA moves jointly with the avatar as the latter walks around the virtual room. It reports the presence of both objects and structures when colliding with them. When an obstacle is detected in front of the avatar, the noFoA makes it stop and reports the type of obstacle. Participants can make the avatar turn left or right to avoid obstacles. When there are no obstacles in front of the avatar anymore, the noFoA reports the event. When an obstacle is detected either to the left or right of the avatar, the noFoA reports its type, but the avatar keeps walking. Again, when there are no obstacles to the left or right of the avatar anymore, the noFoA reports the event. The blind person can make the avatar walk and stop whenever he wants.

In the case of the noFoA configuration, participants can control the direction of the line of sight, the avatar's walking status (stationary or walking), and the walking direction. Participants can modify the direction of the line of sight by spinning around themselves with the smartphone screen facing towards themselves, either when the avatar is stationary or walking; in the latter case, rotating the smartphone also makes the avatar turn and change walking direction. Participants may change the avatar's walking status by tapping the smartphone touch screen. The avatar always moves forward. The smartphone vibrates once per avatar's step to provide feedback regarding the walking status. When there is an obstacle in a two-meter range away from the avatar, in the direction of the line of sight, the noFoA beeps as a pulse train. The tone of each pulse varies according to the obstacle height (low, medium, high). Also, the period between pulses decreases as the avatar comes closer to the obstacle. The beeping shuts down as soon as the obstacle gets out of the avatar's line of sight. If the noFoA ends up colliding frontally with an obstacle, it makes the avatar stop and reports the obstacle type and the fact that it is two steps away. The noFoA reports this information by playing a voice message over the speaker. When an obstacle collides with the noFoA out of the avatar's line of sight, the noFoA reports the type of obstacle and its location (left or right). When the said obstacle is no longer within the range of the noFoA, it reports the fact that there is a free way to the left or right. Feedback is provided, once again, by playing a voice message over the speaker.

2.3. Quality index substudy

The reliability of the SUQI as a cognitive-map quality assessment tool was tested. The SUQI is based on the Mahalanobis distance. Said distance metric requires (i) modelling a cognitive map in the form of a quantitative vector, and (ii) computing a covariance matrix to account for the variability differences across different vector features.

The study was divided into three phases. In the first one, the statistical properties of the dataset were analysed. In the second one, the SUQI was compared to human assessment and

other methods of spatial product assessment. In order to do so, all fifty four spatial products to be assessed were used to compute the required covariance matrix.

- First, it was hypothesised that a SUQI-based assessment of cognitive maps would be equivalent to human assessment, thus, supporting the choice of both cognitive map features as representative vector elements and their corresponding quantification metrics.
- Second, it was hypothesised that accounting for variability differences across vector features would improve reliability in a significant factor.
- In the third place, it was hypothesised that the SUQI would outperform other metrics capability to replicate human assessment.

In a practical scenario, it is only possible to compute an estimate of the covariance matrix. Such an estimate will be based on a finite set of spatial products from a limited sample of blind people. The least expensive scenario is one where spatial products from a single scene of reference can be used to compute a covariance matrix valid for any other scene. Hence, in the third phase, the capability of different covariance matrix estimations to produce equivalent outcomes was tested.

- Thus, as a fourth hypothesis, it was hypothesised that a covariance matrix based on a single scene would be suitable to assess spatial products representing other scenes.
- Finally, it was hypothesised that different estimations of the covariance matrix would be able to produce equivalent assessment outcomes for the same set of spatial products.

Figure 19 below, summarises these hypotheses.

Figure 19. Hypotheses in the quality index substudy.

2.3.1. Variables

Key Points

- Descriptive statistics (i.e., mean and standard deviation values) were computed for each feature in the SUQI. Eigenvectors and eigenvalues from the covariance matrix were examined.
- The SUQI and percentage of landmarks capability to mimic human assessment were assessed in the form of inter-rater reliability tests.
- The capability of SUQI scores from different covariance matrix estimations to mimic each other was assessed in the form of inter-rater reliability tests.

The following variables in Figure 20 were assessed in the quality index substudy:

Figure 20. Variables assessed in the quality index substudy.

2.3.1.1. Statistical features of the dataset

Descriptive statistics. Mean values and standard deviation values were computed for each feature in the SUQI. It was done by making use of all fifty-four spatial products in the dataset.

Covariance matrix. All fifty-four spatial products were used to compute a covariance matrix. Its eigenvectors and eigenvalues were calculated using the *base* package in the R statistical software, version 3.4.3.

2.3.1.2. Equivalence between the SUQI and human assessment

Equivalence between the SUQI and human assessment was assessed to test whether assessing a set of spatial models with the SUQI produces subjective-like outcomes. In order

to do so, fifty-four spatial models were ranked according to their quality by making use of three different methods, namely, the subjective human assessment, the SUQI, and the Euclidean distance. Finally, inter-rater reliability (IRR) estimates were computed to compare outcomes from the SUQI and the Euclidean distance with the outcomes from subjective assessment.

Equivalence between these two methods was defined as the inter-rater reliability between these two assessment methods to compute the ranking positions of a set of spatial products. Three different rankings of spatial products were produced, namely, the subjective-ranking, the SUQI-ranking, and the Euclidean-ranking according to the following procedures.

1. The subjective-ranking: each rater built a ranking of spatial models according to their similarity to their corresponding original scene. The raters were instructed about the three original layouts (i.e., office, pub, and bedroom) and the initial exploration location in each virtual scene. They were not instructed about the characteristics of the SUQI design. They iteratively compared each unrated photo with the already ranked ones, starting from the lowest position in the ranking and moving the unrated photo up until its quality was exceeded by an already ranked one's. The highest position in the ranking has a value of one and the lowest a value of fifty-four. After checking the IRR between the three human raters, the final subjective-ranking was produced by computing the mean values of ranking positions for each spatial model (see Figure 21).

Figure 21. Outcomes of the human ranking process.

2. The SUQI-ranking: members of the research team computed SUQI scores for all fifty-four spatial models in the dataset which were accordingly ranked. The highest position in the ranking (first position) belonged to the lowest SUQI score while the lowest position in the ranking (fifty-fourth position) belonged to the highest one, see Figure 22(a) and Figure 22(b).

Figure 22(a). Computation of the covariance matrix for all fifty-four spatial products in the e-Glance dataset.

Figure 22(b). Computation of SUQI scores and the corresponding SUQI-ranking for all fifty-four spatial products in the e-Glance dataset.

3. The Euclidean-ranking: members of the research team computed Euclidean scores for all fifty-four spatial models in the dataset which were accordingly ranked. Like in the case of the SUQI-ranking, the highest position in the ranking (first position) belonged to the lowest Euclidean score while the lowest position in the ranking (fifty-fourth position) belonged to the highest one, see Figure 23.

Figure 23. Computation of Euclidean scores and the corresponding Euclidean-ranking for all fifty-four spatial products in the e-Glance dataset.

2.3.1.3. Equivalence of human assessment with both landmark percentage and bidimensional regression

Equivalence between human assessment and these two methods was assessed to test whether the SUQI outperforms previously available metrics for the assessment of spatial models. In order to do so, the fifty-four spatial models in the dataset were ranked according to their quality by making use of two additional methods, namely, the percentage of correctly placed landmarks and bidimensional regression. Finally, IRR estimates were computed to compare outcomes from these two methods with the outcomes from subjective assessment.

Again, equivalence was defined as the inter-rater reliability between the methods to compute the ranking positions of a set of spatial products. Two additional rankings were produced, namely, the percentage-ranking and the regression-ranking according to the following procedures.

1. The percentage-ranking: members of the research team computed the percentage of correctly placed landmarks for all fifty-four spatial models in the dataset which were accordingly ranked. The highest position in the ranking (first position) belonged to the highest percentage score, while the lowest position in the ranking (fifty-fourth position) belonged to the lowest one.
2. The regression-ranking: members of the research team computed correlation coefficients for all fifty-four spatial models in the dataset which were accordingly ranked. The highest position in the ranking (first position) belonged to the highest correlation coefficient while the lowest position in the ranking (fifty-fourth position) belonged to the lowest one.

2.3.1.4. Estimations of the covariance matrix

In a practical scenario, it is only possible to compute an estimate of the covariance

matrix. Computing a different covariance matrix for each scene in a training programme would be expensive because, before being able to assess the spatial models produced by any given blind trainee, it would be necessary to conduct a tedious process. It would be necessary to gather a group of blind volunteers, have the new virtual scene explored by them, ask them to externalise their cognitive maps into the respective spatial models, quantify each of those spatial models into a vector according to their fundamental properties, and, finally, compute the requested covariance matrix. It would be simpler and less expensive if the process described above could be conducted only once by making use of a single virtual scene of reference.

Consequently, it was tested whether the SUQI would produce equivalent outcomes if different estimations of the covariance matrix were used to assess the same set of spatial products. For example, would the assessment outcomes still be equivalent if the covariance matrix were not computed with the entire set of fifty-four spatial models in the dataset but with a subset of eighteen spatial models instead? Furthermore, would there be any changes if the covariance matrix got to be computed with a different set of another eighteen spatial models? In order to do so, different subsets of the fifty-four spatial models were ranked according to their SUQI scores by making use of three different estimations of the covariance matrix, namely, the office-matrix, the pub-matrix, and the bedroom-matrix, see Figure 24(a) and Figure 24(b). Finally, inter-rater reliability (IRR) estimates were computed to compare outcomes from all three matrices with outcomes from subjective assessment; and to compare outcomes from all three matrices to each other.

Figure 24(a). Distribution of spatial products according to scene to which they belong.

Figure 24(b). Computation of three covariance matrices, each with a different dataset: office (left) pub (middle) and bedroom (right).

Equivalence between human assessment and the outcomes resulting from the use of different estimations of the covariance matrix was defined as the inter-rater reliability between them to compute the ranking positions of a set of spatial products. Three additional rankings, namely, the office-ranking, the pub-ranking, and the bedroom-ranking, were produced. They were used to test whether different estimations of the covariance matrix kept unaltered the SUQI equivalency to subjective assessment. The members of the research team computed SUQI scores for all thirty-six spatial models representing the pub and bedroom scenes by making use of the office-matrix. The resulting SUQI scores were then accordingly ranked into the office-ranking. Analogously, members of the research team computed SUQI scores for all thirty-six spatial models representing the office and bedroom scenes by making use of the pub-matrix. The resulting SUQI scores were accordingly ranked into the pub-ranking. Finally, members of the research team computed SUQI scores for all thirty-six spatial models representing the office and pub scenes by making use of the bedroom-matrix. The resulting SUQI scores were accordingly ranked into the bedroom-ranking. See Figure 25.

Figure 25. Computation SUQI scores and the corresponding rankings by making use of three different covariance matrices: office (top) pub (middle) and bedroom (bottom).

On the other hand, equivalence between the outcomes resulting from the use of different estimations of the covariance matrix was defined as the inter-rater reliability between them to compute the scores of a set of spatial products. Three additional sets of SUQI scores, namely, the office-suqi-scores, the pub-suqi-scores, and the bedroom-suqi-scores, were produced. They were used to test whether different estimations of the covariance matrix gave a given spatial model the same numeric SUQI score. The members of the research team computed SUQI scores for all fifty-four spatial models by making use of the office-matrix; which resulted in the office-suqi-scores set. Analogously, members of the research team computed SUQI scores for all fifty-four spatial models by making use of the pub-matrix; which resulted in the pub-suqi-scores set. Finally, members of the research team computed SUQI scores for all fifty-four spatial models by making use of the bedroom-matrix; which resulted in the bedroom-suqi-scores set. See Figure 26.

Figure 26. Computation SUQI scores for all fifty-four spatial products in the e-Glance dataset by making use of three different covariance matrices: office (top) pub (middle) and bedroom (bottom).

2.3.2. Quality assessment methods

Key Points

- Four different methods were used to assess cognitive map quality.
- The SUQI is defined as the Mahalanobis distance between a given spatial product and its corresponding original scene. Spatial products are represented by a four-dimensional vector where each element represents a different error-term; namely, identification error, location error for structures, absolute-location error for objects, and relative-location error for objects.
- Human assessment of externalizations. Each human rater built a ranking of spatial products according to their relative quality.
- Percentage of correctly placed landmarks. Any miniature in a spatial product was considered to be correctly-placed if both its distance and direction attributes had been set to zero when computing its absolute-location error-term in the SUQI.
- Bidimensional regression. Correlation coefficient as computed by Friedman's & Kohler's (2003) implementation.

2.3.2.1. The SUQI

The SUQI was described in section 2.1.2.

2.3.2.2. Human Assessment of Externalizations

Three independent adults, two women and a man, between 41 and 69 years of age, acted as evaluators of the similarity between spatial products and their corresponding original scenes. They were selected according to the following inclusion criteria: (i) being above 18 years old, (ii) not being familiar with the SUQI nor with the e-Glance study, and (iii) having normal color vision and normal or corrected-to-normal visual acuity. They did not receive any kind of compensation whatsoever.

2.3.2.3. Percentage of correctly placed landmarks

Quality scores are, according to this metric, computed as the sum of correctly placed landmarks in each spatial model divided by the total number of landmarks in the corresponding original scene. This metric is, by definition, bounded between zero and one; the higher the score, the higher the quality. Any miniature in a spatial model was considered to be correctly-placed if both its distance and direction attributes had been set to zero when computing its absolute-location error-term in the SUQI.

2.3.2.4. Bidimensional regression

Quality scores are defined as the correlation coefficient, which was computed by making use of Friedman's & Kohler's (2003) implementation of the bidimensional regression

algorithm. Said implementation is available as supplemental material at dx.doi.org/10.1037/1082.989X.8.4.468.suppl. This correlation coefficient is bounded between zero and one. Zero represents minimum quality and one represents maximum quality.

3. RESULTS

3.1. Cognitive interface substudy

Figure 17, at the beginning of section 2.2 summarises the variables assessed in this study.

3.1.1. The exploration process

Key Points

- There is a 24% improvement in the effectiveness of the fFoA compared to proximity exploration (p-value=0.0006); and a 12% improvement in the effectiveness of the sFoA compared to proximity exploration (p-value=0.0039).
- Distant exploration with the fFoA entails a 53% reduction in discovery duration, compared to proximity exploration (p-value= 0.0027).
- A trend is observed for differences in exploration duration (p-value=0.067). Post-hoc tests show a 38% reduction by using the fFoA with respect to proximity exploration (p=0.024).
- Extra time lasts longer when four walls were detected during the discovery stage. Due to the proximity of type I error in t-test assumptions to the 0.05 threshold, both parametric (p-value = 0.012) and non-parametric tests (p-value for unequal variances = 0.0012; p-value for non-normality = 0.0036) were run.

3.1.1.1. Effectiveness of the exploration process

The effectiveness of the exploration process was defined as the total number of obstacles (both structures and objects) detected during the exploration of a virtual room. Table 3 summarizes the values of effectiveness for the three configurations under study. Figure 27 shows a graphical comparison of effectiveness relative to the total number of obstacles in the room.

fFoA	sFoA	noFoA
14.1 (sd=1.1) 93.7%	12.7 (sd=2.9) 84.5%	11.3 (sd=2.3) 76.0%

Table 3. Effectiveness of the exploration stage.

Figure 27. Effectiveness of the exploration stage.

The dependence of effectiveness with the FoA configuration was assessed with a Friedman test that resulted statistically significant (Friedman chi-squared = 12.59, df = 2, p-value = 0.0018). Pairwise comparison between types of FoA was conducted by applying a Fisher's LSD test with Holm correction. Both the fFoA and the sFoA showed a statistically significant difference with the noFoA. In particular, there is a 24% improvement in the effectiveness of the fFoA compared to proximity exploration (p-value=0.0006); and a 12% improvement in the effectiveness of the sFoA compared to proximity exploration (p-value=0.0039). On the other hand, however, the 11% difference between the two distant configurations under study, i.e., fFoA and sFoA, was not found to be statistically significant (p-value=0.079).

3.1.1.2 Efficiency of the exploration process

Efficiency was modelled as discovery duration, which was defined in section 2.2.1. Table 4 summarizes the values of discovery duration for the three FoA configurations under study. Figure 28 shows a graphical comparison of the time spent during discovery with three different FoAs.

fFoA	sFoA	noFoA
234.4 s	412.1 s	496.5 s

Table 4. Duration of the discovery stage.

Figure 28. Duration of the discovery stage.

The dependence of discovery duration with the type of FoA was assessed with a repeated measures ANOVA, after checking assumptions for this kind of test. Data from all three groups showed a normal distribution according to the Kolmogorov-Smirnov test (see Table 5).

fFoA	sFoA	noFoA
D = 0.259, p = 0.15	D = 0.266, p = 0.13	D = 0.213, p = 0.34

Table 5. Results from Kolmogorov-Smirnov tests (discovery stage).

Homoscedasticity was also met as showed by a Levene's test ($F = 1.793$, $df = 2$, $p = 0.18$). A Mauchly's test, however, showed that sphericity was not met ($W = 0.532$, $p = 0.0064$); so a Greenhouse-Geisser correction was applied ($GGe = 0.68$).

This repeated measures ANOVA test resulted statistically significant after Greenhouse-Geisser correction ($F = 5.645$, $df = 2$, $p = 0.018$). Pairwise comparison between types of FoA was conducted by applying a Tukey pairwise comparison test. Distant exploration with the fFoA entails a 53% reduction in discovery duration, compared to proximity exploration (p -value = 0.0027). There is no statistically significant difference between sFoA and proximity exploration (p -value = 0.54), nor between the two configurations of distant exploration, i.e.,

fFoA and sFoA, (p-value=0.066). Nonetheless, in the latter case, a trend is observed that must be studied with a sample of greater size.

3.1.1.3. Exploration duration

Exploration duration was defined in section 2.2.1. Table 6 summarizes the values of exploration duration for the three FoA configurations under study. Figure 29 shows a graphical comparison of the time spent during exploration with three different FoAs.

fFoA	sFoA	noFoA
436.2 s	549.7 s	729.8 s

Table 6. Duration of the exploration stage.

Figure 29. Duration of the exploration stage.

The dependence of exploration duration with the type of FoA was assessed with a repeated measures ANOVA, after checking assumptions for this kind of test. Data from all three groups showed a normal distribution according to the Kolmogorov-Smirnov test (see Table 7).

fFoA	sFoA	noFoA
D = 0.300, p = 0.052	D = 0.275, p = 0.093	D = 0.209, p = 0.33

Table 7. Results from Kolmogorov-Smirnov tests (exploration stage).

Homoscedasticity was also met as showed by a Levene's test ($F = 1.37$, $df = 2$, $p = 0.26$). A Mauchly's test, however, showed that sphericity was not met ($W = 0.392$, $p = 0.00035$); so a Huynh-Feldt correction was applied ($HFe = 0.645$).

This repeated measures ANOVA test resulted not statistically significant after Huynh-Feldt correction ($F=3.452$, $p\text{-value}=0.067$); however, it can be considered that a trend is observed since the p-value is low despite the low power of the sample in use. A post-hoc pairwise comparison was conducted in the form of a Tukey test (read [Games, 1971] in order to find an explanation for the justification of a pairwise comparison in case of trends). The Tukey test resulted statistically significant for the 38% reduction obtained by using the fFoA with respect to proximity exploration ($p=0.024$).

3.1.1.4. Extra time

Extra time was defined in section 2.2.1. After observing the significance of wall-detection effectiveness during the externalization stage (see section 3.1.2.1.), its impact on exploration behaviour was studied. Table 8 summarizes the values of extra duration for two groups, namely, total detection (four walls detected) and partial detection (less than four walls detected). Figure 30 shows a graphical comparison of the extra time spent during exploration with the two groups.

Total detection	Partial detection
225.6 s	108.6 s

Table 8. Duration of the extra time.

Wall-detection effectiveness
Figure 30. Duration of the extra time.

The dependence of extra time with wall-detection effectiveness was assessed with a two-sample t-test, after checking assumptions for this kind of test. Data from both groups showed a normal distribution according to the Kolmogorov-Smirnov test (see Table 9).

Total detection	Partial detection
D = 0.206, p-value = 0.068	D = 0.179, p-value = 0.62

Table 9. Results from Kolmogorov-Smirnov tests (extra time).

Homoscedasticity was also met as showed by a Levene's test ($F = 3.713$, $df = 1$, $p = 0.059$).

Due to the proximity of type I error in t-test assumptions to the 0.05 threshold, besides the parametric two-samples t-test ($t = 2.319$, $df = 52$, $p\text{-value} = 0.012$), two non-parametric versions of said test were run, namely, a Welch's t-test for unequal variances ($t = 3.186$, $df = 51.77$, $p\text{-value} = 0.0012$) and a Wilcoxon rank sum test for non-normality ($W = 444$, $p\text{-value} = 0.0036$). All three of them resulted statistically significant.

3.1.2 Quality of cognitive maps

Key Points

- The dependence of quality scores with the FoA configuration resulted not statistically significant (p-value = 0.21). Individual error-terms did not show a dependence with the type of FoA either (p-values = (0.23, 0.45, 0.98, 0.26)).
- Further analysis of the identification error terms showed that 75% of fully-correct wall-identifications (i.e., remembering four walls during the externalization stage) are independent of the number of walls detected during exploration.
- The dependence of fluency with the type of FoA did not result statistically significant (p-value = 0.33).

In order to evaluate the quality of the cognitive maps generated during exploration, the content of these maps was assessed together with the fluency with which participants were able to remember said content. Deviations from the original scene are computed as the Mahalanobis distance of two four-dimensional vectors (identification error for obstacles, location error for structures, absolute-location error for objects, relative-location error for objects) where the original scene is represented by (0, 0, 0, 0) coordinates. The lower the value of the deviation, the better the quality of the cognitive map. On the other hand, fluency to remember the content of cognitive maps is modelled as the time spent building a model of the previously explored room.

3.1.2.1. Overall quality of cognitive maps

Table 10 summarizes the mean overall quality scores for the three different FoA configurations under study. Please, notice that the score represents the deviation from the original scene. Thus, the lower the value of the score the better the quality of the cognitive map. Figure 31 shows a graphical comparison of these deviations relative to the maximum deviation.

fFoA	sFoA	noFoA
3.3 34%	3.4 35%	3.7 38%

Table 10. Deviation of the content of cognitive maps.

Figure 31. Deviation of the content of cognitive maps.

The dependence of overall quality with the FoA configuration was assessed with a Friedman test that resulted not statistically significant (Friedman chi-squared = 3.111, $df = 2$, p -value = 0.21). Given that result, each score-dimension was studied separately; and none of them showed a dependence on the type of FoA:

1. In the case of the identification error, obstacles were modelled as a nominal variable with three levels, namely, correct identifications, omissions, and insertions. Its dependence with the type of FoA was assessed with a Mantel-Haenszel test of general association (Cochran-Mantel-Haenszel $M^2 = 5.598$, $df = 4$, p -value = 0.23).
2. In the case of the location error for structures, success in model choice was modelled as a dichotomous variable. Its dependence with the type of FoA was assessed with a Cochran-Mantel-Haenszel test for general association (Cochran-Mantel-Haenszel $M^2 = 1.6$, $df = 2$, p -value = 0.45).
3. In the case of the absolute-location error for objects, the error value was modelled as an ordinal variable with four levels. A level for deviations lower than 25%, another level for deviations between 25% and 50%, another level for deviations between 50% and 75%, and a level for deviations over 75%. The dependence of this variable with the type of FoA was assessed with a Mantel-Haenszel mean score test ($chisq = 0.0377$, $df = 2$, p -value = 0.98).
4. In the case of the relative-location error for objects, the error value was modelled as an ordinal variable with the same levels as the previous dimension. The dependence of this variable with the type of FoA was assessed with a Mantel-Haenszel mean score test ($chisq = 2.657$, $df = 2$, p -value = 0.26).

The absence of dependence in the case of the identification error was particularly intriguing because the effectiveness of obstacle detection during an exploration did show a dependence with the type of exploration (see section 3.1.1.); so the reasons why the identification dimension does not preserve this dependence were studied more carefully. The dependence of detection status and identification status with the type of FoA was studied separately for walls, windows, and objects.

3.1.2.1.1. Walls

Both the detection and identification statuses of walls were modelled as dichotomous variables. In the case of detection status, walls can count either as detected or missing. In the case of identification status, they can count as either identified or omitted (see Figure 32).

Figure 32. Detection of walls (left) vs. Identification of walls (right).

The dependences of both detection and identification statuses with the type of FoA were assessed each with a Mantel-Haenszel test of general association, which resulted significant in the case of detection status (Cochran-Mantel-Haenszel $M^2 = 7.787$, $df = 2$, $p\text{-value} = 0.02$); but not significant for identification status (Cochran-Mantel-Haenszel $M^2 = 2.176$, $df = 2$, $p\text{-value} = 0.34$).

In particular, while the fFoA shows perfect reciprocation between fully correct detections (i.e., detecting four walls during exploration) and fully correct identifications (i.e., identifying four walls during the post-exploration interview); in the case of both sFoA and noFoA configurations, there are more fully correct identifications than fully correct detections. The dependence of both fully correct detections and fully correct identifications with the FoA configuration was assessed by modelling both of them as dichotomous variables and executing two Mantel-Haenszel tests of general association, which resulted significant in the case of fully correct detections (Cochran-Mantel-Haenszel $M^2 = 8.6$, $df = 2$, $p\text{-value} = 0.014$); but not significant in the case of fully correct identifications (Cochran-Mantel-Haenszel $M^2 = 3.6$, $df = 2$, $p\text{-value} = 0.17$).

Given this result, the attributable risk relationship between fully correct identifications and fully correct detections was studied. The result shows that 75% of fully correct identifications are independent of the number of walls detected during exploration.

3.1.2.1.2. Windows

Both the detection and identification statuses of windows were modelled in a similar way to the case of walls (See Figure 33).

Figure 33. Detection of windows (left) vs. Identification of windows (right).

Their respective dependence with the type of FoA were assessed each with a Mantel-Haenszel test of general association which resulted significant for detection status (Cochran-Mantel-Haenszel $M^2 = 11.395$, $df = 2$, $p\text{-value} = 0.0034$); but not significant for identification status (Cochran-Mantel-Haenszel $M^2 = 0.345$, $df = 2$, $p\text{-value} = 0.84$).

3.1.2.1.3. Objects

Both the detection and identification statuses of objects were modelled in a similar way to the case of walls and windows (See Figure 34).

Figure 34. Detection of objects (left) vs. Identification of objects (right).

Their dependencies with the type of FoA were assessed each with a Mantel-Haenszel test of general association which resulted significant for both detections (Cochran-Mantel-Haenszel $M^2 = 21.68$, $df = 2$, $p\text{-value} = 1.96e-05$) and identifications (Cochran-Mantel-Haenszel $M^2 = 9.500$, $df = 2$, $p\text{-value} = 0.0087$).

3.1.2.2. Fluency

Fluency to remember the content of cognitive maps was modelled as the time spent building a model of the previously explored room. The lower the time, the more fluent the participant was. Table 11 summarizes the values for the three different types of FoA under study. Figure 35 shows a graphical comparison of said values.

fFoA	sFoA	noFoA
4 min 9 s	3 min 34 s	3 min 56 s

Table 11. Duration of the model building stage.

Figure 35. Duration of the model building stage.

The dependency of fluency with the type of FoA was assessed with a repeated measures ANOVA, after checking assumptions for this kind of test. Data from all three groups showed a normal distribution according to the Kolmogorov-Smirnov test (see Table 12).

fFoA	sFoA	noFoA
D = 0.162, p = 0.64	D = 0.221, p = 0.27	D = 0.221, p = 0.27

Table 12. Results from Kolmogorov-Smirnov tests (fluency).

Homoscedasticity was also met as showed by a Levene's test ($F = 0.193$, $df = 2$, $p = 0.82$). A Mauchly's test showed that sphericity was also met ($W = 0.852$, $p = 0.26$); so no correction was necessary for the results of the repeated measures ANOVA test; which resulted not statistically significant ($F = 1.144$, $p = 0.33$).

3.1.3. Usefulness of cognitive maps

Key Points

- The difference between task-completion status for different types of FoA resulted not significant for all three types of tasks; i.e., egocentric ($p\text{-value} = 0.24$), allocentric ($p\text{-value} = 0.76$), and orientation tasks ($p\text{-value} = 0.89$).
- The difference between SUQI scores for different task-completion status is significant both

for egocentric (p-value = 0.050) and allocentric tasks (p-value = 0.031), but it is not for orientation ones (p-value = 0.58).

- As expected, SUQI scores are lower for successfully completed tasks.

To evaluate the usefulness of the cognitive maps generated during a virtual visit, success on completing three types of tasks in the real equivalent of the virtual room was assessed. Egocentric, allocentric and orientation tasks were assessed (See Figure 36).

Figure 36. Distribution of successfully completed task.

Success was modelled as a dichotomous variable for each type of task. The dependence of success with the type of FoA was assessed with a Mantel-Haenszel test of general association for each type of task which resulted not significant for all of them. In the case of egocentric tasks (Cochran-Mantel-Haenszel $M^2 = 2.889$, $df = 2$, p-value = 0.24); in the case of allocentric tasks (Cochran-Mantel-Haenszel $M^2 = 0.545$, $df = 2$, p-value = 0.76); and in the case of orientation tasks (Cochran-Mantel-Haenszel $M^2 = 0.222$, $df = 2$, p-value = 0.89).

The relationship between success status of real tasks and quality of the cognitive maps was studied. The mean SUQI scores of cognitive maps were computed for both successfully completed tasks and failed tasks (See Figure 37).

Figure 37. Mean deviation scores for different success status and type of task.

The difference between successfully completed tasks and failures, for different types of tasks, was each assessed with a two-sample t-test, after checking assumptions for this kind of test. Data from both groups showed a normal distribution, for all three types of task, according to the Kolmogorov-Smirnov test (see Table 13).

	Success	Failure
egocentric	D = 0.0743, p-value = 0.99	D = 0.128, p-value = 0.86
allocentric	D = 0.0943, p-value = 0.99	D = 0.179, p-value = 0.36
orientation	D = 0.108, p-value = 0.76	D = 0.130, p-value = 0.97

Table 13. Results from Kolmogorov-Smirnov tests (success vs. failure).

Homoscedasticity was met for egocentric and allocentric tasks, but not for orientation ones, as shown by a Levene's test (see Table 14).

egocentric	F = 3.040, df = 1, p = 0.088
allocentric	F = 0.007, df = 1, p = 0.93
orientation	F = 4.203, df = 1, p = 0.046

Table 14. Results from Levene's tests (success vs. failure).

Thus, egocentric and allocentric data were assessed with two-sample t-tests, and orientation data was assessed with a Welch's t-test for unequal variance. The fact that deviations of successfully completed tasks are lower than deviations of failed tasks resulted statistically significant for egocentric tasks ($t = -1.682$, $df = 46$, $p\text{-value} = 0.050$) and allocentric tasks ($t = -1.923$, $df = 40$, $p\text{-value} = 0.031$); but not for orientation tasks ($t = -0.574$, $df = 14.123$, $p\text{-value} = 0.58$).

3.2. Quality index substudy

3.2.1. Statistical features of the dataset

Key Points

- Room shape is the primary source of variability among the selected cognitive map features ($sd = 0.499$). Should we not take into account the variability difference across features, such a high value of variability will make of room shape the main feature to determine the quality of cognitive maps.
- The eigenvectors from the covariance matrix represent the coordinate axes that are suggested by the data themselves. The direction of maximum variance is still equivalent to the room-shape feature.

The descriptive statistics in Figure 38 show that the room shape feature is the main source of variability among the selected features. Since the error term corresponding to room shape was modelled as a dichotomous variable with values either zero or one, the value of the standard deviation ($sd = 0.499$) means that almost half the spatial products contain an incorrect recognition of the room shape. Should we not take into account the variability difference across features, such a high value of variability will make of room shape the main feature to determine the quality of cognitive maps. The Mahalanobis distance accounts for variability differences because it scales each axis by their corresponding standard deviation.

The eigenvectors in Figure 39 represent the coordinate axes that are suggested by the data themselves. The first one represents the direction of maximum variance, and the rest of them are orthogonal vectors that are sequentially computed to maximise variance along their particular direction. Visual inspection of the elements in the first eigenvector shows that the direction of maximum variance is still equivalent to the room-shape feature. The square root of the eigenvalues gives the standard deviation in each direction.

3.2.1.1. Descriptive statistics

Figure 38 shows a summary of statistical parameters for each feature in the SUQI.

Figure 38. Descriptive statistics of the dataset.

3.2.1.2. Covariance matrix

Figure 39 shows the covariance matrix together with the resulting eigenvectors and the corresponding eigenvalues and standard deviations.

Figure 39. Analysis of the covariance matrix.

3.2.2. Equivalence between the SUQI and human assessment

Key Points
• IRR between human evaluators was excellent $ICC(A, 3) = 0.994$, $H1: ICC > 0.9$ $p = 2.83e-33$, 95% CI (0.991, 0.996).   • IRR between the SUQI and human assessment was excellent: $ICC(A, 1) = 0.999$, $H1: ICC > 0.9$ $p = 2.53e-35$, 95% CI (0.997, 0.999).   • IRR between the Euclidean distance and human assessment was good but not excellent: $ICC(A, 1) = 0.794$, $H1: ICC > 0.9$ $p = 0.997$, 95% CI (0.669, 0.875).

IRR between different rankings was assessed by means of computing the intra-class correlation coefficient (ICC). ICC estimates and their 95% confidence intervals (CI) were

calculated using the *irr* package in the R statistical software, version 3.4.3. In the case of IRR between human raters a mean-rating, absolute-agreement, 2-way model was applied; while in the case of subjective-ranking IRR with the SUQI-ranking and the Euclidean-ranking two single-rater, absolute-agreement, 2-way models were applied.

As recommended by Koo & Li (2016, p. 155), “[b]ased on the 95% confident interval of the ICC estimate, values less than 0.5, between 0.5 and 0.75, between 0.75 and 0.9, and greater than 0.90 are indicative of poor, moderate, good, and excellent reliability, respectively”. See Figure 40.

Figure 40. Inter-rater reliability levels.

3.2.2.1. IRR between human evaluators

ICC was excellent: $ICC(A, 3) = 0.994$, $H1: ICC > 0.9$ $p = 2.83e-33$, 95% CI (0.991, 0.996) thus, the subjective-ranking was produced by computing the mean values of ranking positions for each spatial model.

3.2.2.2. IRR between the subjective-ranking and the SUQI-ranking

Inter-rater reliability between the subjective-ranking and the SUQI-ranking was excellent, $ICC(A, 1) = 0.999$, $H1: ICC > 0.9$ $p = 2.53e-35$, 95% CI (0.997, 0.999) in fact, the SUQI ranking completely mimicked human assessment. This result supports the choice of identifications, room shape, absolute location, and relative location as characteristic properties of human cognitive maps. It supports, as well, the criteria defined to quantify them, despite their computational simplicity. Finally, this result also means that the choice of the Mahalanobis distance as a similarity metric or, better said, dissimilarity metric, is highly appropriate. The extent to which such a remarkable resemblance remains if the spatial models under assessment were not involved in the computation of the covariance matrix was studied in section 3.2.4.; while section 3.2.3. focuses on the SUQI ability to outperform other assessment methods.

3.2.2.3. IRR between the subjective-ranking and the Euclidean-ranking

IRR between the Euclidean distance and human assessment was good but not excellent: $ICC(A, 1) = 0.794$, $H1: ICC > 0.9$ $p = 0.997$, 95% CI (0.669, 0.875) which means that the SUQI-ranking mimics the subjective-ranking better than the Euclidean-ranking, see Figure 41, the confidence intervals of their corresponding IRR estimates do not overlap with each other. This result also reinforces the choice of the Mahalanobis distance as a similarity metric or, better said, dissimilarity metric, as highly appropriate because the only difference between the SUQI and the Euclidean distance is the use of a covariance matrix; thus,

accounting for differences in variability between different cognitive-map properties proved to play a vital role in mimicking human assessment.

Figure 41. IRR between the SUQI and human assessment (left) vs. IRR between the Euclidean distance and human assessment (right). Their corresponding confidence intervals do not overlap with each other.

3.2.3. Equivalence of human assessment with both landmark percentage and bidimensional regression

Key Points

- IRR between landmark percentage and human assessment was moderate, not even good: $ICC(A, 1) = 0.720$, $H1: ICC > 0.75$ $p = 0.681$, 95% CI (0.561, 0.828).
- IRR between bidimensional regression and human assessment was poor: $ICC(A, 1) = 0.250$, $H1: ICC > 0.9$ $p = 1$, 95% CI (-0.021, 0.485).

IRR between different rankings was assessed by means of computing the intra-class correlation coefficient (ICC). ICC estimates and their 95% confidence intervals (CI) were

calculated using the *irr* package in the R statistical software, version 3.4.3. Both IRR between the subjective-ranking and the percentage-ranking and IRR between the subjective-ranking and the regression-ranking were based on a single-rater, absolute-agreement, 2-way model.

3.2.3.1. IRR between the subjective-ranking and the percentage-ranking

IRR between the subjective-ranking and the percentage-ranking was moderate, not even good: $ICC(A, 1) = 0.720$, $H1: ICC > 0.75$ $p = 0.681$, 95% CI (0.561, 0.828).

3.2.3.2. IRR between the subjectiv-ranking and the regression-ranking

Inter-rater reliability between the subjective-ranking and the regression-ranking was poor, $ICC(A, 1) = 0.250$, $H1: ICC > 0.9$ $p = 1$, 95% CI (-0.021, 0.485).

These two results mean that the SUQI outperforms both the percentage of correctly placed landmarks and the correlation coefficient from bidimensional regression, as shown in Figure 42, the confidence intervals of their corresponding IRR estimates do not overlap with each other.

Figure 42. IRR between subjective assessment and the correlation coefficient from bidimensional regression (left) vs. IRR between subjective assessment and the SUQI (middle) vs. IRR between subjective assessment and the percentage score (right). Their corresponding confidence intervals do not overlap with each other.

Note that human raters were not asked to provide a numeric score for each spatial model

but, instead, they were asked to rank them according to an ordinal relationship of relative quality. Bidimensional regression performance is particularly poor, even when compared to landmark percentage. The main difference between bidimensional regression and landmark percentage comes from the fact that the latter one, though implicitly, accounts for missing landmarks. None of them accounts for unexpected landmarks in a spatial product. The impact of neglecting the effect of missing landmarks is in fact high. For instance, applying bidimensional regression to a spatial model missing all but one landmarks will give a perfect score as long as that lonely landmark stands in the correct spot; but such a spatial model is obviously not resembling the original scene.

3.2.4. Estimations of the covariance matrix

Key Points

- Excellent equivalence between different covariance matrices and human assessment is not guaranteed.
- ICC between different estimations of the covariance matrix was good to excellent: $ICC(A, 1) = 0.886$, $H1: ICC > 0.9$ $p = 0.705$, 95% CI (0.825, 0.929).

IRR was assessed by means of computing the intra-class correlation coefficient (ICC). ICC estimates and their 95% confidence intervals (CI) were calculated using the *irr* package in the R statistical software, version 3.4.3. Both IRR between the subjective-ranking and each of the three rankings (office-ranking, pub-ranking, and bedroom-ranking) and IRR between the three sets of scores (office-suqi-scores, pub-suqi-scores, and bedroom-suqi-scores) were based on a single-rater, absolute-agreement, 2-way model.

3.2.4.1. IRR between subjective assessment and the rankings from each scene-specific matrix

A deterioration in ICC was observed, as shown in Figure 43 and depicted in Figure 44. 95% CI suggests that IRR is good to excellent. This result still supports that the cognitive map of a given scene can be assessed with a covariance matrix based on a different scene.

Figure 43. IRR and 95% CI for the SUQI computed with three different estimations of the covariance matrix and compared to human assessment.

Figure 44. IRR between human assessment and the SUQI computed with three different estimations of the covariance matrix.

3.2.4.2. IRR between scores from different covariance matrices

ICC was good to excellent: $ICC(A, 1) = 0.886$, $H1: ICC > 0.9$ $p = 0.705$, 95% CI (0.825, 0.929).

A minor deterioration in IRR was observed when the spatial models under assessment were not involved in the computation of the covariance matrix. Said deterioration still keeps IRR between good and excellent levels, as supported by the 95% CI values. Thus, it is valid to compute the covariance matrix in the SUQI from a scene different from the one under assessment. However, the detrimental effect in the IRR is greater when SUQI scores are directly compared across different estimations of the covariance matrix, instead of comparing ranking positions. In such a case, IRR remains good, but, in order to ensure comparability between the scores of two different spatial models, it would be better to have them calculated by making use of the same covariance matrix. Note that all three scenes in the present study are of similar size and shape and contain the same number of obstacles. Scenes showing different complexity levels between one another might not comply with the present observations.

4. DISCUSSION

4.1. Cognitive interface substudy

To the best of our knowledge, this is the first work using distant exploration and comparing it with proximity exploration.

Evidence supports the initial hypothesis of greater efficacy associated to distant exploration; and, despite the limited sample-power, does so with a very low p-value (in the case of the flat spotlight the effectiveness rise reaches 24% with p-value = 0.0006). Despite showing better effectiveness, the identification error dimension in the quality score did not show differences for different types of FoA. Although a deterioration in the conversion of object detections into identifications is observed for all types of FoA, object identification remains better for the flat spotlight; but in the case of walls and windows, conversion rates do not preserve differences. While overall conversion rate for walls was over 100% for all types of FoA, in the case of windows, different configurations show different behaviours. Proximity exploration and the spherical spotlight showed conversion rates over 100% as well, but the flat spotlight showed a conversion rate below 100%. Also, an analysis of attributable risk shows that 75% of the time, participants reported the correct number of walls regardless how many of them they actually detected during exploration. We interpret it as blind people tending to rely on their preconceived ideas regarding the usual structure of a room. In particular, the idea of rooms having four walls is particularly strong. Additional studies, where virtual rooms show a wider variety of walls configurations, could be useful to confirm this point.

Evidence also confirmed that, together with this rise in effectiveness, distant exploration was also associated with greater efficiency. Again, despite the limited sample-power, a low p-value was observed (in the case of the flat spotlight reduction in discovery time reaches 53% with p-value = 0.0027). Distant exploration, therefore, allowed blind people to detect a greater number of obstacles while spending less time in the process. We assumed that the impact of efficiency and the impact of effectiveness on exploration behaviour would point in opposite directions. While greater efficiency would foster shorter exploration stages, greater effectiveness would require the use of extra time to learn the disposition of and relationships between a greater number of obstacles. Although the p-value is not low enough (p-value = 0.067), evidence suggests that distant exploration might indeed be associated to a reduction in the duration of the exploration stage (pairwise comparison in the case of the flat spotlight showed a reduction reaching 38% with p-value = 0.024). Despite the effects of low sample-power increasing the probability of extreme results, type I error remains low. In addition, low power also increases the probability of making a mistake by not rejecting the null hypothesis. Thus, the chances of a larger sized study corroborating the reduction in exploration time, are high.

A dependence of the extra time after the end of the discovery stage with wall detection

was observed ($p\text{-value} = 0.012$); supporting the hypothesis of previously-observed preconceived-ideas having an impact on exploration behaviour. Extra time was in fact longer when blind people detected all the four walls. The following interpretation is proposed: once blind people detect the expected number of walls, the absence of novel obstacle detections was interpreted as a sign of achievement; and some extra time was spent on improving knowledge about layout disposition. On the other hand, as long as wall detections did not reach the expected value, the absence of novel obstacle detections was interpreted as a waste of time; and led them to quit exploration.

No differences were observed for cognitive-map quality between different types of FoA. Although in line with our initial hypothesis (i.e., changes from distant exploration do not have a detrimental impact on cognitive-map quality) mean scores are worse than expected. Identification error remains reasonably low, so the location errors rise as the source of the discrepancy. The novelty of the distant exploration paradigm suggests that blind people might need longer training periods to better capture the nature of information regarding obstacle location; but the fact that proximity exploration was designed to resemble the act of walking around a physical room, suggests that additional underlying factors, like suboptimal feedback configurations, might be present. Limitations imposed by the study design did not allow for the exploration of these hypotheses.

Success in egocentric and allocentric tasks shows, regardless the type of exploration, a dependence with deviation scores. No dependence is observed for orientation tasks. Orientation tasks are the result of physically walking around the real room, and they help to update blind people's cognitive map regardless the previous exploration configuration; which also explains the greater number of successful orientation tasks. No differences were observed in the usefulness of cognitive maps for different types of exploration in any of the three types of tasks. This result is consistent with the fact that no dependence was found between the quality of cognitive maps and the type of exploration.

A trend is observed for the flat spotlight being 11% more effective ($p\text{-value} = 0.079$) and 21% more efficient ($p\text{-value} = 0.0659$) than the spherical spotlight. Again, despite the effects of low sample-power increasing the probability of extreme results, type I error remains low. Also, low power also increases the probability of making a mistake by not rejecting the null hypothesis. Thus, the chances of a larger sized study corroborating the improvement in effectiveness and efficiency, are high.

In their proximity exploration study, Lahav & Mioduser (2004) report mean exploration times of thirty minutes for a room of similar size and complexity than the three spaces used in the e-Glance study. Said mean exploration times are considerably longer than those found in the e-Glance study (fFoA = 7 min, sFoA = 9 min, noFoA = 12 min). The main difference in proximity exploration mechanisms between the two studies was that, while in the former one, participants had to identify obstacles by learning their shape via haptic feedback, in the e-Glance study, obstacle functionality was directly reported by the feedback interface via voice messages. Obstacle identifications in the e-Glance study are similar or better than those

reported in Lahav & Mioduser (2008a): objects (84% vs. fFoA = 86%, sFoA = 70%, noFoA = 75%), windows (25% vs. fFoA = 67%, sFoA = 72%, noFoA = 69%), doors (46% vs. fFoA = 74%, sFoA = 73%, noFoA = 74%), and columns (48% vs. fFoA = 59%, sFoA = 71%, noFoA = 41%); they do not report figures for wall detection. There is a difference between their reported successful model-choice (95%) and those found in the e-Glance study (fFoA = 56%, sFoA = 67%, noFoA = 50%). The main difference in model-choice stage between the two studies was that the former one offered three options with different shapes and sizes, while in the e-Glance study shape and sizes remain the same and changes are observable in the disposition of doors and windows only. They also report better location of miniatures within the models (46% vs. fFoA = 31%, sFoA = 30%, noFoA = 25%) however, somewhat low compared to success in real tasks: egocentric (81% vs. fFoA = 56%, sFoA = 67%, noFoA = 50%), allocentric (71% vs. fFoA = 50%, sFoA = 33%, noFoA = 44%) (Lahav & Mioduser, 2008b). It is interpreted as a manifestation of the previously discussed effect of cognitive map updating during physical exploration of the room. Other previous studies did not use spaces of comparable size and complexity.

Coming from a within-subjects design, the e-Glance study results are well suited to remove individual differences among the participants as a source of error. However, since none of the variables are related to time, they are susceptible to adverse carry-over effects, i.e., the order in which the different scenes were to be experienced could bias the study outcomes. In addition, the study outcomes might get biased as well if each scene were explored with the same spotlight configuration by all participants. This circumstance was addressed by applying the latin square in section 2.1.1.3. However, it has to be noted that the reduced sample size of the study can reduce the power of said randomization to control carry-over effects. Being this study a first approximation to the topic, a limit to the duration of the experiment was applied. In order to choose a proper sample size, the order of magnitude identified in previous proximity-based studies was preserved; while taking into account the restrictions imposed by the availability of physical spaces and the size of the research team. A study with a larger sample and a between-subjects design would be appropriate to address said drawbacks.

4.2. Quality index substudy

The similarity of fifty-four different spatial products and their corresponding original scenes was assessed by applying a novel quality assessment model for cognitive maps known as the SUQI. The SUQI is based on the use of the Mahalanobis distance as a similarity metric. As a consequence, both spatial products and their corresponding original scenes must be expressed in the form of numeric vectors. These numeric vectors were defined as four-dimensional vectors based on fundamental cognitive-map-properties. Their corresponding quantification criteria were defined in the form of error terms. Outcomes from human assessment were used as a reference to decide whether the SUQI is an appropriate assessment model. Inter-rater reliability between the SUQI and human assessment can be considered to be excellent, according to the observed statistical significance. This observation supports the choice of obstacle identifications, room shape, absolute location, and relative location as

characteristic properties of cognitive maps, as well as their corresponding quantification criteria. Computation of error-term values is simple and even susceptible of becoming an automated process, thus removing the costs of the resource-consuming use of human raters. Values of identification error and values of location error for structures arise from the data straightforwardly. Absolute- and relative-location error for objects, however, leave some room for interpretation. Some error tolerance factor may be applied when assessing miniature placement because said task is difficult for blind people. Further studies are suggested to be conducted in order to test both the qualitative and quantitative impact of different error tolerance values.

Evidence supports the key role of accounting for variability across vector elements. The Mahalanobis distance accounts for said effect in the form of a covariance matrix that led the SUQI to mimic human-assessment and resulted in a quantum leap when compared to Euclidean distance. Whether human-assessment processes are actually related to some kind of covariance matrix computation is beyond the scope of the present thesis. A covariance matrix is an estimation of the expected variability in a population, computed from a set of previously observed instances. However, it is unlikely, since human evaluators in this study had no prior access to the set of spatial models, so they should have applied a previously acquired model. It is suggested to conduct further studies in order to determine the actual nature of said model and the corresponding acquisition mechanisms.

Evidence shows that, besides mimicking subjective-assessment outcomes, the SUQI outperforms the usual quality assessment methods as well. Performance differences between landmark percentage and bidimensional regression suggest that accounting for incorrectly identified obstacles is vital, and consequently is a major drawback against the use of bidimensional regression for the assessment of spatial models in cognitive mapping contexts. Regardless, landmark percentage penalises a misplaced landmark as much as an omission, so the effect of misplaced landmarks might be overestimated.

The SUQI is to be used in the context of blind-people's training. It was designed to assess either people's proficiency level in the use of a given cognitive-mapping aid and the utility of cognitive-mapping tools themselves. In the first case, assessing people's proficiency level, the SUQI would act as a test for progress assessment throughout a training programme. Such a training programme would involve multiple stages where blind people have the opportunity to train their cognitive mapping abilities in scenes showing different complexity levels. In the second case, outcomes from different cognitive mapping aids can be compared to one another so that the spatial products showing higher quality would belong to more effective aids. All the spatial products, of course, should be developed by equally proficient individuals. In both cases, the computation of the required covariance matrix raises some practical issues for it requires a sample of spatial products to be collected prior to the exploration stage of a given trainee. In an ideal scenario, it would be possible to design a virtual scene of reference, at least a single one for each complexity level, and use it to collect a number of spatial products, from a number of non-trained blind volunteers, and use their covariance matrix to compute SUQI for spatial products of other scenes. Also, in an ideal scenario, the sample of blind

people producing the spatial products of the scene of reference need not match subsequent trainees. Such a scenario would prevent trainers from being compelled to collect a separate set of spatial-products and compute a different covariance matrix for each virtual scene in their training programme. Evidence shows a deterioration in IRR when the SUQI scores are computed for spatial products that were not involved in the computation of the covariance matrix. In such a case, statistical significance levels do not guarantee an excellent IRR between the SUQI and human assessment, yet it can be considered good to excellent. Analogously, statistical significance levels do not guarantee an excellent IRR between SUQI scores computed with different estimations of the covariance matrix, yet it can still be considered good. Further characterization of optimal sets of spatial products from a scene of reference could help to improve IRR results. In the absence of such a dataset, however, SUQI outcomes can be obtained relative to a fixed scene of reference. The effect of personalization could not be tested because the e-Glance dataset holds only three externalizations per blind subject, each from a different scene.

The SUQI was defined as a measurement of spatial understanding regardless of the nature of the source of impairment. Thus, besides measuring blind people's levels of spatial understanding, the SUQI is susceptible of being appropriate for doing so in additional contexts, such as cognitive impairment or other types of dementia, as well as attention deficit disorders, with or without hyperactivity.

In the absence of a formal definition of complexity level, all three original scenes in the e-Glance study consisted of three different rooms with the same size and shape; and were designed to hold the same number of obstacles (both structures and objects) with a similar disposition of volumes. It is possible that different levels of scene complexity will result in different variability levels across scene features; thus, requiring different covariance matrices. Another candidate to have an impact on the validity of a given covariance-matrix estimation is proficiency level. A set of spatial products produced by skilled subjects in the use of a given cognitive-mapping tool is likelier to show less variability than one produced by untrained ones. It was not possible to test for said differences because all blind participants in the e-Glance study were untrained subjects. It is possible that said proficiency differences will have an impact on the quantitative value of SUQI scores but not on their ordinal relationship. One last limitation of the study comes from the fact that, in all the tests in this study, the set of spatial products to be rated was produced by the same pool of people that produced the set of spatial products for the computation of the covariance matrix.

Inefficiencies in the externalisation process (e.g., a suboptimal externalisation tool or participant's poor skills to express his spatial knowledge) may result in spatial products that show lower quality (*ExtQual*) than the actual quality of their corresponding cognitive maps (*ActualQual*). Assuming that said deterioration behaves as an efficiency coefficient (*ExtProcEff*), Equation 7 would reflect the relationship between spatial-product quality and cognitive-map quality.

$$\textbf{Equation 7. } \textit{ExtQual} = \textit{ActualQual} \times \textit{ExtProcEff}$$

Quality terms in Equation 7 are described in the form of a normalised quality score (i.e., a score bounded between one, for maximum quality, and zero, for minimum quality). But, conversely, the SUQI is a distance (i.e., zero represents maximum quality). Theoretically, a distance value can grow indefinitely, but the SUQI is bounded. The identification-error term, though theoretically unbounded, is limited by the boundary conditions of the e-Glance externalization procedure: the number of obstacle insertions is limited by the number of choices offered to participants during the modelling stage. The other three error terms are bounded by definition. Thus, the SUQI can easily be turned into a normalised quality score by subtracting SUQI scores from the upper bound and normalising the result by said upper bound. Equation 7 could be applied, should we have a proper characterisation of the efficiency coefficient.

5. CONCLUSIONS

5.1. Cognitive interface substudy

Key Points

- This is the first work comparing distant and proximity exploration.
- Preconceived ideas interfere with objective feedback, and even prevail over it.
- Effectiveness of wall detection alters exploration behaviour.
- Obstacles are more easily detected with distant exploration configurations.
- Said ease is not enough to build better cognitive maps.

The first objective of the present thesis: finding a novel model for spatial exploration able to narrow the effort gap between blind and sighted people without a detrimental impact on cognitive-map quality; was successfully achieved. Such a novel exploration model is based on the use of VR to augment blind people's perceptual range and make them able to access information from distant locations. Visits to simulations of real spaces in virtual reality had been previously proposed as a means for blind people to gain spatial knowledge of a place before actually visiting it, but the proximal nature of their exploration model did not allow for distant feedback. The distant exploration model proposed in the present thesis and implemented in the form of the flat spotlight successfully addressed that limitation. In order to provide empirical support, the following hypotheses in Figure 45 were tested.

HYPOTHESES

- Distant exploration improves efficacy and efficiency of the exploration process.
- Greater efficiency is associated to shorter duration of the overall exploration stage.
- Adoption of distant exploration does not have a detrimental impact on quality or usefulness of the resulting cognitive maps.
- A distant-exploration configuration with greater scope and lesser degrees of freedom performs better than the reciprocal configuration.

Figure 45. Hypotheses in the cognitive interface substudy.

5.1.1. Distant exploration improves efficacy and efficiency of the exploration process

Distant exploration is associated with greater effectiveness during the exploration stage

(i.e., more obstacles are detected than with proximity exploration). However, said difference is not preserved during the externalization stage. This discrepancy is a sign of blind people tending to rely on their preconceived ideas regarding the usual structure of a room. In particular, the idea of rooms having four walls is particularly strong.

Distant exploration is associated with shorter duration of the discovery stage because less time is necessary to detect obstacles for the first time.

5.1.2. Greater efficiency is associated to shorter duration of the overall exploration stage

A trend is observed to support a shorter duration of the overall exploration stage. The sample size limits the power of the result, but a study with a larger sample size has good chances of corroborating it.

Nevertheless, alternative scenarios were initially taken into consideration, like exploration duration remaining unaltered as a consequence of greater effectiveness requiring the use of extra time to learn the disposition and relationships between a greater number of obstacles; and, in fact, wall-detection effectiveness drives behaviour during the exploration stage. Once blind people detect the expected number of walls, the absence of novel obstacle detections is interpreted as a sign of achievement; and some extra time is spent on improving knowledge about layout disposition. On the other hand, as long as wall detections do not reach the expected value, the absence of novel obstacle detections is interpreted as a waste of time; and leads blind people to quit exploration.

5.1.3. The adoption of distant exploration does not have a detrimental impact on quality or usefulness of the resulting cognitive maps.

Neither quality nor usefulness of cognitive maps decreased as a consequence of exposure to the distant approach. However, there is still room for cognitive-map improvement; unfortunately, the limitations imposed by the study design did not allow for looking for the factors that affect cognitive-map quality scores. Duration of the training periods and feedback configurations are suggested as potential candidates.

In addition, successfully completed physical tasks (egocentric and allocentric) are related to better quality scores.

5.1.4. A distant-exploration configuration with a greater scope and lesser degrees of freedom performs better than the reciprocal configuration.

The flat spotlight shows all the benefits associated to distant exploration. The spherical spotlight, on the other hand, shows mixed results. Thus, the flat spotlight seems indeed to

perform better than the spherical one, but further studies are suggested to corroborate this result.

5.1.5. Study limitations

The within-subjects nature of the study makes variables susceptible to adverse carry-over effects, and the sample size may not be big enough for the latin-square randomization to control for these effects. A study with a larger sample and a between-subjects design would be appropriate to address said drawbacks.

5.2. Quality index substudy

Key Points

- The SUQI is able to mimic human assessment because it accounts for variability across cognitive-maps relevant features. It does so via a covariance matrix.
- Landmark identity, room shape, absolute location of objects and relative location of objects were identified as cognitive-maps relevant features.
- The SUQI accounts for the effect of forgotten landmarks on cognitive-map quality.
- A deterioration of reliability is observed when rating cognitive maps that were not involved in the computation of the covariance matrix.

The second objective of the present thesis: finding a novel model for cognitive-map characterization able to account for incorrectly identified landmarks; was successfully achieved. Such a characterization model is based on the fundamental properties of cognitive maps. The third objective of the thesis: finding a model for cognitive-map quality assessment able to mimic human assessment outcomes; was successfully achieved as well. Such a quality assessment model takes the form of a distance metric and is based on acknowledging the impact of variability differences across the different features in the cognitive-map characterization model. Previous characterization and assessment models were based on either landmark locations or landmark identification but failed to both acknowledge the contribution of the environment shape and combine all these three features into a single numeric value. The use of the Mahalanobis distance successfully addressed those limitations. In order to provide empirical support, the following hypotheses in Figure 46 were tested.

Figure 46. Hypotheses in the quality index substudy.

5.2.1. A SUQI-based assessment of cognitive maps is equivalent to human assessment

The SUQI is a cognitive map assessment method able to assess multiple cognitive map features into a single score while accounting for the absence of forgotten elements and the presence of non-existent ones. It is a valid model for assessing and comparing blind people's cognitive-map quality because, despite computing scores from low dimensional vectors and the simplicity of error-terms quantification-criteria, is able to rank different sets of spatial products resulting in human-like outcomes.

5.2.2. Accounting for variability differences across vector features improves reliability in a significant factor

Accounting for variability differences across cognitive-maps relevant features is responsible for the excellent levels of IRR between the SUQI and human assessment. This statement is supported by the fact that, conversely, assessing the same set of cognitive-map features with the Euclidean distance, which is different to the SUQI only because it does not account for said variability differences, only shows moderate IRR with human assessment. Said differences in variability arise from a set of previously obtained externalization vectors in the form of a covariance matrix. Whether human assessment processes are actually related to some kind of variability-expectation computation is out of the scope of the present study.

5.2.3. The SUQI outperforms other metrics capability to replicate human assessment

Besides outperforming plain Euclidean distance, the SUQI outperforms the use of the percentage of correctly located landmarks.

5.2.4. A covariance matrix based on a single scene would be suitable to assess spatial products representing other scenes

Using the SUQI to rate spatial products that were not previously involved in the computation of the covariance matrix results in a deterioration of IRR with a minor effect on the ordinal relationship of SUQI scores. Thus, it is feasible to assess spatial products of multiple virtual scenes using an estimation of the covariance matrix based on spatial products from a different virtual scene as long as the outcomes are compared to a fixed virtual scene of reference.

5.2.5. Different estimations of the covariance matrix would be able to produce equivalent assessment outcomes for the same set of spatial products

The SUQI is a suitable candidate as a blind-people's progress assessment criteria within cognitive-mapping-aids training programmes. However, in order to achieve comparability between different cognitive-mapping aids, further characterization of setup datasets or reference standards for covariance matrices are necessary.

SUQI outcomes can be converted from distance scores to normalised quality scores and be entered into efficiency models of the externalization process.

5.2.6. Study limitations

Further studies are necessary to overcome the limitations found during the present work: (i) the impact of scene complexity on the choice of covariance matrix; (ii) the impact of the proficiency of blind subjects during the setup stage on assessment outcomes; and (iii) the impact of using different pools of people as trainees and setup subjects.

5.3. In conclusion...

The similar levels of cognitive map quality observed between people using the spotlight as a distant exploration approach and the same people using a usual proximity exploration approach means that the spotlight is a valid model of the act of glancing down at a scene and that it is appropriate for blind people. In addition, the higher levels of effectiveness and efficiency observed for the flat spotlight means that the proposed model reduces the effort gap between blind and sighted people. Obstacle identifications, room shape, the absolute location of objects, and the relative location of objects were identified as the fundamental properties of cognitive maps; still, in order to mimic the outcomes from subjective assessment, it is necessary to account for the variability differences across those four properties. Such variability shall be accounted for by applying the Mahalanobis distance, which requires the computation of a covariance matrix. It is not necessary to calculate a covariance matrix for each target scene. It is possible to estimate a single covariance matrix from a given scene of reference and use it to assess spatial products representing other scenes.

However, to ensure the comparability between scores from different scenes, being consistent in the use of the covariance matrix is advised. Hence,

the evidence presented in the present dissertation confirms both initial hypotheses:

- 1. it is possible to create a model of the act of glancing down at a scene and replicate it in situations in which the observer lacks vision. Therefore, it is possible for blind people to use an implementation of the said model to learn a room layout from a single observation point.**
- 2. it is possible to predict the outcomes of human assessment of spatial models by characterising those spatial models according to the fundamental properties of cognitive maps and not just the geometrical properties of their landmarks. In fact, such a characterisation of spatial models was proven as well to involve a significant improvement compared to the outcomes from the usual assessment methods.**

6. FURTHER WORK

6.1. Computerized attention models

As stated in the background section, volitional control over where and when attention is directed upon is a crucial requirement to successfully learn the spatial layout of a scene (Chrastil & Warren, 2012, 2013, 2015; Picinali, Afonso, Denis, & Katz, 2014; Voss, Gonsalves, Federmeier, Tranel, & Cohen, 2011). The spotlight allows blind people for fixating targets by controlling the phi coordinate of the avatar's line of sight and the depth of the spotlight location along said line of sight. On the occurrence of a line-of-sight direction change, the spotlight gets automatically fixated on the closest obstacle in the new line of sight; which means that control over the spotlight is momentary lost, and there may be a mismatch between the user's intended region of interest and the location of the target that gets fixated by the spotlight. Said mismatch might be hampering user experience and lowering the quality of the resulting cognitive maps. I hypothesise that blind people could find additional benefits if some formal model of attention deployment got incorporated into the spotlight behaviour. In fact, "... after 25 years of relative inactivity, the study of gaze control in scenes has recently experienced a rebirth." (Henderson, 2003, p. 498).

Attention allocation, that drive the behaviour of eye movements, has been described as a combination of two different types of inputs, namely, bottom-up stimuli and top-down knowledge (Authié, Berthoz, Sahel, & Safran, 2017; Henderson, 2003; Ivanov et al., 2016; Wu, Wick, & Pomplun, 2014). Bottom-up models describe eye movements as driven by visual saliency, i.e., by the visual characteristics of the image or the scene under observation. On the other hand, top-down models are based on Yarbus's (1967) findings and describe saccadic eye movements as a result of cognitive processes; thus, the next target is selected according to the particular goal or task in hand.

Predictive models of the distribution of eye movements have been previously developed (Wu, Wick, & Pomplun, 2014). Bottom-up models, also known as saliency maps or feed-forward models, were developed by Kowler et al. (1995); Findlay (1997); Itti and Koch (2001); and Bruce and Tsotsos (2009). On the other hand, Borji & Itti (2013) list a number of models that added top-down components into saliency maps. Saliency models are based on the physical features of the obstacles in a scene (e.g., colour, size, etc.). On the other hand, top-down models account for their semantic content (Wu, Wick, & Pomplun, 2014) see Figure 47.

Figure 47. Semantic content in a scene.

6.2. Tracking

The spotlight allows blind people for inspecting a scene from a given observation point. In order to allow them to freely move around a room, the virtual world must be able to track people's location in the corresponding physical counterpart. Indoors localization and tracking is currently a hot topic that generates a massive amount of scientific outcomes every year. Analogously to navigation aids, tracking systems may be classified into two main groups. On the one hand, those that do not require equipping the environment with additional hardware. In such a case the user's location has to be computed from the data provided by the sensors carried by the user himself. A widely studied option for this approach is pedestrian dead-reckoning. It is based on the mathematical integration of acceleration readings from inertial measurement units (IMUs) to compute someone's current location relative to his last known location. Heading information is extracted from gyroscope and magnetometer readings in the same IMUs. This method is theoretically consistent and only requires the parametrization of two border conditions, namely, initial location and initial speed. The implementations of this method are only limited by the spurious drifts in IMUs readings that accumulate over time as a consequence of the integration process. Research focuses on algorithms able to periodically reset the drift (Bose, Gupta, & Handel, 2017; Jimenez, Seco, Prieto, & Guevara, 2009; Liao,

Chiang, & Zhou, 2016; Zeng, Liu, Wang, & Wang, 2017; Zhang, Li, Wei, Ji, & Yuan, 2017). Inertial sensors onboard smartphones have been proposed as a source of input data for dead-reckoning algorithms to avoid requiring people to carry additional devices (Hsu, Gu, Huang, & Kamijo, 2016; Kim, Eyobu, & Han, 2018; Racko, Brida, Perttula, Parviainen, & Collin, 2016) this approach is limited by the fact that dead-reckoning algorithms perform differently depending on the particular location of inertial sensors on the body; researchers are currently working to address this issue (Huang, Qi, Yang, Zhao, & Zou, 2016; Tian, Salcic, Wang, & Pan, 2016). A different approach consists of extracting location information from wearable systems based on stereo vision (Brock & Kristensson, 2013; Kirner, Gonçalves Kirner, Wataya, & Valente, 2012). These systems are too bulky to gain user acceptance.

On the other hand, there are tracking systems that do require equipping the environment with additional hardware. A widely studied option for this approach is the use of attenuation patterns of electromagnetic waves from existing connectivity technologies like Wi-Fi or RFID (Alghamdi, Schyndel, & Alahmadi, 2013; Bai, Chiu, Hsu, & Leu, 2017; Gmar', Dyuldina, Snopko, Shakhgeldyan, & Kryukov, 2017; Jacq, Chatonnay, Bloch, Canalda, & Spies, 2017). These systems require the deployment of emitting or receiving stations and providing the users with the reciprocal device. Wi-Fi is very a very widespread technology, so systems based on its use require minimal additional deployment but it is susceptible to spurious dynamic changes in the environment that result in unwanted changes in the electromagnetic fingerprint (Gao & Prasad, 2016; He & Chan, 2016; Varshney, Goel, & Qadeer, 2016). Nakajima & Haruyama (2013, 2012) describe an indoors navigation system that updates blind people location within a map as they pass under light bulbs with visible light communication capabilities. These light bulbs communicate with blind people's smartphones that use their information to reset their own gyroscope readings. Appart from the fact that visible light communication is not widespread, the spatial resolution of such a system depends on the distance between light bulbs.

6.3. Interaction devices

The smartphone as an interaction device to control the spotlight is very obtrusive. It requires the use of both hands, which is particularly annoying for blind people because it interferes with the use of the long cane. The solution might be to embed the interaction device into daily life objects. The long cane is a straightforward option for blind people.

6.4. The ageing domain

The distant exploration model proposed in the present thesis is useful beyond the blindness domain. The ageing population can benefit from it in several ways. Falls, for instance, are a major problem for the elderly. Although the incidence of falls varies among countries, approximately 30-40% of people aged of 65 and over fall each year (Blake et al., 1988) increasing to 45-50% for those over 75 years of age (Tinetti, Speechley, & Ginter, 1988). The consequences of a fall vary from serious injuries, even death, to adopting passive

lifestyles in response to fear of further falls. Falls occur as a consequence of exposure to one or several risk factors (AGS, BGS, & AAOS, 2001; Bergland, 2012; Rubenstein, 2006). Vision deficit and cognitive impairment are among the most relevant risk factors (AGS & BGS, 2011; Ambrose, Paul, & Hausdorff, 2013; Bergland, 2012; Boelens, Hekman, & Verkerke, 2013; Deandrea et al., 2010; Rubenstein, 2006). One of the standard interventions to address these two risk factors consists of sending a team of members of a fall clinic to the patient's home to detect and revert dangerous obstacle layouts (AGS & BGS, 2011). Thus, the distant exploration model proposed in the present thesis, enhanced with the computerized attention models in section 6.1., would be useful to direct the attention of patients with a high risk of falls to dangerous obstacles in their way and help them to avoid them.

Cognitive decline has a detrimental impact beyond raising the risk of falls. People suffering from mild cognitive impairment, severe cognitive impairment, dementia, Alzheimer's disease and other related conditions lose their autonomy and independence because they find difficulties to keep track of their tasks and assess their progress and outcomes (Aldridge, Fisher, & Laidlaw, 2017; Johansson, Björklund, Sidenvall, & Christensson, 2017; Lorenz, Freddolino, Comas-Herrera, Knapp, & Damant, 2017). Again, top-down attention models in section 6.1. could assess their progress and outcomes and highlight the most relevant targets and actions. The required interfaces for the ageing and cognitive impairment domains are very different from those required for blind people for the former ones may involve graphical displays.

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APPENDIX A. STATISTICS

The present appendix is intended to explain the criteria that drove the choice of the statistical tools in section 3. Section 3.1. (cognitive interface substudy) relies on hypothesis testing tools and involves the use of the attributable risk concept. Section 3.2. (quality index substudy) relies on inter-rater reliability (IRR) tests.

A.1. Hypothesis testing

A.1.1. Test selection criteria

A.1.1.1. The dependent variable (scale of measurement)

The first criterion driving the test choice is the scale of measurement of the dependent variable, see Figure 48.

Figure 48. Scales of measurement for dependent variables.

Nominal variables are the paradigmatic example of categorical variables. Their values act as a label and have no numerical value and no inherent order. An example of a nominal variable is the type of weather; prototypical values would be *cloudy*, *rainy*, *windy*, and *sunny*; which may be encoded as-is or with alternative labels (e.g., C, R, W, S; 0, 1, 2, 3; etc.). Nominal variables whose values are represented by two labels are known as dichotomous variables. Gender is an example of a dichotomous variable. Variables that still have no numerical value but show an inherent order are known as ordinal variables (e.g., when the intensity of a magnitude is coded as *low*, *medium*, or *high*). Discrete counts act as a particular case of ordinal variables and move along the border between categorical and numerical scales of measurement. These type of variables show numerical values indeed, but their range is so small that the assumptions for the standard linear model for continuous data are not met. Some authors argue that a variable involving ten or more categories can safely be analyzed as a continuous one. A threshold of sixteen categories has also been proposed; and some other authors even lower the threshold to 5 categories.

Categorical variables are arranged in the form of contingency tables where columns represent the dependent variable and rows represent the independent variable. Each cell in the table holds the count of cases that show the corresponding outcome value under the corresponding independent variable condition. In the case of within-subjects studies, the data get arranged in strata.

Interval variables represent some meaningful order and the quality of equal intervals between measurements (equal changes in the quantity of whatever is being measured). Finally, ratio variables act as interval data but, in addition, they have a natural zero point (e.g., temperature).

A1.1.2. The independent variable

Independent variables in hypothesis testing studies are of the categorical kind. Their levels match the different conditions in which the values of the dependent variable are to be compared. In the present thesis, most of the tests measure the dependence of a given dependent variable in relation to an independent variable with three different levels, namely, the flat spotlight (fFoA), the spherical spotlight (sFoA), and proximity exploration (noFoA).

When a categorical dependent variable is to be tested, different combinations of categorical scales of measurement lead to different test choices, see Figure 49.

Figure 49. Types of categorical hypothesis testing studies according to the scale of measurement.

When a numeric dependent variable is to be tested, two different features must be taken into account, namely (i) the number of independent variables, aka factors; and (ii) the number of values in the independent variable, aka factors (see Figure 50).

Figure 50. Types of univariate numeric hypothesis testing studies according to the numbers of factors and levels.

A.1.1.3. Study design

The third criterion is the type of study design. There are two types of designs, namely, between-subjects and within-subjects. Between-subjects designs use different subject samples for each level in the independent variable. Conversely, within-subjects designs use the same set of subjects for all the levels in the independent variable. Between-subjects designs result in studies with higher power than within-subjects designs (for the same sample size) but are sensitive to individual differences between subjects. Within-subjects designs are able to remove the effect of said individual differences, but they are sensitive to carry-over effects. Within-subjects designs are particularly appropriate in longitudinal studies when the objective is to study the behaviour of a given variable over time.

A.1.1.4. Distribution assumptions

Finally, the fourth criterion is the basis to decide whether to use a parametric test or a non-parametric variant. Parametric tests are the default recommended option, but they assume that the dataset distribution fulfills a number of assumptions, and when it fails to do so non-parametric tests must be used instead. Different tests involve different sets of assumptions.

A.1.2. Post-hoc tests

Tests for study designs involving independent variables with more than two levels just unveil whether any of the levels have any effect on the dependent variable, but do not signal which of them differs from the others. In order to do so, an additional pairwise comparison test must be carried out. Different post-hoc tests are recommended depending on the initial test used for hypothesis testing.

A.1.3. Hypothesis testing throughout the present thesis

The present subsection is an explanatory study of the test selection process for all hypothesis testing methods used in the results section.

A.1.3.1. Friedman test

The Friedman test is used in section 3.1.1.1. to study the effectiveness of the exploration process and in section 3.1.2.1. to study overall quality of cognitive maps.

The effectiveness of the exploration process in section 3.1.1.1. was defined as the total number of obstacles (both structures and objects) detected during the exploration stage. According to that definition, effectiveness can be considered to be a discrete count which can be treated as a continuous variable due to its high number of levels, seventeen levels. In fact, it could be modelled as a ratio level variable for its values represent a meaningful order, different consecutive values are separated by equal intervals, and it has a natural zero point. Second, the independent variable is the type of spotlight which has three levels (i.e., sFoA, fFoA, and noFoA) so its number of levels is greater than two; and said independent variable is the only factor under study. Third, the study was conducted under a within-subjects design. So, wrapping up the analysis, the recommended parametric test is a repeated-measures ANOVA.

The next step in the process requires that the corresponding assumptions were checked. Assumptions for a repeated-measures ANOVA test are the following ones:

- A dependent variable of the interval or ratio-level kind.
- An unbounded dependent variable.
- Dichotomous or categorical factors.
- Normal distribution of the data in each factor level.
- Homoscedasticity (i.e., homogeneity of data variance between all factor levels).
- Sphericity.

Effectiveness is bounded between zero and sixteen, so the second assumption is not met. As a consequence, a Friedman test was used instead of the repeated-measures ANOVA.

The test in section 3.1.1.1. resulted statistically significant, meaning that different types of spotlight result in different levels of effectiveness. In order to identify pairwise differences, a post-hoc test was conducted. A Fisher's LSD test with Holm correction was used because it was recommended in the literature for statistically significant Friedman tests.

A.1.3.2. Repeated-measures ANOVA

The repeated-measures ANOVA is used in section 3.1.1.2. to study the efficiency of the exploration process, in section 3.1.1.3. to study exploration duration, and in section 3.1.2.2. to study the fluency of the model building stage.

Efficiency of the exploration process in section 3.1.1.2. was defined as the discovery time which is a continuous variable of the ratio-level type (i.e., numeric, represents a meaningful order, different consecutive values are separated by equal intervals, and it has a natural zero point). Second, the independent variable is the type of spotlight, just as in the case of effectiveness in the previous section, which has three levels (i.e., sFoA, fFoA, and

noFoA) so its number of levels is greater than two; and said independent variable is the only factor under study. Third, the study was conducted under a within-subjects design. The recommended parametric test is again a repeated-measures ANOVA, but the corresponding assumptions were met this time.

- A dependent variable of the interval or ratio-level kind.
- An unbounded dependent variable.
- Dichotomous or categorical factors.
- Normal distribution of the data in each factor level. Normality is tested with a Kolmogorov-Smirnov test. This assumption will be met if the test is not significant.
- Homoscedasticity (i.e., homogeneity of data variance between all factor levels). Homoscedasticity is tested with a Levene's test. This assumption will be met if the test is not significant.

The efficiency data in section 3.1.1.2. met all the assumptions above so the parametric repeated-measures ANOVA test may be used. However, the resulting statistical significance value will not be valid unless an additional condition, referred to as sphericity, is met. Sphericity is tested with a Mauchly's test. This assumption will be met if the test is not significant; otherwise, a correction factor should be applied to the p-value in the ANOVA test. Both Greenhouse-Geisser and Huynh-Feldt corrections may be applied.

The efficiency of the exploration process resulted statistically significant after applying a Greenhouse-Geisser correction. In order to identify pairwise differences a post-hoc test was conducted. A Tukey pairwise comparison test was used because it was recommended in the literature for statistically significant repeated-measures ANOVA tests.

A.1.3.3. Two-sample t-test

The two-sample t-test was used in section 3.1.1.4. to study the relationship of extra time in the exploration process and the number of detected walls; it was also used in section 3.1.3. to study the relationship between overall quality of cognitive maps and success status in physical tasks.

The dependent variable in the extra time leading example is, just like in the repeated-measures ANOVA example above, of the ratio-level kind. The main difference comes from the fact that the independent variable (i.e., the number of detected walls) was modelled to have two levels (i.e., all four walls detected vs. less than four walls detected) so the appropriate test is of the t-test type. In this case, the values are not paired across the two groups, so the between-subjects variant was chosen. The recommended parametric test under those conditions is a two-sample t-test, but it will be appropriate only if the corresponding assumptions are met:

- The values in the two samples are not paired.
- Normal distribution of the data in each level of the independent variable. Again, this assumption is tested with a Kolmogorov-Smirnov test. The assumption will be met if the test is not significant.

- Homoscedasticity, which is tested with a Levene's test. This assumption will be met if the test is not significant.

The extra time dataset met all the assumptions below. However, both the statistical significance values for normality and homoscedasticity were close to the 0.05 threshold so, in addition to the parametric two-sample t-test, a test for non-normality and a test for heterogeneity of variances were conducted. In the first case (non-normality) the recommended test is the Wilcoxon rank-sum test; while in the latter case the recommended one is the Welch's test.

Any case the test resulted statistically significant. No post-hoc tests were necessary because the factor (independent variable) had two levels only.

A.1.3.4. Mantel-Haenszel test of general association

The Mantel-Haenszel test of general association was used in section 3.1.2.1. to study the relationship between the identification error and the type of spotlight and to study the relationship between the structure locations error and the type of spotlight; in addition, it was used in section 3.1.2.1.1., section 3.1.2.1.2., and section 3.1.2.1.3. to study the relationship of detections and identification with the type of spotlight for walls, windows, and objects, respectively. It was also used in section 3.1.2.1.1. to study the relationship of walls full detections and walls full identifications with the type of spotlight, and in section 3.1.3. to study the relationship between success in physical tasks and the type of spotlight.

Dependent variables in all these sections are of the categorical kind. In fact, all of them are dichotomous but the identification error, which is nominal. Values for the identification error are *correct identifications*, *omissions*, and *insertions*. Values for the structure locations error are *success* and *failure*. Values for detections are *detected* and *missing*. Values for identifications are *identified* and *omitted*. Values for full detections are *success* and *failure*. Values for full identifications are *success* and *failure*. Finally, values for success in physical tasks are *success* and *failure*. The study design is of the within-subjects kind. The recommended parametric test is the Mantel-Haenszel test of general association but it will be appropriate only if the combined row sample sizes in the corresponding contingency tables are large (greater than thirty is a common threshold). This assumption was met in all cases.

A.1.3.5. Mantel-Haenszel mean score test

The Mantel-Haenszel mean score test was used in section 3.1.2.1. to study the relationship of both absolute location error for objects and relative location error for objects with the type of spotlight. The only difference with the examples above is that the dependent variables (i.e., both location errors) are of the ordinal type. The Mantel-Haenszel mean score test is valid if:

- All categories in the dependent variable are mutually exclusive.
- No cells in the contingency table are lower than one.
- Less than twenty percent of the cells show a value lower than five.

All the assumptions were met for both types of error.

A.2. Inter-rater reliability tests

Inter-rater reliability (IRR) tests are used to quantify the level of agreement between different assessment tools or different raters using the same assessment tool. General purpose correlation coefficients, like Pearson's r , Kendall's tau, or Spearman's rho may be used as IRR tests but more specific tools, like the intraclass correlation coefficient (ICC), are more appropriate because they account for both correlation and agreement (Koo & Li, 2016).

Inter-rater reliability tests are appropriate when novel rating methods are to be validated against a previously existing gold standard, when the objective is to measure the level of agreement between the exact scores assigned by different raters using the same assessment tool, and when the objective is to assess how much different raters or assessment tools agree to qualify different performance instances as better or worse than the other ones; which is the case in the present thesis.

The intraclass correlation coefficient was used to test IRR. It is a flexible and powerful tool that covers a great number of different situations due to its ten different configurations. Configurations are selected by identifying the proper model, type, and definition. Their corresponding values are identified by answering the questions in Figure 51; and possible values for model, type, and definition are shown in Figure 52 (Koo & Li, 2016).

Figure 51. Questions for ICC configuration choice (Koo & Li, 2016, p. 157).

Figure 52. Valid options for model, type, and definition.

As recommended by Koo & Li (2016, p. 155), “[b]ased on the 95% confident interval of the ICC estimate, values less than 0.5, between 0.5 and 0.75, between 0.75 and 0.9, and greater than 0.90 are indicative of poor, moderate, good, and excellent reliability, respectively”. See Figure 53.

Figure 53. Inter-rater reliability levels.

A.3. Attributable risk

The attributable risk is a usual measure in epidemiology. It represents the excess risk of disease in the exposed group versus the unexposed group. It is designed to acknowledge the fact that part of the population affected by a disease was not exposed to a given risk factor. The attributable risk percentage is a derivative measurement that represents the proportion of cases in the exposed population that can be attributed to the exposure and would be prevented by eliminating said exposure.

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