Meaningful Data Treatment from Multiple Physiological Sensors in a Cyber-Physical System

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Abstract. **— Once specific Smart Sensors are designed and manufactured in the newest nanoelectronics technology, and a Wireless Sensor Network is designed for being used on wearable applications (Cyber-Physical System) with optimum performance (data rate, power consumption, comfortability, etc.) the next step is the treatment applicable to the large amount of data collected. This can be a very general, and sometimes an unaffordable problem, but considering a system collecting physiological data from smart sensors on a human body, the range of possibilities is restricted to health or leisure but also to safety. In this case, a finite, and well-located, number of physiological sensors are producing few data per unit of time, which are locally processed for obtaining a reduced set of characteristics that are globally analyzed. In this paper, an analysis on different approaches for combining data from smart sensors attached to human body, with the purpose of determining the main emotion present in the person, is presented. Machine learning, selection of the best characteristics from raw sensor data, databases for system training, etc. are the key aspects in this problem. The conclusions of the analysis will help in the design of a new application, where emotion detection can be used for personal safety (domestic violence, sexual violence, bullying, etc.). Attention is paid on the locally and globally data processing in terms of hardware and software, together with low-power behavior.**

Keywords- Smart Sensors, Wireless Sensor Networks, Machine Learning

I. Introduction

Smart Sensors, designed and manufactured in the newest nanoelectronics technology are aimed to improve human life in a sustainable way, from the point of view of the planet environment. Better knowledge of users' condition is obtained thanks to recent smart sensors making possible, and affordable, the arising of new applications for health care, leisure, sports, house care, safety and security. Emotion recognition is a receiving an increasing interest in these applications.

Affective computing is an area of computer science that connects human emotions with modern computer technologies, allowing and improving human-machine interactions, where the application will be able to adapt itself to the user's needs, not only in a physical way, but in an emotional way too. However, different challenges must be addressed to reach that level of cognitive learning, [1].

Internet of things, wearables and affective computing; an incredible combination which is not new, wearing something that checks and communicates our physiological or emotional state has been there since the 70's, the "mood rings". Far from those rings, affective wearables give endless possibilities of new health, medical, violence detection, and other applications which will make a difference in today's technology. Obviously, the sensors involve in these new cyber-physical systems are improving year by year, being smaller, smarter, consuming less power and having a better performance than previous ones. The development of smart wearable sensors is making the affective wearable technology possible, the research on this topic has exploded in the last years [2][3].

The first step is to obtain repeatable and emotion-related data from users with a wearable sensor network. Physiological sensors have been proven as one of the best options for unique emotion mapping. Further treatment of sensor data is a key aspect, the affective state prediction performed by the system must be as accurate as possible. So, machine learning methods are producing very competitive identification solutions [4][5]. Machine learning is a field of artificial intelligence which relates the problem of learning from data to the general concept of interference; it has been applied to many different fields, achieving predicting systems with high accuracy rate [6].

There is not a standardized way to induce an emotion, therefore, most of the experiments cannot be totally compared, due to different sensor data collected or different emotion's trigger. In this sense, in the last decades, a large effort has been done for providing a standardized set of input stimuli and for classifying emotions. The International Affective Picture System (IAPS) [7][8], AV space (Arousal and Valence classification space) [9], self-assessment manikins (SAM) [10], and others like the four-dimensional classification [11] are examples of this effort.

The paper is organized as follows. Section II discusses human emotion detection from physiological signals. Section III details an approach for solving the emotion classification problem, based on machine learning techniques, as well as analyzes the different databases available for emotion recognition through physiological signals. Section IV, outlines an application system for detecting dangerous situations from the point of view of victims of violence. Finally, section V states the conclusions of the paper.

II. Emotion Detection from Physiological Data

Emotions are stated as affective states, subjective reactions to environment coming with organic changes in the human beings. These organic changes are unvolunteered physiological reactions affecting many human body systems, such as autonomous nervous system (SNA), endocrine system, skin, muscles, perception, etc., to set an optimum internal state to deal with the situation in the best way. Also, there are other effects in human behavior that can be related with emotions, speaking, face expressions, body movement, etc. From the point of view of identifying the emotion of an individual in any situation and location, physiological variables are preferred, as they can be tested with wearable sensor solutions.

From a long time, scientists have intended to map physiological variables measured in humans with the related emotions. This is a debated question as there are many approaches. In [12] Cacioppo and Tassinary explain the complex connections between psychological and physiological domains and state it is not possible to infer the emotions considering physiological variables separately, but combining them can make unambiguously the mapping. This assumption is adopted by many researchers to infer emotions from a set of physiological variables measured on individuals [13][14].

The first step to be accomplished in the task of recognizing emotions is their classification. As commented in section I, IAPS (International Affective Picture System) and AV space (Arousal and Valence classification space) are the classical ways to deal with emotion stimulation, recognition and classification. The valence-arousal model by Russel [16][9] classify emotions, according to a two-dimensional plane characterized by valence and arousal, horizontal and vertical axes respectively. Valence represents pleasantness (positive valence) or unpleasantness (negative valence), while arousal indicates the activation/excitement or deactivation in terms of individual awareness, Figure 1. Every human emotion is set in a unique point in this two-dimensional space.

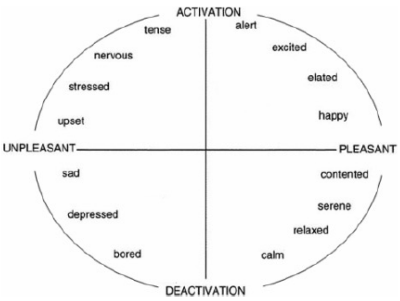

Figure 1. Arousal-Valence two-dimensional plane for Emotions Classification [16]

The International Affective Picture System, [7][8], is a standardized set of images that provoke different emotions, according to AV space. It has been generally adopted by research community and massively used as inputs for emotion recognition experiments. On the other hand, *self-assessment manikins (SAM)* [10], are also often used for stating the emotion achieved during experiments. These are a set of pictures to rate the level of arousal and valence when experimenting an emotion, Figure 2.

To handle emotion recognition in a standardized way, several experiments have been undertaken to produce different databases which connects the stimuli (from different nature) with the emotion produced. These databases are very useful to assess and validate different methods to identify human motions through distinctive characteristics. The databases are not only connecting the stimuli with the emotion, but also compiling large sets of physiological variables, measured through different sensors and smartly processed for best feature extraction. Correlations between these signals and the desired classification are also provided by the databases.

Raw data provided by sensors measuring physiological variables present a high degree of variability, depending on the experiments subjects, the environmental conditions, the type of stimuli, etc. The standardization proposed by these databases goes beyond the experimental conditions to the interpretation of these signals characteristics [17]. These databases and their main characteristics are outlined in section IV, together with an analysis of data provided by them.

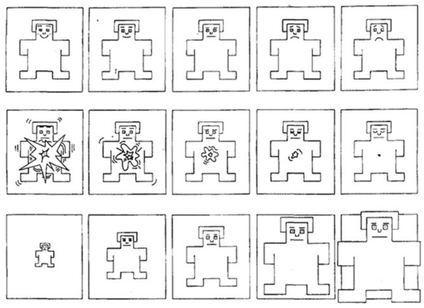

Figure 2. Self-Assessment Manikins (SAM) for emotion recognition [10]

Among all possible physiological variables connected to emotion inferring, the most popular for wearables sensor devices, are *Skin Conductance* (GSR, Galvanic Skin Response), *Heart Rate* (HR; or Blood Volume Pulse (BVP)), *Skin Temperature*, *Respiration, Electromyogram, Blood Pressure* and *Electroencephalogram*. It is commonly assert *GSR* and *HR*, and features derived (acceleration, mean, etc.) provide very accurate emotion classifications [7]-[9],[13],[14].

Skin Conductance, or Galvanic Skin Response, stands for the conductivity of the skin, and it is related with the sweating level of the skin (directly connected to the response of autonomous nervous system to an emotion experienced by an individual). It is measured applying a small voltage on the skin. Sensors measuring GSR are available in market with a very low cost, low power consumption and high accuracy.

Heart Rate, or Heart Pulse, stands for the number of pulsations per unit of time, and represent the activity of the heart while pumping blood within the human body. As stated by physiologists, this rate, and its variation, is modified when individual is affected by an emotion. The measurement of heart rate can be done in diverse ways, but the best solution, in terms of power consumption, noise immunity, movement immunity, simplicity and accuracy, is the use of optical sensors. This is the most extended solution in medical applications.

Whatever the number or type of data received from sensors were, a feature extraction is required in to leverage information from different individuals and environments. So, data provided by these sensors, or their extracted features, are often combined with other type of sensors, in a multimodal analysis, as they allow an accurate emotion recognition, by means of cluster identification. This identification requires an intelligent system, which implies a non-negligible computational effort, including machine learning, correlations and/or expert system definition, which could analyze and connect features inputs with emotion in a straightforward manner. For example, in [14] four emotions are recognized through SCR, Skin Temperature and Hear Rate First Derivative, producing a well differentiated set of clusters, Figure 3 and Figure 4.

There are several researches on identifying and recognizing human emotions through physiological variables. Most of these approaches are aiming to human well-being, welfare or, even, human-machine interaction. But, there is still additional effort to be done with respect to identifying those emotions related with fear, panic or distress, which could help people in danger situations. In this sense, authors are proposing a new system for identifying vulnerable victims of intentional physical attacks, with a wearable, cheap and accurate system, as well as helping them by means of flagging local or global alarms.

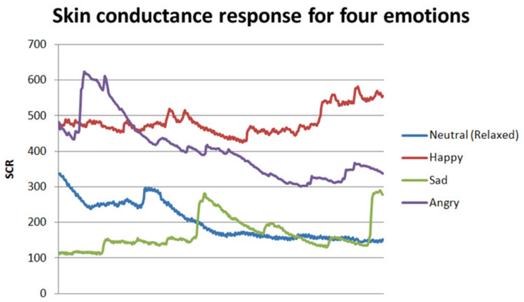

Figure 3. Skin Conductance response in [14] for emotion recognition (µS)

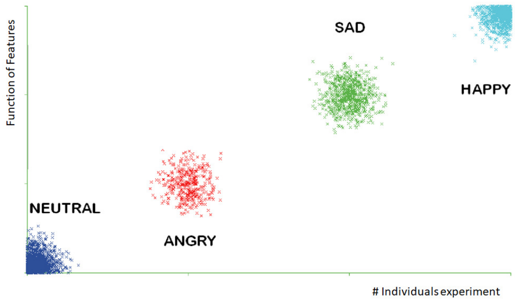

Figure 4. Clusters identification for 4 emotions in [14]

III. Data Processing

In this paragraph, the most common processing method for clustering emotions from physiological variables is detailed, Machine Learning (ML). Apart from it, direct correlation could also be applied, but the complexity of the managed data advised against it. In subsection III.A, the main concepts of Machine Learning are reviewed, [18]-[20]. Next Machine Learning for Emotion Recognition is described in subsection III.B. as well as its practical application to existing Emotion Databases (subsection III.C). Finally, an analysis of data provided by these databases is presented in subsection III.D.

A. General Machine Learning Concepts

i. Supervised and Unsupervised Learning Methods

Every learning process in ML is composed of two general phases: i) generation of a model based on identifying unknown dependences from a training dataset and ii) application of the model to predict new outputs from a testing dataset.

When generating a prediction model, there are two main types of ML methods: supervised and unsupervised learning methods. A third possibility is to combine both supervised and unsupervised learning strategies, which is known as semi-supervised-learning.

In a supervised learning method, a labeled training dataset is considered to map the input data to the expected response. There are two main types of supervised learning methods: classification and regression. In classification, the learning method categorizes the data into a set of finite cases. In regression, the method maps the data into a real-valued variable.

In the case of unsupervised learning, there is no labeled training dataset and then the notion of output is not considered during the learning process. Instead, the model finds the categories or clusters which describe the initial dataset. This approach is known as clustering.

ii. Suitability and Correctness of Data

When applying ML, it should be taken into consideration that the suitability and correctness of data are one of the most critical aspects to generate an accurate prediction model.

As in any experimental data acquisition, we find issues related to data quality, such as outliers, the presence of noise, missing data, and data which is biased-unrepresentative. Besides controlling such quality aspects, it is highly recommended to perform a preprocessing step known as dimensionality reduction to make the raw data more suitable for further analysis. This action is based on the fact that prediction models perform better when dimensionality is lower [21]. This preprocessing step is particularly interesting when each sample in a dataset includes many features/variables. In general, there are two types of methods for performing this preprocessing step: feature selection and feature extraction.

In feature selection, a subset of the initial variables is selected based on a given criterion, e.g., guided by accuracy or information gain. In feature extraction, the method transforms a high-dimensional space with many variables to a space of fewer dimensions. To this end, the method combines the initial variables. In general, this combination is performed in a linear fashion, e.g., Principal Component Analysis (PCA). However, there also exist non-linear approaches, such as Kernel PCA.

iii. Performance Assessment

The accuracy of a prediction model is computed based on the results obtained while applying the model to the testing dataset, i.e., how accurate is the prediction for the testing set compared to the expected output. To this end, the testing dataset should be labeled. Note that both training and testing datasets should be sufficiency large and independent to get a reliable performance assessment, and in consequence, a reliable prediction system.

There are standard methodologies in the literature, which define how to split the whole dataset into the training and testing datasets to evaluate the accuracy of the prediction model. These methods are Holdout method, random sampling, cross-validation, and bootstrap.

B. Machine Learning for Emotion Detection

In line with the ML concepts presented before, the emotion detection problem is identified as a classification problem, in which physiological sensors provide a wide range of measures and the goal is to identify what emotion is feeling an individual.

As introduced in Section II, the variety of information needed to describe an emotion through physiological sensors implies that the intelligent system must manage a large amount of data and variables. Moreover, it is known that most physiological output variables show marked variations when analyzing different subjects [17]. This fact means that it is needed to correct the measure before inserting it into the intelligent system, increasing the uncertainty of the system.

As a result, the design of an intelligent system applying ML tools for solving the emotion detection problem involves two important difficulties. On the one hand, we have a high-dimensional problem with variables which could increase the uncertainty of the system, leading to learning/prediction errors. On the other hand, both handling large amounts of data and the use of ML tools usually require large computing capacities. However, these computation resources could be limited if we choose a wearable/low-power device, as in our proposal.

C. *DataBases for Emotion Detection with Physiological Data*

As explained in section II, there are databases connecting input stimuli with inferred emotions and physiological variables, proposed by scientists. There are five databases which include peripheral physiological signals. Table 1 presents the summary of detailing the number of individuals used for collecting physiological data and the way of provoking the emotions. These databases have different type of input stimuli, different classification of emotions and different sets of physiological variables. Therefore, not all of them are comparable in terms of sensor data or emotion inferred. Main characteristics are described in this section.

i. MIT

This database [4] was one of the first to consider day-to-day variations on the recorded physiological signals. It classified physiological patterns for a set of eight emotions (*no emotion, anger, hate, grief, platonic love, romantic love, joy, and reverence*) by applying pattern recognition techniques. The output of the experiment is the prediction accuracy rate for a specific emotion. The experiment was done following the Clynes protocol [24], and using auxiliary images pre-rated by the patient**¡Error! No se encuentra el origen de la referencia.**.

Database	Participants	Induced or Natural
MIT [4]	1	Natural
HUMAINE [16]	Multiple	Both
DEAP [7]	32	Induced
MAHNOB-HCI [17]	27	Induced
EMBD [19]	32	Induced

Table 1. Databases for Emotion Recognition with Physiological Data

Four measurements were collected through four different sensors: a triode electromyogram measuring tension in the masseter, a photoplethysmyograph measuring blood volume pressure, a galvanic skin conductance sensor and a Hall effect respiration sensor. Finally, they obtained a confusion matrix showing the predictive results of the system against the real emotions. The best prediction accuracy obtained is 81.25%.

ii. DEAP.

The Database for Emotion Analysis using Physiological Signals (DEAP) [7] presents a multimodal (physiological signals, EEG and face video) dataset for the analysis of affective states. Instead of having the classical two-dimensional AV-space characterization, DEAP uses a four-dimensional space: arousal, valence, dominance, liking and familiarity. Forty music video clips were chosen to evoke the emotion, these videos were subjectively rated by the patients and using an online APP. At the end, they provide a decision fusion of the classification results using the different employed modalities against the pre-rated music video clips labels; however, they conclude that single-trial classification is challenging due to several factors as: physiological signal noise, individual physiological differences, limited quality of self-assessments, and others. They showed different accuracy results based on the classification modality used.

iii. MAHNOB-HCI.

MAHNOB-HCI [23] is another multimodal for human affect recognition database. A preliminary study with 155 video clips was made over more than 50 different participants to rate those video clips. The clips with the highest number of identical tags were chosen, a total of fourteen different videos, which were tagged with different emotions. At the end, they showed results only for twenty videos, which have six different emotional tags: *disgust, amusement, joy, fear, sadness and neutral*. The output classification was made based on a four-dimensional space: arousal, valence, dominance and predictability. Five different physiological signals were recorded and analyzed during the experiment: *Electrocardiogram, galvanic skin response, respiration amplitude and skin temperature*. They provide different results based on different statistical and machine learning techniques applied and different classification modalities used. The maximum accuracy rate for the valence parameter is 74%.

iv. EMDB.

The Emotional Movie Database (EMDB) [25] used 52 movie clips (pre-rated), which were classified within a three-dimensional space: arousal, valence and dominance. They found a pattern for two different physiological signals sampled during the experiment, observing that heart rate deceleration is translated into a GSR increase.

D. *Analysis on Data from BBDD*

i. Raw data comparison from databases MIT and DEAP

Authors have analyzed the similarities in the raw data from sensors in relation with the emotion output by two databases (MIT and DEAP). For example, it could be supposed *Heart Rate* evolves in the same way under a given emotion for any individual under experimentation, but different experiment conditions deny this hypothesis.

Within the AV-space, "Hate" and "Joy" have different arousal values. Based on [4], "Hate" is characterized by a low arousal value, while "Joy" has a medium-high arousal value. Taking into account that arousal is proportionally related with the skin conductivity (GSR), comparing skin conductivity data from different databases will produce the same pattern. Histograms of GSR data for "Joy" and "Hate" emotions, for both databases, are represented in Figure 5 for MIT Database and Figure 6 to Figure 8 for DEAP Database. It can be observed that GSR value is higher in Joy emotion than in Hate emotion for MIT database (1 individual), while for two patients (out of 32) arbitrarily chosen from DEAP database show different behaviour. The GSR value (μS) among the two patients from the DEAP analysis are not identical, because of physiological variability between patients. For patient 6, the GSR value increases for “Joy” while for patient 8 it decreases.

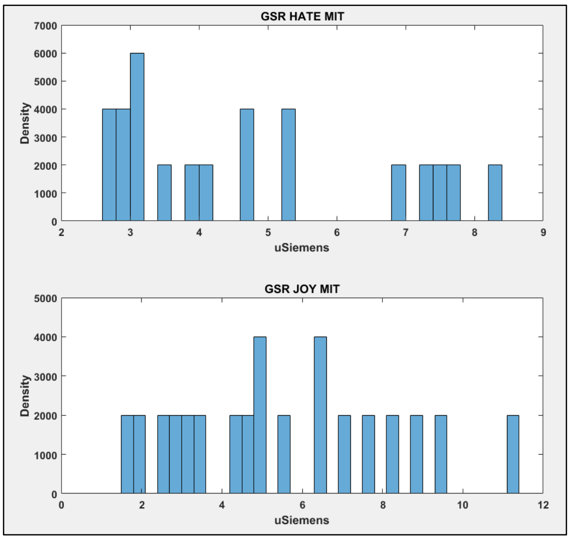

Figure 5. GSR Histogram for Hate and Joy in MIT Database

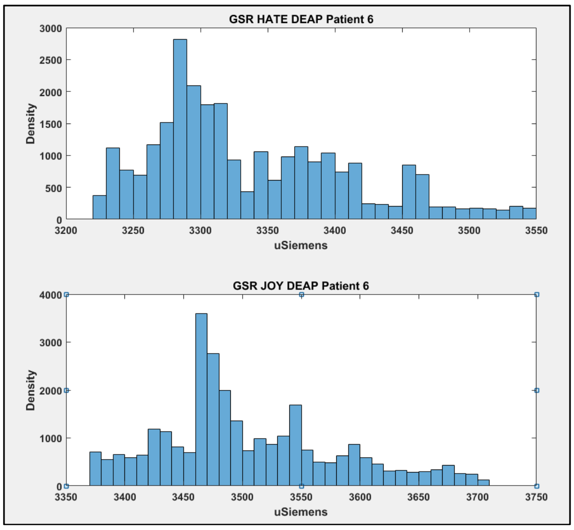

Figure 6. GSR Histogram for Hate and Joy in DEAP, patient 6

It is difficult to extract common patterns and physiological characteristics from different databases. The distinct input stimuli used for inferring the emotion, together with the way of emotion inferring (natural vs induced) produce different values of physiological variables, although commonly accepted as directly related to the emotion. Thus, different reactions patient and physiological differences will occur. A common standardized protocol for experiments to infer human emotions, measuring physiological variables, will be welcome for future applications designers and developers. Even, further research should be done on analyzing these differences.

ii. Raw data classification using Machine Learning

As comented in previous sections, the need for a set of good characteristics extracted from the raw data is essential. It is possible to consider to analyse raw data right from the sensors. This analysis fits into *deep learning* topic. Therefore, authors have analyzed raw data from MIT database, in order to obtain the confusion matrix (cluster identification for different emotions) with Matlab2016b® and the classification learner toolbox. From this matrix, shown in Figure 8, a large decrease in the classification accuracy is observed, with respect to data published by MIT [4]. Choosing a k-nearest-neighbor as the classifier, which is one of the classifiers used in [4], the accuracy is decreased more than 10%. Therefore, the use of a good set of features will make your system performs better and predict the output with more accuracy, as the info given to the classifier if bigger than giving just the raw data.

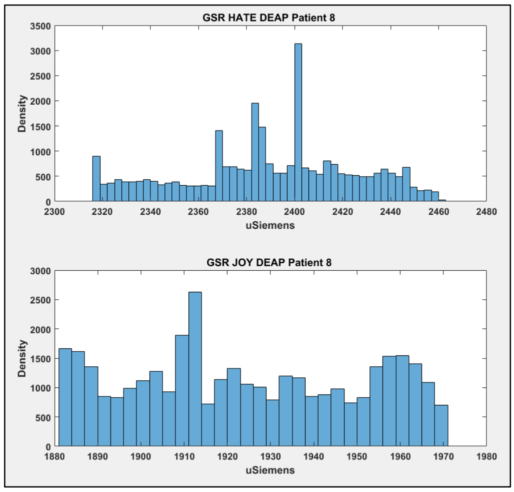

Figure 7. GSR Histogram for Hate

Figure 8. Confusion matrix for MIT DB from raw Data with ML and Joy in DEAP, patient 8.

IV. DETECTION OF DANGEROUS SITUATIONS SYSTEM

The iGlove is a wearable IoT platform that is currently being developed to be used in emotion recognition research. The main idea is to collect different physiological signal such as HR or GSR to detect emotional states related to potentially risk for the person wearing the system, reacting quickly and autonomously to avoid danger. In order to accomplish this task the gadget has several sensor and a Bluetooth Low Energy interface to communicate with a smartphone. Daily use recommends a non-intrusive, comfortable and low power consumption, for extended battery life, system. This not only limits the physical aspects but also the signals obtained from the sensors, making the development more challenging.

The system consist of a microcontroller connected to a set of physiological sensors and a wireless Bluetooth module and a smartphone, Figure 9. Data processing is divided between the microcontroller and the smartphone to obtain the best low power operation. The microcontroller only manages the sensors and the data recollection extracting the useful features from raw signals, leaving the heavier data analysis, clustering and interpretation, to the smartphone microprocessor. This configuration, also, allows the use of cloud services to store the data and to do further processing.

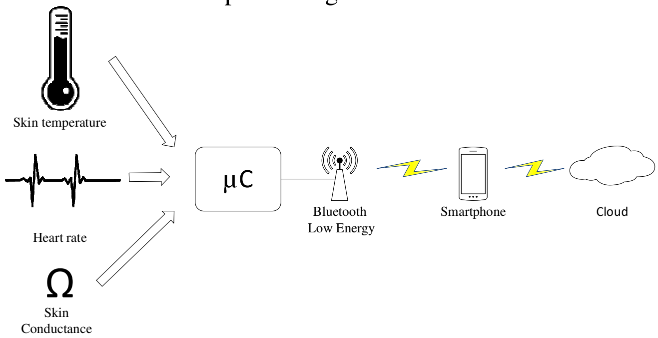

Figure 9. iGlove Architecture.

The selection of the sensors is a critical point in the design of the system. As comfortability and non-intrusiveness are mandatory, EEG (Electroencephalogram) is totally discarded. Moreover, the sensor has to be low power to maximize the time of use. Taken into account these specifications three sensors have been selected: Skin conductance, heart rate and skin temperature. These bio signals have a strong relation with emotions as mentioned in section II.

The heart rate sensor is an integrated solution manufactured by Maxim Integrated, the MAX30102. The working principle is the PPG (photoplethysmogram) that consist in detect the change in the reflection of the light with the change of blood vessels' volume. This sensor includes the optical emitter, the detector, the analog front end and the ADC. This device is intended to be used in wearable system, is small and low power, therefore it adapts perfectly to the iGlove.

For the measurement of the skin temperature have been selected two devices from the same manufacture as the heart rate sensor, Maxim Integrated. One of them is the DS7505 and the other one is the MAX30205. Both sensosr are high precision digital thermometer, but the MAX30205 is especially designed for the human body temperature range.

The skin conductance sensor has been designed especially for this task. It is composed of a resistance divisor, a buffer, an amplifier stage that amplifies the signal and subtract a value of DC voltage to avoid saturation.

V. Conclusions

In this paper, an analysis on different approaches for combining data from smart sensors attached to human body, with the purpose of determining the main emotion present in the person, has been presented. The conclusions of the analysis will help in the design of a new application, where emotion detection can be used for personal safety (domestic violence, sexual violence, bullying, etc.). The intrinsic variability of the physiological signals makes emotion recognition, based on physiological sensors, a real challenge. Two databases have been analyzed and studied in detail and the obtained results will be used in further analysis for panic or fear emotion detection.

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DCIS 2017 notification for paper 69

1 mensaje

DCIS 2017 <dcis2017@easychair.org> 17 de julio de 2017, 13:47
Para: Jose Manuel Lanza <jm.lanza@upm.es>

Dear Jose Manuel Lanza,

It is our pleasure to inform you that your paper entitled Meaningful Data Treatment from Multiple Physiological Sensors in a Cyber-Physical System has been accepted for presentation at the DCIS 2017 conference. Please take into account the reviewers comments and their suggestions for improvement in the preparation of the final version of your paper. The final version of the paper is due on 30th of September.

Please note that only papers with at least one registered author will be included in the proceedings. One author registration covers up to two papers.

We look forward to meeting you in Barcelona.

Best regards,

The DCIS 2017 Organizing Committee

----------------------- REVIEW 1 ---------------------
PAPER: 69
TITLE: Meaningful Data Treatment from Multiple Physiological Sensors in a Cyber-Physical System
AUTHORS: Jose Angel Miranda Calero, Manuel Felipe Canabal, Jose Manuel Lanza, Marta Portela-Garcia, Celia Lopez-Ongil and Teresa Riesgo

Overall evaluation: 1 (weak accept)

----------- Overall evaluation -----------
The paper deals on an actual interest topic.
Though the sections are correctly introduced and presented, some improvements are necessary:
- There is not an right presentation of the algorithms implemented to obtain the results: the machine learning methods are presented, but there are not an explanation of the algorithms implemented by the authors.
- A more concrete language must be used in a scientific paper. E.g., in Section C, authors say "...there are some existing databases..."; section IV, "...a microcontroller connected to some physiologicsl sensor...", ... Avoid 'some', and make it explicit.
- A better explanation of all the experimental system setup should be introduced.

In respect to the presenton of the paper,
- Letter size in the figures should be increased.
- Separations between figures/figure explanation, and figure explanation/text must be respected.

----------------------- REVIEW 2 ---------------------
PAPER: 69
TITLE: Meaningful Data Treatment from Multiple Physiological Sensors in a Cyber-Physical System
AUTHORS: Jose Angel Miranda Calero, Manuel Felipe Canabal, Jose Manuel Lanza, Marta Portela-Garcia, Celia Lopez-Ongil and Teresa Riesgo

Overall evaluation: 2 (accept)

----------- Overall evaluation -----------
Good topic, good description of the different alternatives, but small number of conclusions.

----------------------- REVIEW 3 ---------------------
PAPER: 69
TITLE: Meaningful Data Treatment from Multiple Physiological Sensors in a Cyber-Physical System
AUTHORS: Jose Angel Miranda Calero, Manuel Felipe Canabal, Jose Manuel Lanza, Marta Portela-Garcia, Celia Lopez-Ongil and Teresa Riesgo

Overall evaluation: 2 (accept)

----------- Overall evaluation -----------
In this paper, an analysis of different approaches for emotion detection based on smart sensors is presented. Authors combine Internet of things, wearables and affective computing to get to a better solution for the problem. In the reviewer's opinion, it is not clear the inclusion of Cyber physical systems in the title. Anyway, the quality of the paper is good and the topic is very interesting and innovating.
I think that the analysis made in the paper is useful and should be presented at DCIS17

---------------------- REVIEW 4 ---------------------
PAPER: 69
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AUTHORS: Jose Angel Miranda Calero, Manuel Felipe Canabal, Jose Manuel Lanza, Marta Portela-Garcia, Celia Lopez-Ongil and Teresa Riesgo

Overall evaluation: -1 (weak reject)

----------- Overall evaluation -----------
I do not see any new and significant contribution in this paper. It is well known the difficulty on extracting distinguished features from "emotional" signals and the application of deep learning techniques is a possible approaching way to provide solutions, but I am not able to see what is the proposal of authors.

I think the most valuable part of the paper is its tutorial apparience. It is clear and well written.