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Additional Information

## Emotions Detection on an Ambient Intelligent System Using Wearable Devices

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### Abstract

This paper presents the Emotional Smart Wristband and its integration with the iGenda. The aim is to detect emotional states of a group of entities through the wristband and send the social emotion value to the iGenda so it may change the home environment and notify the caregivers. This project is advantageous to communities of elderly people, like retirement homes, where a harmonious environment is imperative and where the number of inhabitants keeps increasing. The iGenda provides the visual interface and the information center, receiving the information from the Emotional Smart Wristband and tries achieve a specific emotion (such as calm or excitement). Thus, the goal is to provide an affective system that directly interacts with humans by discreetly improving their lifestyle. In this paper, it is described the wristband in depth and the data models, and is provided an evaluation of them performed by real individuals and the validation of this evaluation.

*Keywords:* Multi-agent Systems; Emotional Agents; Internet of Things

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## 1. Introduction

Ambient Assisted Living (AAL) is increasing rapidly and a large number of projects are being developed with the aim of providing assistance to elderly and disabled people [1, 2, 3]. What we are able to observe is that most of them have  
5 as a goal to provide a simple interaction with the users with minimal effort. One common issue that most possess is that they rely on automatism and static user profiles.

While they are effective in terms of simple tasks they do not encompass the ability of cater to changes that are part of the complex human states (like  
10 boredom), which changes the user profile [4].

The modulation of a user profile that emulates one's decision process must have the ability of representing emotional states [4, 5, 6]. The emotional states affect greatly the human decisions, where one decision to a specific situation may vary from one opposite to another if the current emotional state of a person  
15 is happy or sad.

One way to address this issue is to ask the user every time for his or her consent to every action/decision, which defeats the purpose of being discrete and ubiquitous [6].

Another solution is using an adaptive system that is able to perceive these  
20 emotional changes. The information of these systems can be used to transparently support a decision according to one's emotional response. Moreover, emotional profiles may be created to provide common responses that were expected from the person that was emulated.

To capture the emotional status there are several ways that may be used,  
25 but one of the most discrete way is to monitor human physical changes. The way that humans perceive the world influences their emotional state and that has a repercussion on the physical level [7, 8].

There are signals that the human body inadvertently displays, like skin/muscle  
30 tensioning, pupil dilatation and micro-movements. Most of them have a corresponding bio-electrical impulse, which in turn can be captured by sensors.

In this paper we propose the usage of a wearable device in form of a wristband, named *Emotional Smart Wristband* (ESW) that sends information to the iGenda (an AAL platform), enabling it to schedule new tasks according the emotional status. Furthermore, the ESW plays an important part in Intelligent Virtual  
35 Environments, where the deployment environments can be simulated to test multiple outcomes of real interactions.

We also present in detail the composition of the ESW and the procedures and architecture of translating bio-signals into emotions using the PAD (Pleasure, Arousal, Dominance) concept and neural networks. We then establish the ground  
40 work of the operational part of the system and how can the ESW contribute to other projects through giving real data or simulated scenarios in accordance to the collected data.

The objective is to create a complete AAL platform, using the ESW and the iGenda combined, that is able to cater to its users in a discrete way, and  
45 gather emotional information that enriches the iGenda's knowledge about the user, such as likes and decisions. Thus, being able to forecast future decisions of these users, being able to implement them in virtual scenarios where they are tested and validated.

### 1.1. iGenda

50 iGenda is the base structure for communicating with the users. The aim of the iGenda is to manage the daily activities of the care-receivers and caregivers, using their agendas [9, 10]. The intention is to streamline the interaction and to minimize the intrusion that forced interaction may require. iGenda uses a multi-agent system that connects with the ESW and uses the care-receiver' emotional  
55 status to schedule/remove activities or events based on the feelings demonstrated, as well as send notifications to the caregivers about abrupt emotional changes. This way we are able to shape the users' environment as transparently as possible.

The use of the ESW has a motive: understanding how the user feels about the iGenda suggestions. iGenda contains several information about its users  
60 and their responses but the issue is that these interactions may be biased. Our

belief is that detecting the user's emotions we are able to obtain an unbiased response, thus being able to be more true to the users preferences and possibly adapt faster to them. Moreover, there are some extra features that the ESW has that can be used by the iGenda, like detecting heart problems or an heart attack and reporting the vital signs, which can be used to create health reports for the caregiver. iGenda has been extensively explained in previous articles [11, 9, 10]. Thus, in this paper our aim is to explain the ESW features and architecture, focusing on the interpretation of the emotions and how we translate electrical signals into emotions.

The paper is structured as follows: section 2 shows the related projects in the AAL and emotion detection areas; section 3 presents the ESW architecture, the emotional model and the virtual actor concept and the wristband components and operation; section 4 presents the evaluation of the proposed models and hardware with real subjects with the resulting data and its interpretation; finally, section 5 presents the conclusion and future developments.

## 2. Related work

The AAL area is currently very prolific, as it is object of various developments and novel projects. The AAL domain is very complex (providing healthcare services to elderly and mentally/physically challenged people) and presents an important social strand that affects a numerous people, thus it is very relevant. AAL proposes systems and platforms that use technological helpers to perform daily tasks in a home environment. These helpers have the role of enhancing the task of the caregivers, providing extra help when the caregivers are not available and constantly monitoring the care-receivers for dangerous situations that they may encounter.

The Caregiver's Assistant project uses RFID and a database with activities and a fast inference mechanism that allows the identification actions being performed [12]. It uses RFID cards to track the users location and beacons that remotely read them, thus being able to locate accurately each user position. One

90 issue with the hardware is that the beacons have a limited range, requiring that  
the users are in almost direct contact with them, thus they are very invasive  
and require effort to work and the users are aware of the procedures.

The CoME project [13] uses wearable sensors to monitor the platform users  
and smartphones to interact with them and to collect reports from them. Addi-  
95 tionally, the platform has tutorials about how to perform certain activities that  
are showed to the caretakers to localize and access health reports from their  
assigned users. The platform aimed environments are elderly homes or similar  
places that care for a community of elderly people. The goal is to optimize  
the care provided by few caretakers to many care-receivers. Technologically,  
100 each deployed system is connected with the rest of the network and shares and  
receives information from the wearable sensors, adjusting constantly the services  
provided.

The ALADIN [14] allows the users to control the home environment (lights'  
brightness and colour) according to their emotional state. The users use a glove  
105 that reads biosignals (photoplethysmography), which transmits that information  
to the server, and according to their pulse/heart-rate the illumination is dimmed  
or colour changed. The goal of this project is to create comfort and peace by  
adjusting the environment to the user emotions. The glove limits the user to  
a confined space and it cannot get wet or be used to manage heavy objects.  
110 Thus it is very invasive, possibly biasing the results as the users are aware of  
apparatus and operation.

Pepper is a result of a private effort from the SoftBank company and is a  
servant humanoid robot [15]. Its aim is to interact with human beings, reading  
their emotions to create an empathic connection, and perform light tasks. It was  
115 designed to be a social companion, doing tasks like receiving people and provide  
useful information about a topic or task. The idea behind this robot was to  
create a companion for elderly people that was able to follow them around their  
home and proactively interact with them. The robot has a powerful processing  
unit and several sensors. It uses cameras and voice modulation to obtain the  
120 emotion status of the person that is interacting. Relying on imprecise sensors

(cameras and microphones) means that the robot can only detect 4 emotions on exceptional environmental conditions (joy, sadness, anger and surprise). Those conditions are hard to achieve, thus, most of the times Pepper is unable to detect the emotions, being unreliable, and most of the time relying in artificial intelligence to show a probable emotion.

The works by [16, 17] introduce an architecture for emotion detection in smart environments (medical and residencies). The aim is to provide a system that is able to fuse multiple sources of information (physiological signals, facial expression and behaviour) to obtain the emotional state of the monitored users. With this information, the authors propose the regulation of sound (music), colour and light to achieve calm and happy emotions on the users. They have devised a wearable that is able to detect the electro-dermal activity and blood volume, which they measure the tensioning and relaxation of the body. Furthermore, with cameras they capture facial expressions and movement in the environment. With the facial expressions the application is able to capture directly the emotional state, and to compensate the natural unreliability of this process (that requires appropriate lightning, head position, distance, ...) a ceiling camera is available, to capture the movement of the users, detecting erratic movements and common patterns. The issue with these systems is the scalability problems and the fusion of distinct sensor systems. Albeit the authors use recent methodologies (like neural networks) to do the heavy lifting, correlating very distinct concepts (physical and psychological) may open the door to a high number of false positives due to the causation effects.

One common problem revealed of these projects is that they are interested in the implementation and the execution of their components but do not reveal any particular interest on the opinion of the users towards the devices that they are using.

Commonly, most of these projects overlook the opinion and emotions that the users have towards them. They may be liked by the users, and that does not pose a problem, but if they are disliked by the users it is very hard to know that information to improve them. Furthermore, in terms of personalization there is

a reduced number of projects that tackle the perspective of using emotions to model services and visual interactions.

The recognition of emotions is a relatively easy task for a human: simply listening the nuance in the voice of a person or looking at her face. During the last few years, different methods for the automatic recognition of emotions have been studied. One of the best known techniques is based on the use of videos and images [18]. Moreover, the use of Electroencephalography (EEG) [19] approaches have provoked very significant improvements. This is because they allow direct measurement of the brain. However, we can find other studies the change in the diameter of the pupil, since this changes are related to human cognitive process. This techniques called *Pupillometry* [20] measure the pupil diameter when the people is exposed to a different stimuli. The pupillometry is used in different aspect as *Language Processing, Memory and Decision Making, Perception, Cognitive Development and Emotion*.

Nevertheless, these two approaches have drawbacks, video image requires a high processing load and the EEG is a very invasive method.

According to this last consideration, other human parameters have been considered lately, like body posture [21] or bio-signals from the body [22]. Regarding this last approach, bio-signals are a very interesting field of research to try to automatically recognize emotions in humans. This is due to the existence of a great amount of different signals that can be measured in a human body, e.g., Galvanic Skin Response (GSR), Electromyography (EMG), Electrocardiography (ECG), Electrodermal Activity (EDA), Blood Volume Pulse (BVP), Peripheral Temperature (SKT), and Respiration (RESP).

Due to the large number of existing bio-signals, one of the problems is the selection of the most appropriated bio-signals to be used as a method for the transformation of signals into emotions [23, 24]. Thus, for the measurement of bio-signals it is crucial to employ appropriate sensors and a great precision is needed to obtain good reliability.

Current approaches try to place different sensors on complex devices, and this way the device can measure from different sensor types and different sensors



sources. Typically, these devices are called smart devices or smart sensors [25]. These devices also offer services to the rest of the system through some kind of connectivity functionality like bluetooth, wi-fi, . . . In this sense, the devices are perceived by the rest of the entities of the system as a resource that offers services [26].

Next it is presented the ESW architecture, that tries to tackle the issues of the projects presented in this section.

### 3. Emotional Smart Wristband

This section describes the proposed platform which allows the schedule of new tasks according to the emotional status of the users. To do this, the platform is mainly formed by an Emotional Smart Wristband (ESW) and the iGenda system [10, 11, 9]. The ESW monitors the GSR and the Photoplethysmogram, and transforms it into an emotion classification.

With this information, the iGenda is able to use it to associate that emotion with the suggestions sent to the users. The goal is to synchronize the conscious decision with the subconscious one and obtain an unbiased classification based on the emotional response. The iGenda learning algorithms adjust the data to be in accordance to the user likes, improving the future suggestions, evolving along with the user. Moreover, iGenda is able to receive the information of multiple ESW and process them individually or in group. The reason behind the group emotion detection is that it is very useful to determine the global emotion status of an environment that is populated by multiple people, like a nursing home.

AAL promotes the individual as the most important element in the system, but that is applicable only when it is considered only one individual, which is not always the case. For instance, when we consider multiple individuals (like in nursing homes) we find that the best way to obtain a harmonious ambient is when most of the people tend to an overall emotion (considering varying degrees). The people in nursing homes behave socially, so there are natural

forming groups with leaders and followers roles [27], thus the group is influenced by the leader decision even if the people individually do not like/agree with that decision. Tracking the groups emotional state is useful to understand the social bound between the users and to extract the real emotional response of each user even when influenced by the group. Thus, avoiding a very biased set of activities that the leader enjoys and the rest only tolerates. By using the ESW the users can respond unbiased of what their feelings are towards an activity. Tracking the community responses results in the overall likeness and in the social aspect identify if the leader is a good one or not.

### 3.1. Architecture

The ESW platform is mainly composed of a set of smart wristbands which monitor the emotional state of a group of people and transmit the information to the iGenda platform (see Figure 1). Moreover the ESW platform includes special agents that calculate the group emotion (or Social Emotion) of the participants, the Social Emotion Agent (SEtA), and resorting to machine learning techniques and makes it available for consumption [28, 29]. Moreover, the platform also includes an Intelligent Virtual Environment, where the deployment environments can be simulated through the employment of virtual actors.

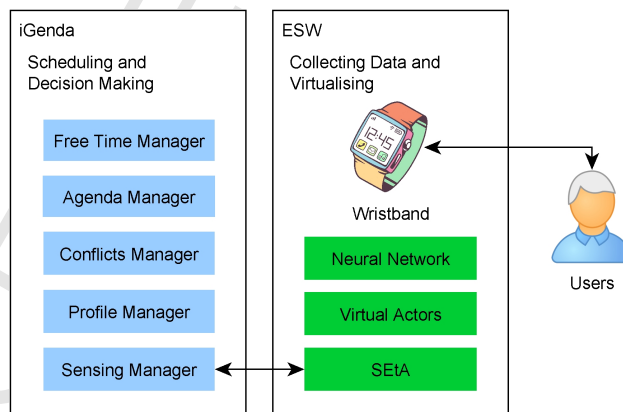


Figure 1: Integration between the ESW and the iGenda platforms.

230 The voltage outputted from the sensors is captured locally (in the wristband)  
and pre-processed there, thus the information fed to the agents is in form of  
text or meta-data. Additionally, the multi-agent system has dedicated agents  
that grab that information and verify against the adopted models to extract the  
current emotion, joining it to the rest of the agents community that represent  
235 other users. The overarching result is the availability of the immediate emotion  
of each user and the global emotion of all users and the emotional trends and  
evolution. The trend of the group emotion is important as it is easier to find  
the culprits of the emotional changes.

For instance, consider a bar, it contains a group of friends and has music  
240 playing. Now consider that some of these friends have different musical tastes. If  
a music is playing that is enjoyable to 90% of the group we are able to notice an  
emotional progression towards "satisfied", while if it is the opposite (90% dislikes)  
we can observe movement in the opposite direction. One of the possible aim of  
this analysis is obtaining a playlist that is enjoyable to most of the group with a  
245 specific alignment of songs that cater to each individual like. This specificity is  
used to avoid reaching a tension point where one or more persons have reached  
a saturation point and refuse any further change or abandon the environment.

The task of the iGenda is to consume this information and use its scheduling  
features to change the events of each participant, based on his/her profile, to  
250 achieve a specific emotion, thus guiding the group to a common emotional  
state. The emotional states are measured and placed in the PAD [30, 31] model,  
outputting a representation of the emotional state, easing the task of the iGenda  
on choosing new events. We have adopted the PAD model due to the simplicity  
and the datasets available. Furthermore, we are able to project the information  
255 captured into a 3D space, which facilitates the way the information is perceived.

### *3.2. Background on physiology signals*

The signals exposed in this section are used by the wristband to detect human  
emotions, however we acquired an ECG signal to correlate the PPG signal.  
This correlation allows us to know if the peak of the ECG (complex QRS) was

260 corresponding to that detected by the wristband (using PPG). However, another  
 265 technique used is the Blood Volume Pulse (BVP). The BVP signals is derived of  
 a PPG and is obtained using the PPG, the BVP measures the changes in blood  
 volume in arteries and capillaries by shining an infrared light (a light-emitting  
 diode) through the tissues. The infrared light reflected is captured by the PPG  
 sensor's photodetector and is proportional to the volume of blood in the tissue.

Figure 2 shows three signals: (i) the blue signal corresponding to the GSR  
 measure; (ii) the green signal corresponding to the ECG signal; and (iii) corre-  
 sponding to the PPG signal. It is important to take into account that all the  
 signal was acquired without any kind of filtering.

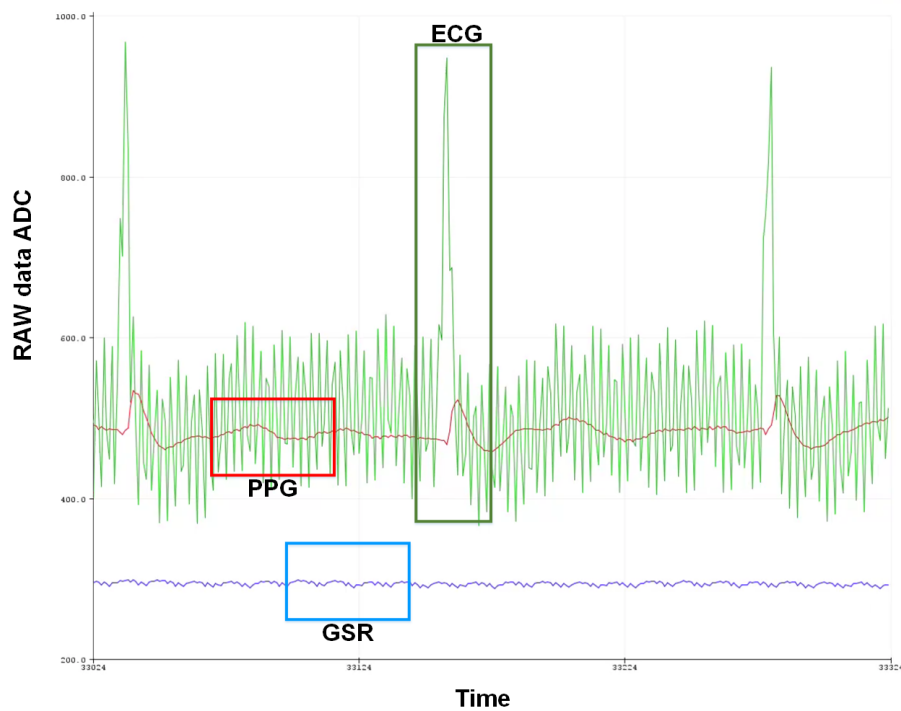


Figure 2: ECG, PPG, GSR bio-signals capture over time.

## 270 3.3. The PAD model

The model seen in Figure 3 is a granular visual representation of the PAD model where the *Valence* replaces the *Pleasure* as in the psychological area is more representative and has a larger range of values [32]. The model has 12 sub-quadrants that are 30 degrees from each other. The emotion is represented by the vector  $\vec{E}(Ag) = [Arousal, Valence]$  and the representation of emotions uses polar coordinates, constituted by the angle and the magnitude of the vector.

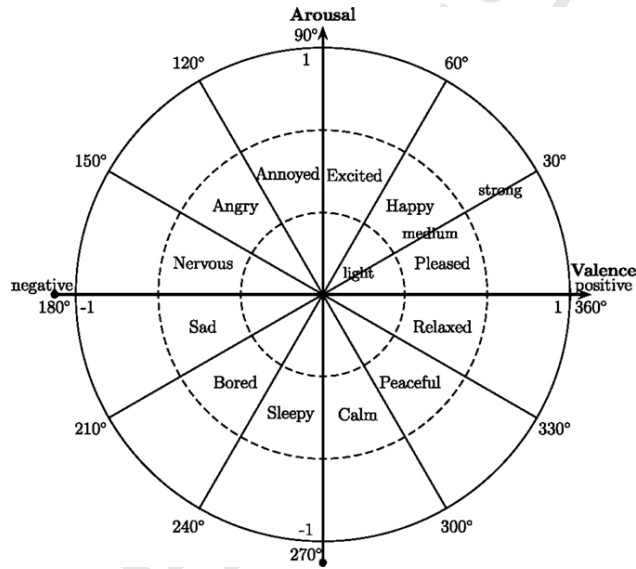


Figure 3: Emotions circle [33].

We use a fuzzy logic process that transforms qualitative values to quantitative values that are able to be placed in the model showed in Figure 3. Thereon, a neural network is trained using the DEAPdataset<sup>1</sup> to achieve a real-world result from real humans. The correlation between the data captured and the dataset is established in the neural network, meaning that each processed electrical input can be translated into an emotion.

<sup>1</sup><http://www.eecs.qmul.ac.uk/mmv/datasets/deap/>

### 3.4. *Virtual Actors*

A new development is the inclusion of virtual actors in the system that  
285 emulate the real participants. This feature aims to enhance the decision-making  
process of the system, detecting in advance the possible emotional states and  
preparing changes to the participants surrounding environment to accommodate  
these changes and proactively shift them to other states if the expected state is  
not desirable [34, 35].

290 In this case specifically, when related to the elderly there is little margin  
for experimentation, as they have a large number of health issues (physical  
and/or cognitive disabilities) and are very fragile. The emotional profile helps  
to preview the possible reactions to changes on their daily routines and their  
daily emotion when performing specific activities. The group emotion is very  
295 useful in environments like nursing homes and residential elderly communities.  
In this type of environment is very common to perform group activities and to  
generate teams of elderly people. One common issue is the user verbal response  
and the real feeling, e.g., one "enjoyable" activity may be so due to peer pressure  
or to social engagement with the caregivers [36, 37]. If the caregiver is able to  
300 receive unbiased information about how one feels about an activity it is easier  
to schedule similar or different activities or group that person with other people  
[38].

Another benefit from using virtual actors is the possibility of introducing  
Intelligent Virtual Environments (IVE). In this specific case, the IVE's would  
305 be used to project the environments where the users reside and to simulate all of  
the possible components, meaning that every sensor/actuator is mapped as an  
agent, thus it is able to directly interact with the human agents. This forwards  
our research by having safe environment enabled to test multiple outcomes of  
real interactions in fractions of second and project the optimal actions to achieve  
310 a certain outcome.

### 3.5. Wristband Description

This section describes the main aspects of the proposed Emotional Smart Wristband. With the introduction of wearable devices in recent years in our society, a growing boom has begun in the design of smart bracelets. This is  
 315 mainly due to the reduction of the size and manufacturing costs of the electronic components. Thanks to this, in recent years we have been able to observe intelligent bracelets that measure our oxygen saturation (SPO<sub>2</sub>), heart rate and monitor the way we sleep. However, it is possible to use these new technologies in order to detect our emotional states. This detection is performed using  
 320 biosignals, such as those measured so far by commercial bracelets. However, it is necessary to add more signals, in order to obtain better detection and classification of emotions. Previous studies [39] demonstrated that variations in skin resistance could be associated with stress levels in humans. Other studies [5],[40] also shown that the heartbeat and body temperature could be associated  
 325 with emotional changes. Based on these studies, we have designed a bracelet able to capture and process biosignals, with the aim of detecting emotional states and thus creating applications in IoT and AAL areas. The proposed bracelet incorporates four sensors, with which four basic emotions are detected in the circumplex model [41] (Happy, Angry, Sad and Relaxed). To detect emotional  
 330 states present in the circumplex model, the designed wristband incorporates the following sensors:

- EDA (see Figure 4a) - for measuring the changes in the electrical conductance of the skin. This includes GSR, which results from sympathetic neuronal activity. EDA is a sensitive psychophysiological index of changes  
 335 in the autonomic sympathetic excitation which is used for the detection of the emotional and cognitive states [42].
- Bluno Ble V1.0<sup>2</sup> (see Figure 4b) - the microcontroller. It has low consumption bluetooth communication (BLE). It has an 8-bit Atmega328 CPU

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<sup>2</sup><https://www.dfrobot.com/>

and is compatible with Android 4.3+ devices with BLE4.0 and iOS 7.0+ devices.

340

- Temperature sensor (see Figure 4c) - for measuring the irradiated temperature as infrared light that our body emits, according to our moods.
- Photoplethysmography sensor (see Figure 4d) - for measuring the variations in blood flow. Using these variations it is possible to obtain the heart rate, which have been used in the detection of stress levels [43].
- Inertial Measurement Unit (IMU) (see Figure 4e) - a combination of accelerometer and a gyroscope. The accelerometer measures the acceleration of the wrist in the three axes [X, Y, Z]. The gyroscope allows us to measure the angles of rotation of the wrist and the angular speed.

345

In order to integrate these sensors into a wristband, several designs were made to improve the position of the sensors and minimize the size. The final ESW prototype can be seen in Figure 5. The IMU and the microcontroller are above another board containing the rest of the sensors.

350

From controlled experiences (explained in detail below), we have deduced that these sensors allows us to determine the emotional state of an individual. However, not all humans respond in the same way to external stimuli. For this reason, it is necessary to customize the bracelet. This personalization will help to reliably detect the emotional state of each person who uses it. To perform this customization an experiment has been designed in which the subject will be exposed to a series of visual stimuli (images). In each of the sessions the subjects will wear the bracelet that continuously captures the physiological variations. Also, the subjects will be monitored through a camera, which performs a facial analysis of their facial response to the stimuli. Through this facial response, we get additional information about the emotion expressed by the subjects. The usage of cameras will only be used on this personalization procedure.

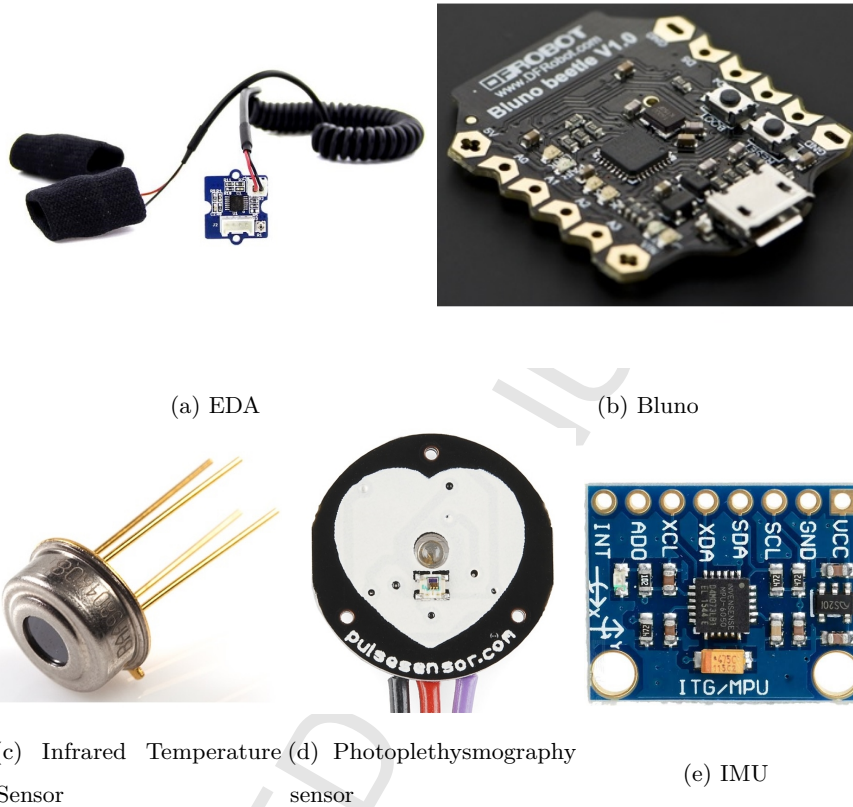
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360

365

The images used to stimulate emotional changes have been obtained from the





(a) EDA

(b) Bluno

(c) Infrared  
Sensor(d) Photoplethysmography  
sensor

(e) IMU

Figure 4: Sensors used to acquire the different biosignals.

*Center for the Study of Emotion and Attentions* of the University of Florida<sup>3</sup> [44]. This center has created a database formed by a series of images, sounds and texts, previously catalogued. In our experiments, we used the International Affective Picture System (IAPS). This system has been developed to provide a set of normative emotional stimuli for experimental research on emotion and attention. In this dataset there is a large set of standardized, emotionally evocative and internationally accessible color photographs, including contents across a wide

<sup>3</sup><http://csea.php.ufl.edu/index.html>

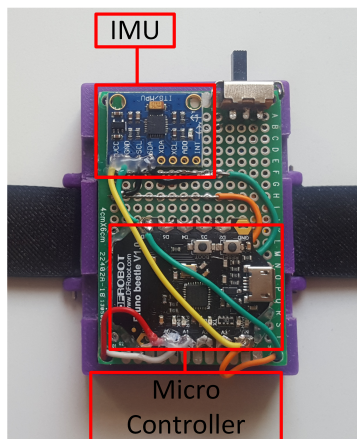


Figure 5: ESW final prototype.

range of semantic categories. In the process of personalizing the bracelet, the  
 375 user is only exposed to these visual stimuli (images). The information obtained  
 as a result of the exposure of these stimuli is stored in a database. This database  
 is structured as follows: [ID\_image, Emotion\_Detected, Bio\_Signals, SAM].

The first field is the identifier of the image of the IAPS database, this will  
 allow us to know the emotion that represents that image or sound. The second  
 380 field is the emotion detected through the camera, this detection is done through  
 the Microsoft <sup>4</sup> API. This API classifies human emotions in eight classes: Anger,  
 Contempt, Disgust, Fear, Happiness, Neutral, Sadness and Surprise. The third  
 field is an array of ten dimensions, six of which are of the IMU and the remaining  
 three correspond to the biosignals acquired by the wristband. These biosignals  
 385 will be captured for 20 seconds, during this time the user look at the pictures.  
 In our tests we use 644 images to create the training dataset and 538 images  
 to do the test. Once has been finished the time, the user will perform a Self-  
 Assessment Manikin (SAM) [45] test (see Figure 6), which corresponds to the  
 last field in our database. SAM is a non-verbal pictographic evaluation technique

<sup>4</sup><https://www.microsoft.com/cognitive-services/en-us/emotion-api>

390 that directly measures the pleasure, arousal and dominance associated with a  
 person's affective reaction to a wide variety of stimuli. It is important to take  
 into account that the images don't represent an emotion and the value of PAD  
 is extracted of SAM test. The emotion detected using the Microsoft API is  
 used to check a correlation of the emotion detected by a visual system with the  
 395 emotions declared in SAM test.

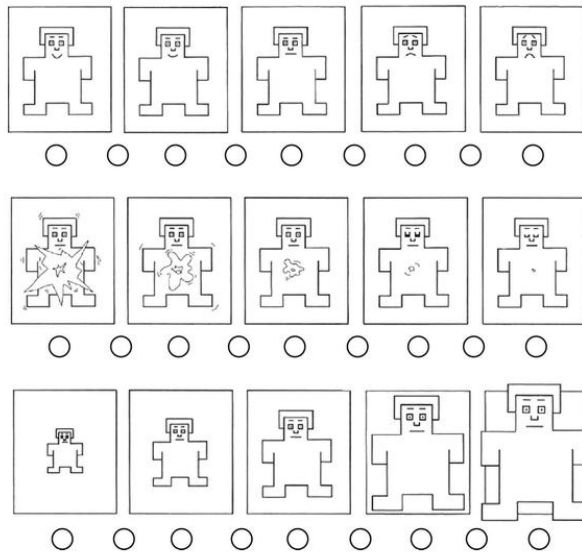


Figure 6: Self-Assessment Manikin (SAM) test.

In summary, for each obtained signal, a vector which includes the values of  
 the previously presented equations is formed. Once the data has been obtained  
 for each of the users, a customized emotion classification model is trained. To  
 perform this training, the techniques of descriptive statistics have been adopted,  
 400 as suggested by Picard et al [46] to perform the extraction of characteristic  
 vectors. For our experiments we have extracted the six following variables:

1. The means of the raw signals
2. The standard deviations of the raw signals
3. The means of the absolute values of the first differences of the raw signals

- 405 4. The means of the absolute values of the first differences of the normalized signals
5. The means of the absolute values of the second differences of the raw signals
6. The means of the absolute values of the second differences of the normalized  
410 signals

Each feature vector has 18 elements because six features are extracted for each signal. This input vector is used by a neural network in order to classify the different emotional states of each test subject. There are different methods to perform this classification, but the most used is neural networks.

415 In our experiments, we have used *Backpropagation*. Our neuronal network consists of 18 input neurons, 100 neurons in the middle layer and 7 neurons in the output layer (one for each emotion: Angry, Disgusted, Fearful, Happy, Sad, Surprised, and Neutral) (see Figure 7). In order to obtain the best results (low value of final recognition error), different experiments were performed leading  
420 to improve the number of neurons in the middle layer. After several iterations, it was concluded that with 100 neurons in the middle layer were enough. These 100 neurons allowed us to obtain the best results when classifying the emotions.

#### 4. Evaluation

Experiments were performed to 20 test subjects, using a database with 1182  
425 images. This database was divided into two sets: the training set of 900 images, and the test set of 282 images.

The tests were done using the following protocol (see Figure 8):

- 430 1. The set of training images (50) was observed by the test subjects for 10 seconds. During these 10 seconds the signals of GSR, PPG, temperature and heart rate were recorded and stored.
2. At the same time, the subject was recorded, which was used to detect the emotion expressed by the subject. This detection was performed

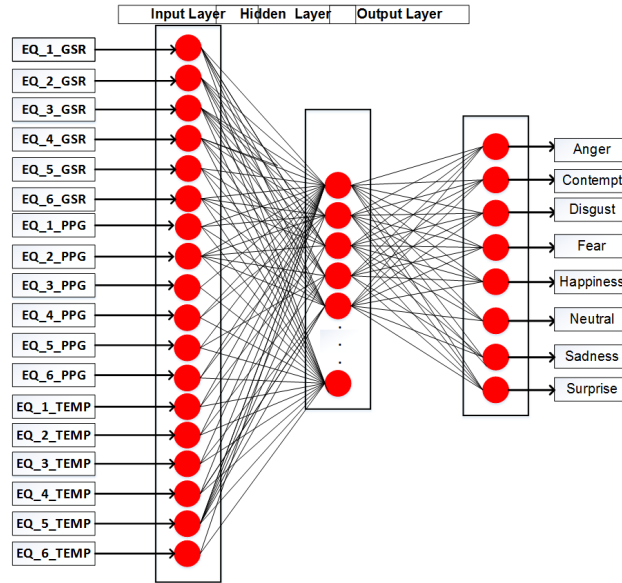


Figure 7: Neural network architecture.

using the Microsoft Detect Emotions Service, which detects the following emotions: Anger, Contempt, Disgust, Fear, Happiness, Neutral, Sadness and Surprise.

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3. After 10 seconds of observation of the stimulus, the subject has 10 seconds more to respond to the SAM test.

Figure 9 shows the signals captured by the wristband, these strips are excerpts of signals recorded in the experiment when the user is exposed to the stimulus.

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It is important to note that the units of the signals are the same:  $mV/s$ . In the case of the temperature sensor, a *temperature-to-voltage* conversion was performed to have the three signals with the same unit. This conversion was performed using Equation 1, which is given by the manufacturer of the sensor. In the equation,  $V_{ir}$  is the raw data of the IR channels,  $To$  is the temperature of the object,  $TA$  is the ambient temperature and  $A$  is the general sensitivity.

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$$V_{ir} = A (To^4 - Ta^4) \quad (1)$$

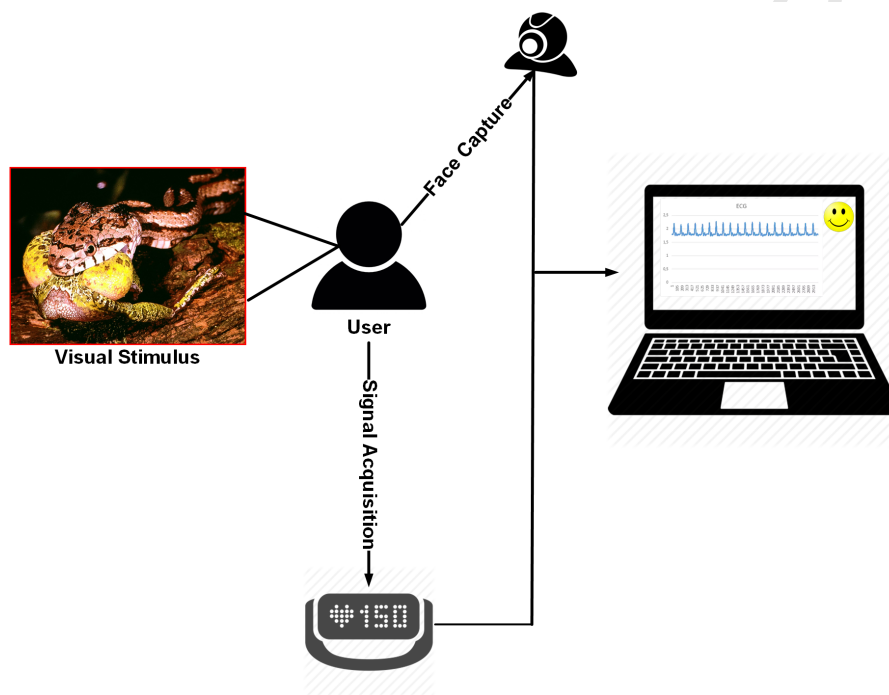
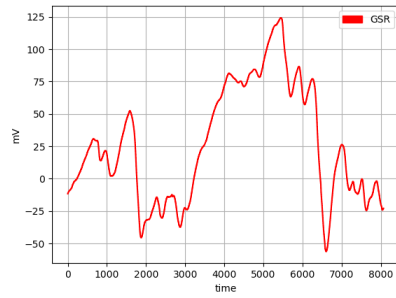


Figure 8: Description of the data capture process.

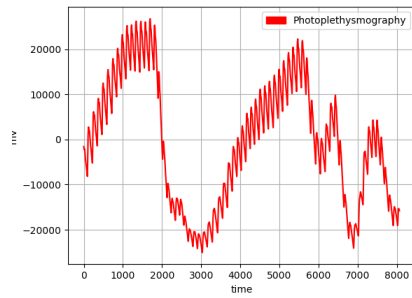
This neural network was trained using 18 features vector. However, our dataset has two outputs the first one corresponding to the emotion detected for the Microsoft API and the second one is the emotion obtained using the SAM test. The output using to supervise the neural network training is the result obtained through the Microsoft API, the SAM test give us a qualitative description emotion associated to the image.

In order to determine the best CNN architecture, the group of 20 subjects was divided into 4 groups of 5 subjects. Each network (corresponding to a group) was modified as the activation function of the middle layer and the output layer. In the same way, the *momentum* and *learning rate* was modified. Table 1 describes the groups and their parameters.

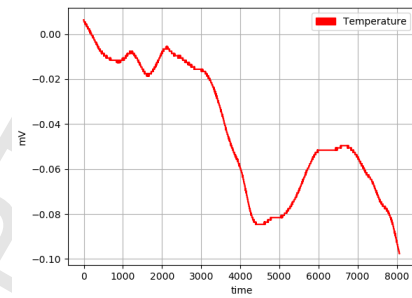
Mean square errors obtained in the experiments (see Figures 10a, 10b, 10c, 10d), allowed us to determine what could be the best neural network architecture



(a) GSR Signal.



(b) Photoplethysmography Signal.



(c) Temperature Signal

Figure 9: Signals captured by the wristband.

to use. It is necessary to emphasize that it is possible to have many combinations  
 460 of architectures and factors that affect the learning of the neural network. Based  
 on the graphs and classification positions obtained in each experiment, it was

Table 1: Testing different configuration parameter for the neural network.

	Medium layer activation function	Output layer activation function	Momentum	Learning Rate
Test Subject 1-5	TanhLayer	SoftmaxLayer	0.1	0.1
Test Subject 6-10	SoftmaxLayer	TanhLayer	0.01	0.01
Test Subject 11-15	LSTMLayer	SoftmaxLayer	0.1	0.0001
Test Subject 16-20	LSTMLayer	LinearLayer	0.00001	0.1

determined that the best architectures were those of subjects *Subject 6-10* and *Subject 11-15*. However, it is important to clarify that there may be many combinations in this type of experiments. It is for this reason that, in future works, the test subjects will be given a personality test to group the subjects by personality similarity, thus being able to assign a neural network architecture according to their personalities.

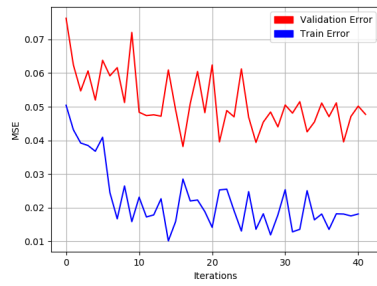
After the evaluation process, we have obtained a CNN that allows us to estimate the emotional state of the wristband's users with a very low error. This error is related directly with the emotion prediction using the wristband and in our experiments we have achieved 20% of misclassification cases. The integration of this ESW response in the proposed platform will allow to manage the community emotion of a set of users (for instance, people in retirement homes) and to send this information to the care-receivers or caregivers through the iGenda system.

## 5. Conclusions

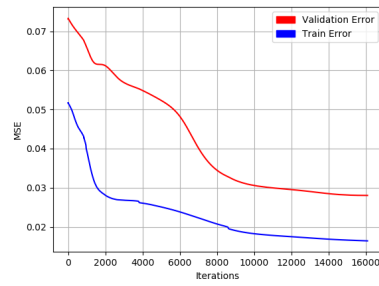
This paper has presented a new Emotional Smart Wristband (ESW) platform that allows capturing and communicate time-stamped bio-signals from a user to be translated to the current emotion he/she feels.

The goal of this platform is twofold: first, it has been designed to be integrated in the iGenda platform, to be used to adjust iGenda platform decisions to changes in the emotions not only of one agent, but of a group (as the platform allows to work with the concept of Social Emotion). The other goal is to record the emotions of a user and have the adjusted response to different stimuli, thus having a proper ESW response. This allows us to have a virtual representation

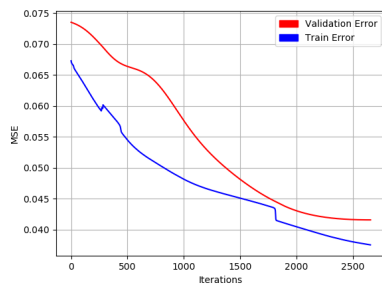




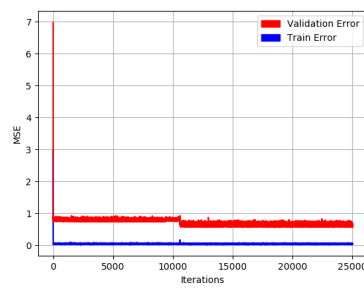
(a) MSE Test Subject 1-5.



(b) MSE Test Subject 6-10.



(c) MSE Test Subject 11-15



(d) MSE Test Subject 16-20

Figure 10: MSE representation of the test subjects.

of the user that can be used in an intelligent virtual environment simulation.

This will allow preparing the settings of tasks and environmental conditions to be used in the iGenda and test them with the subjects without bothering them with changes or avoiding changes that would lead to distasteful experiences  
490 (typically a happy social emotion).

Only the settings carrying the simulation to the goal emotion would be carried out in the iGenda system interacting with the real world.

One of the strengths of this platform is the usage of a recommender process (through the iGenda) that helps an often forgotten population. Most of the  
495 projects are not directly aimed at the general population. Furthermore, the platform has discreet sensor systems, as well as more invasive systems for increased accuracy, although with a properly trained model we are able to use just the wristband, being very unobtrusive.

The modularity that this platform has is also an interesting strength, being  
500 possible several applications to the ESW ecosystem apart from the healthcare area, like: crowd control, visual interfaces management, stress and fatigue monitoring, virtual environments societies, among others.

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