Using non-invasive wearables for detecting emotions with intelligent agents

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Abstract. This paper proposes the use of intelligent wristbands for the automatic detection of emotional states in order to develop an application which allows to extract, analyze, represent and manage the social emotion of a group of entities. Nowadays, the detection of the joined emotion of an heterogeneous group of people is still an open issue. Most of the existing approaches are centered in the emotion detection and management of a single entity. Concretely, the application tries to detect how music can influence in a positive or negative way over individuals' emotional states. The main goal of the proposed system is to play music that encourages the increase of happiness of the overall patrons.

1 Introduction

Over the last few years, research on computational intelligence is being conducted in order to emulate and/or detect emotional states [1]. The emulation of emotional states allow machines to represent some human emotions. This artificial representation of emotions is being used by machines to improve the interaction process with humans. In order to create a fluid emotional communication between human and machines, the machines need first to detect the emotion of the human with the final purpose of improving human-computer interactions [2]. To do this it is necessary to use different techniques such as: artificial vision [3], speech recognition [4], body gestures [5], written text [6] and biosignals [7].

Human beings perceive and analyse a wide range of stimuli in different environments. These stimuli interfere in our commodity levels modifying our emotional states. Before each one of these stimuli, humans generate several type of responses, like varying our face gestures, body movement or bio-electrical impulses. These variations in our emotional states could be used as a very useful information for machines. To do this, machines will require the capability of interpreting correctly such variations. This is the reason for the design of emotional models that interpret and represent the different emotions in a computational way. In this case, emotional models such as *Ortony, Clore & Collins* model [8] and the *PAD (Pleasure-Arousal-Dominance)* model [9] are the most used ones to detect or simulate emotional states. Moreover, emotional states are a very valuable information, allowing to develop applications that help to improve the human being quality of life.

Nowadays, the detection of the joined emotion of an heterogeneous group of people is still an open issue. Most of the existing approaches are centered in the emotion detection and management of a single entity. In this work we propose to detect the social emotion of a group of people in an Ambient Intelligence (AmI) application with the help of wearables. Specifically, we show a system that controls automatically the music which is playing in a bar through the detection of the emotions of the patrons with the use of individual wristbands. Thus, the main goal of the proposed system is to play music that encourages the increase of happiness of the overall patrons. Each one of the individuals will have an emotional response according to his musical taste. This response will be detected and transmitted by the wristbands in order to calculate a social emotion of the set of individuals. This social emotion will be used to predict the most appropriated songs to be played in the bar.

2 State of the Art

The AmI area is rapidly gaining notoriety due to its usage on complex social environments like nursing homes and regular homes. By monitoring fragile users (like elderly or mentally challenged people) the available systems pose as an alternative to regular caregiving services while being cost-effective. Despite the several aims AmI projects have they can be clustered in five clusters of operational areas [10]:

- Daily living activities
- Fall and movement detection
- Location tracking
- Medication control
- Medical status monitoring

In terms of daily living activities there is the project Caregiver's Assistant, which uses RFID and a database with human activities events and a fast inference mechanism that allows the identifications of the actions within a given space [11]. It works by registering the RFID cards that the users carry, which in some cases they have to actively pass them through the readers due to they small communication range. Thus, it is very intrusive to the users of the system as they have to be actively aware of the procedures so that the system is able to correctly access the information.

In terms of fall detection or movement detection, most of the operation methods resort to use cameras to register the visual information and extract information from it, like the projects in [12,13,14]. Although they require no interaction with the users, these systems are very invasive, not to mention the possible loss of privacy, due to the permanent recording of the environment.

The location tracking systems like the one presented on [15] use mobile devices sensors to provide the current location of the user to an AmI system, more specifically to the caregivers. These systems require the constant monitoring of the localization, thus there is no guarantee of privacy, thus being very intrusive systems. This intrusion is not done directly but by allowing 3rd party users to constantly know the location of another person the system becomes very intrusive [16].

Medication control projects consist in systems that help the users to remind the medications that they have to take [17,18]. They play an important role on the users life, as most of the AmI and AAL projects users have some sort of cognitive disability and have trouble in remembering to do activities, such as taking medication. These systems are mostly recommenders and are able to only provide information without being disruptive or actively monitoring the users. Due to the simplicity of the projects premises it is available a large number of simple applications for mobile devices and desktop computers currently.

The medical status monitoring projects like the ones presented in [19,20,21,22] show platforms that are constituted by sensor systems that are directly in contact with the human body. These sensor systems create a body area network and provide information about the carrier vital signs and bodily functions. For instance, all three works presented capture electrocardiograms and reason that information to obtain knowledge about their specific domain. The [21] uses the electrocardiogram information and ballistocardiogram information to assert if the drivers are calm and concentrated or if they are stressed or having some kind of medical issue (as the project is directed to elderly people). The project ALADIN [22] presents a system that manages home lights (brightness and colour) according to the users physical state. The users carry a biosignal reading glove (that captures photoplethysmography) that sends the readouts to the server and according to their pulse/heart-rate the lights are dimmed or changed their colour. The aim of this project is to provide comfort and promote a peaceful living, adapting the environment to the user state or preferences. The glove has to be put by the users and limits its use to a confined range of actions (it cannot be wetted or be used to manage heavy objects) thus being quite invasive, possibly undermining the results as the users become actively aware of their status, thus allowing them to manipulate the system. The issue with these systems is that they require users to attach sensors on their own body (the case of [19,20]) or that the users are in a very controlled environment like the [21].

These projects are a small representation of the plethora of the existent projects and show the current lines of development. 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. Only recently the theme of invasiveness has been considered due to the high reluctance of the users towards clumsy and complex apparatus [23].

In the line of ideas presented by [22], we are aiming to produce a system that increases the comfort level of the users (by managing the current music) through the use of a non-invasive wearable bracelet that performs medical status monitoring to attain the users' emotional status.

3 Problem description

This application example is based on how music can influence in a positive or negative way over emotional states [24], [25], [26]. The application example is developed in a bar, where there is a DJ agent in charge of playing music and a specific number of individuals listening to the music. The main goal of the DJ is to play music making that all individuals within the bar are mostly as happy as possible. To get this, it is necessary to detect the human emotions, and there exist many techniques to do it. But in our case, we decided to use the bio-signals to detect the emotional change. This emotional change is used by the DJ agent to change the musical genre and try that the clients of the bar are mostly as happy as possible. Each one of the individuals will have an emotional response according to its musical taste. This response is reflected in a variation of the bio-signals [27][28]. This variation allows us to calculate the social emotion [29] of the people within the bar. Based on the metric of the social emotion, the DJ agent could change the music genre to move the social emotion to a target emotion. To capture the bio-signals we designed a prototype of an *Emotional Smart Wristband* (Figure 1), that will be explained with more detail in Section 4.

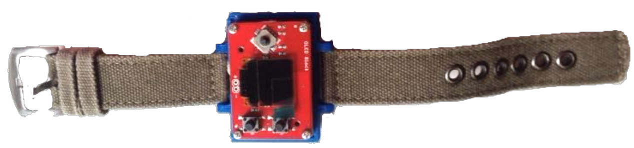


Fig. 1: Prototype of an *Emotional Smart Wristband*.

4 System Proposal

This section explains the different components that constitute the multi-agent system which describes a way to detect emotions based on bio-signals through wearable devices. The main problem in the detection of human emotions is the information capture. This information is normally obtained using image processing, text analysis or voice analysis. These ways are invasive and in some of them is necessary to have the consent of the person. In currently years the use of wearable devices has been growing, devices such as *Samsung*[3] with the *Gear Fit, Gear S2* or *Apple*[4] with the *Apple Watch* are only some examples. These devices can measure heart rate beat or hand movement using the IMU (Inertial Measurement Unit). Based on these devices and using the currently technology in embedded systems, it is possible to create new smart bracelets which include other type of measures, such as the EEG, GSR, Photoplethysmogram or ECG allowing the acquisition of biosignals that can help for the detection of the human's emotions. Using signals of this kind along with the incorporation of complex algorithms based on machine learning techniques, it is possible to recognise how humans change their emotional states.

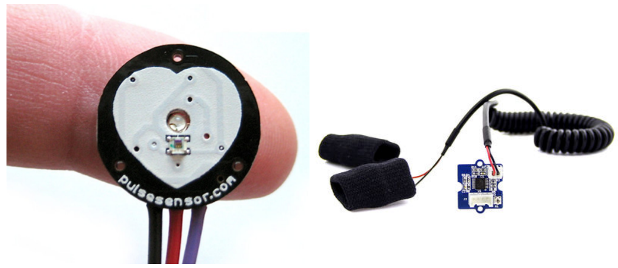
[3] http://www.samsung.com
[4] http://www.apple.com

The proposed multi-agent system is formed by three types of agents. These agents are: the *Wristband agent*, the *Social Emotion Agent*, and the *DJ agent*. The Wristband agent is mainly in charge of: (i) capture some emotional information from the environment and specifically from a specific individual, this is done by interacting with the real world through the employed wristband. The agent captures the different bio-signals, that will be used to detect the emotion of a human being; and (ii) predict the emotional state of the individual from the processed biosignals. In order to analyze these changes and predict emotional states, the Wristband agent employs a classifier algorithm that will be later explained. Once the emotion has been obtained, it is sent to the agent which is in charge of calculating the social emotion of the agent group. This agent is called *Social Emotion Agent* or *SEtA*. The main goal of this agent is to receive the calculated emotions from all the *Wristband agents* and, using this information, generate a social emotional state for the agent's group (details of how this social emotion is calculated can be seen in [29]). Once this social emotion is obtained, the *SEtA* can calculate the distance between the social emotion and a possible target emotion (in this case the target emotion is happiness). This allows to know how far is the agent's group of the target emotion. This can be used by the system to try to reduce that distance modifying the environment. This modification of the environment is made by the *DJ agent*. This agent uses this social emotional value to calculate what is the next song to be played. After different executions, the DJ agent can evaluate the effect that the song has had over the audience. This will help the DJ to decide whether to continue with the same musical genre or not in order to improve the emotional state of the group of people.

Due to the limits of the paper, we only describe in detail the processes made by the *Wristband agent* which are the data acquisition process and the emotion recognition. Moreover, the physical components of the wristband prototype are also described.

4.1 Data Acquisition Process

This process made by the *Wristband agent* is responsible to capture the different needed bio-signals. To do this, the *Wristband agent* uses different sensors. The sensors used are: *GSR and Photoplethysmogram* (Figure2). The GSR measures the galvanic skin response. The measurement is performed by passing through the skin a very low current, and storing small variations in voltage. On the other hand, the Photoplethysmogram is a process of applying a light source measuring the light reflected by the skin. The received signal consists of pulses that reflect the change in vascular blood volume with each cardiac beat. The information captured by each one of these sensors is subsequently preprocessed. This last process allows to convert the measure captured for each sensor in the corresponding units. The GSR sensor converts the measurement of the skin conductance in Ohm and the Photoplethysmogram returns raw data that can be easily processed.



(a) Heart Rate Sensor (b) Skin Resistance Sensor

Fig. 2: View of the employed sensors.

4.2 Emotion Recognition

Once the data has been obtained, it is necessary to implement a machine learning algorithm in order to identify the human emotions. To do this, the process has been divided into two subprocesses. The first one employs a *Fuzzy logic algorithm* in order to obtain the qualitative value (the name of the emotion) of the emotions stored in the employed dataset (which is below explained). The second process employs a *Neural Network* in order to classify new bio-signals inputs from the wristband into emotional values.

The dataset used to train and validate this model is the *DEAPdataset* [7]. The dataset contains physiological signals of 32 participants (and frontal face video of 22 participants), where each participant watched and rated their emotional response to 40 music videos along the scales of arousal, valence, and dominance, as well as their liking of and familiarity with the videos. This dataset integrates different bio-signals as: EEG, GSR, EOG, among other signals. All these signals are associated to the emotional changes using musical videos. Specifically, the authors identified 16 different emotions, which are the following:

1. Pride
2. Elation
3. Joy
4. Satisfaction
5. Relief
6. Hope
7. Interest
8. Surprise
9. Sadness
10. Fear
11. Shame
12. Guilt
13. Envy
14. Disgust
15. Contempt
16. Anger

These emotions are represented following the circumflex emotional model [30][31][32]. This emotional model represents the emotions using three components *Valence, Arousal, Dominance*. In addition, the model evaluates every emotion in a trivalent scale: light, medium, and strong. As a result, the model has 36 possible emotional states.

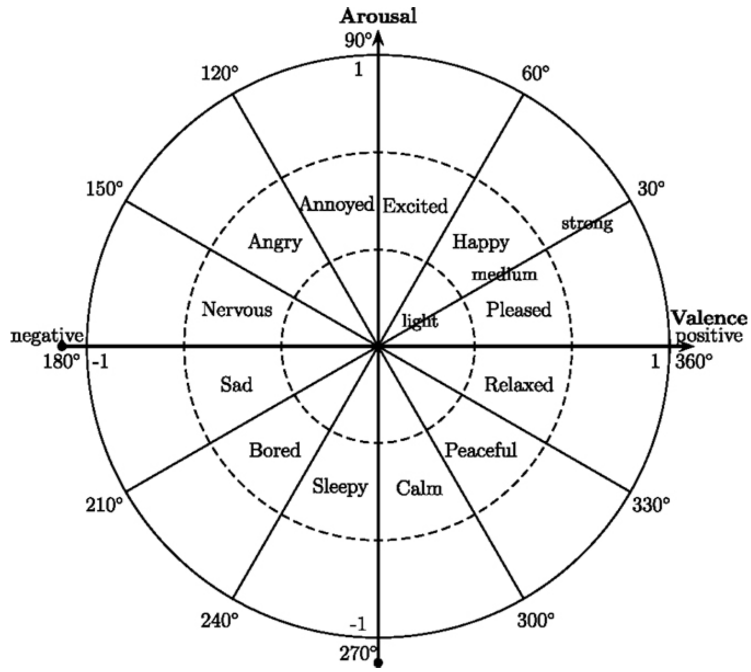


Fig. 3: Circle of emotions (arousal and valence).[31]

This model locates the emotions in twelve sub-quadrants, where each sub-quadrant is discretized in ranges of 30 degrees. The intensity of the emotion is the module of the vector composed by $\overrightarrow{E}(Ag) = [Arousal, Valence]$. The representation of emotions is done using a polar coordinate plane, where one takes into account the angle and the magnitude of the vector (see Equation 1 and Equation 2).

$$r = \sqrt{Arousal^2 + +Valencd^2} \tag{1}$$

$$\theta = \begin{cases} arctan(\frac{Valence}{Arousal}) & if\ Arousal > 0 \\ \frac{\pi}{2} & if\ Arousal = 0 \\ arctan(\frac{Valence}{Arousal}) + \pi & if\ Arousal < 0 \end{cases} \tag{2}$$

Therefore, the emotion is represented as a tuple composed by the radius (r) and the angle (θ) $E(Ag) = \{r, \theta\}$ (all angles are in radians). Based on these data we employ a set of fuzzy logic rules in order to estimate the name of the emotion according to the input values stored in the dataset. These rules allow us to change a quantitative response to a qualitative response. This qualitative response is calculated and stored in the database for all the available registers. Once this has been calculated, the next step is the definition of a neural network, which allow us to identify the human emotions using only the data obtained from the GSR and Photoplethysmogram.

It is necessary to remark that, as each channel of the GSR and the Photoplethysmogram is formed by 8064 different values, it is impossible to build a neural network with these number of inputs. For this reason each channel was sub-sampled, converting each channel in an array of 252 values. Therefore, the neural network has 504 inputs (252 per each channel). The network has also has five hidden neurons and sixteen outputs (each output corresponds with a specific emotion). The architecture of our neural network is shown in Figure 4.

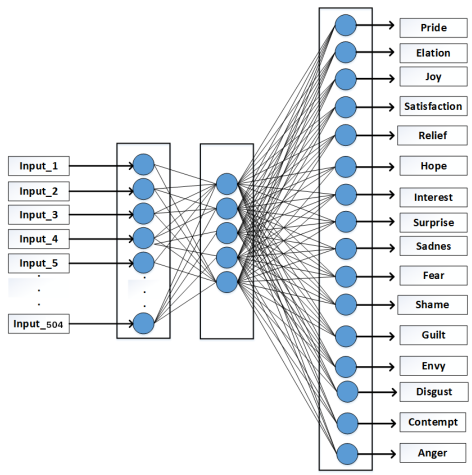


Fig. 4: Neural Network Architecture.

The ANN was trained using a supervised trained methodology, since the objective of the network is to classify the human emotion. Concretely, the training process employed a dataset composed by 1280 entries per channel. As before commented, this information was extracted from the *DEAPdataset*. From the selected dataset, the 20% was used to test and the 80% was used to train.

4.3 Wristband Prototype

This section describes the design of the physical wristband where the *Wristband agent* is executed. The wristband device was programmed in Python and it was embedded in the *Intel Edison* [5] computer-on-module. The Intel Edison (Figure 5) is a new technology designed by Intel which contains a Dual Core IA-32 @ 500 MHz, a 32-bit CPU specially designed for Internet of Things (IoT) applications and wearable computing products.

[5] http://www.intel.la/content/www/xl/es/do-it-yourself/edison.html

Fig. 5: Intel Edison Processor.

The Intel Edison supports *Yocto Linux* [6] and incorporates the *SPADE*[7] platform [33], which is a multi-agent system platform based on Python. As before commented, the prototype has been designed as a wristband in which is deployed the wristband agent. The bio-signals captured in the wristband are passed by an *Analog to Digital Conversion* or *ADC* allowing the discretization of the analogue signals. Figure 6 shows the different components of our wristband prototype which are the following.

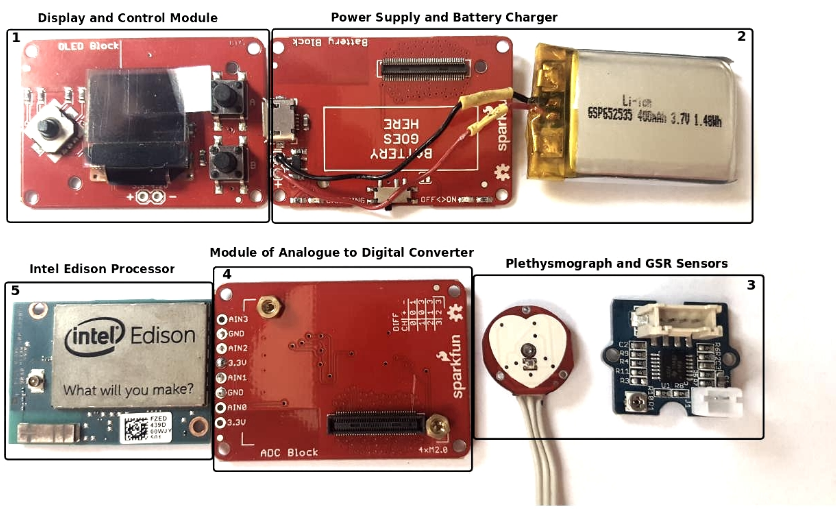


Fig. 6: Components of the Smart Wristband Prototype.

1. Display and Control Module: This module is employed to show information of our emotional state through the LCD screen, and also controls the wristband.

[6] https://www.yoctoproject.org/
[7] https://github.com/javipalanca/spade

2. Power Supply and Battery Charger: This is the power supply system. The wristband uses a 3.7 volt battery.
3. Sensors: Sensors are responsible for carrying out the acquisition of the signals of GSR and Photoplethysmogram.
4. Analogue to Digital Convert: This module is responsible for digitizing the signals captured by the sensors.
5. Intel Edison Processor: This is the microprocessor where the agent is located. It is responsible for performing the processes of emotion recognition and communication with other agents (through the built-in Wi-Fi).

5 Conclusions and future work

This paper presents how to integrate non-invasive biosignals for the detection of human emotional states through an agent-based application. The identification and detection of human emotional states allow the enhancement of the decision-making process of intelligent agents. The proposed application allows extracting (in a non-invasive way) the social emotion of a group of persons by means of wearables facilitating the decision-making in order to change the emotional state of the individuals. As commented before, the application incorporates automatic emotion recognition using biosignals and machine learning techniques, which are easily included in the proposed system. The flexibility and dynamism of the proposed application allow the integration of new sensors or signals in future stages of the project. Moreover, as future work, we want to apply this system to other application domains, specifically the proposed framework fits with the industrial one, for instance representing production lines including the individuals and their emotional states as yet another elements to be considered in the production line.

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