Preliminary Results of IoT-Enabled EDA-Based Analysis of Physiological Response to Acoustic Stimuli

Angelica Poli, Anna Brocanelli, Stefania Cecchi, Simone Orcioni, and Susanna Spinsante(✉)

Department of Information Engineering, Università Politecnica delle Marche, 60131 Ancona, Italy
{a.poli,s.cecchi,s.orcioni,s.spinsante}@staff.univpm.it, a.brocanelli@pm.univpm.it

Abstract. Emotions play a key role in everyday life of human beings, and since several years, researchers have investigated the physiological changes caused by external stimuli, looking for methods to automatically classify the emotional involvement of individuals. The Galvanic Skin Response, or ElectroDermal Activity, is one of the most interesting signals used in emotion research. In this preliminary study, a few participants were submitted to auditory stimuli (i.e., pleasant, neutral and unpleasant sounds) and their skin conductance signals were measured by means of a wireless and IoT-enabled wearable device, the Empatica E4. To investigate the impact of the emotional stimuli, data measured as emotion elicitation and retrieved from the Empatica cloud platform, was analysed in the time domain, showing that pleasant and neutral sounds do not produce evident effects, while listening to an unpleasant sound increases the subjective response, with higher impact when the sound duration is shorter. The preliminary outcomes obtained confirm great intra- and inter-subject variability that deserves further investigation, by involving a bigger population of test users.

Keywords: ElectroDermal Activity · Galvanic Skin Response · Wearable device · Emotions · Acoustic stimuli

1 Introduction

In the last decades, human emotion recognition has gained growing worldwide interest in many application fields, especially healthcare [15] and neuromarketing [25]. Initially, speech analytic [16], facial expressions [7] and self-reports have

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been used for human emotion detection. However, such approaches are not reliable to detect emotions, especially if the subjects under test want to hide their feelings. A reliable approach, on the other hand, may be designed around the use of physiological signals, from which objective measurements can be derived, to detect the actual emotional changes of subjects. Among physiological signals, recently the Galvanic Skin Response (GSR) has gained huge interest, thanks to the availability of wearable devices to measure it, and nowadays it is one of the most involved signals in emotion research. GSR, named also as Electrodermal Activity (EDA) or Skin Conductance (SC), is a biometric index reflecting changes in the electrical properties of the skin [23]. When humans are exposed to stimuli such as images, sounds and physical efforts, the sympathetic division of the Autonomic Nervous System (ANS), with no conscious control, induces a sweat reaction. By using two electrodes positioned on specific regions of the skin surface (e.g., fingers, hand and foot palm), the fluctuations of the skin's electrical properties can be measured [21]. The gathered information is double: the tonic component (i.e., Skin Conductance Level, SCL) related to slow changing baseline levels as individual background characteristics, and the phasic component (i.e., Skin Conductance Response, SCR) corresponding to the fast changing signal contribution which can be event-related [19].

The development of Internet of Things (IoT)-enabled wearable devices with wireless technology support has allowed and facilitated the shift from the measurement of GSR in laboratory settings, usually with bulky wired instruments, to minimally-invasive, comfortable and real-time recordings, in free-living conditions [4] with devices capable of streaming their data to a cloud-based repository.

Hereby we propose an approach to investigate whether and how the GSR signal changes in response to external stimuli, namely auditory ones, by examining the morphological characteristics of this specific physiological signal. In order to measure the impact of auditory emotional stimuli, a small dataset was collected from seven individuals both at rest condition and during the sound listening, using a single wrist-worn device with electrodes located on the bracelet. The information extracted from the GSR signals was compared against the subjects' own evaluation of their emotional status, using a standardised classification scale. After describing the methodology for the acquisition and the elaboration of the GSR signals, the results are evaluated by using statistical metrics.

The paper is organized as follows: Sect. 2 shortly reviews the state-of-the-art about GSR changes under different stimuli and the related issues. Section 3 presents the main steps of the work, including the materials and the methods to collect and process data. Section 5 presents and discusses the results obtained, including statistical metrics used. Finally, Sect. 6 concludes the paper.

2 Background

This section reviews the state-of-the-art about emotion investigation based on the physiological reactions.

By stimulating emotional responses with external stimuli, bodily variations (e.g., heart rate and skin conductance) can be measured. Among the most common stimuli, the video stimuli are widely delivered trying to evoke strong responses [22]. For example, Dominguez et al. [5] used 2 short video clips to elicit sadness, amusement and neutral reactions. The results show that by collecting only the GSR data, the target emotions raised can be well-recognised, especially from Random Forest (RF) classifier (up to 100% of accuracy). However, the physiological changes are highly affected by the subject's personal, cultural and cognitive aspects (e.g., expectations and perceptions) [20]. To tackle this issue, other approaches, like the work proposed by Zhao et al. [27], recorded multi-physiological signals (i.e., EDA, heart rate variability (HRV) and skin temperature), but the average accuracy of the emotion recognition process dropped down to 75.56%. It is interesting to notice how, since the native culture may affect the emotional response, data were collected by Chinese participants before and during watching Chinese video clips.

Other studies employed 2D visual stimuli selected from the International Affective Picture System (IAPS), a large database of pictures [3]. For example Dumitriu et al. [6] evaluated different emotion classification techniques, by extracting 166 images, among which pleasant and unpleasant pictures for exciting feelings, and neutral ones for calm emotions. Also in real-life scenario, Myroniv et al. [14] used images from IAPS as a triggering mechanism for the investigation of positive, neutral, and negative emotions. The proposed system included three off-the-shelf wearable biosensors (i.e., heart rate, EDA, and skin temperature sensors) to measure physiological signals, and six different Machine Learning (ML) algorithms were applied to recognise the corresponding emotional statuses. From the experiments, the proposed system achieved up to 97% recognition accuracy by adopting the k-Nearest Neighbour (k-NN) classifier.

An alternative to visual stimuli is represented by auditory stimuli. In this case, the International Affective Digital Sounds (IADS) [26] database is among the most used repositories, containing a huge collection of sound clips, together with classification labels generated by using the Self-Assessment Manikin (SAM) and three basic-emotion rating scales. However, relatively few studies have investigated the GSR response under auditory stimuli. Pozzi et al. [9], in his master thesis, aimed to understand how the relationship between music and emotion is structured. To do this, he suggested to investigate and to merge the features from both physiological and audio signals. Although the framework reached good results, some issues due to the subjective nature of emotion perception are declared (e.g., the reliability of ground truth data and the evaluation of prediction results). Such issues strongly affect the recognition accuracy, as detailed in [13] where the final percentage shifts from 95% to 70% for subject-dependent and subject-independent classification, respectively. According to Duncan et al. [24], the GSR data are also strictly influenced by the interaction between music and familiarity, which induces learned emotional responses rather than totally unconscious experiences. For this reason, other researchers such as Hu et al. [11], explored the possibility of using combinations of physiological signals (i.e., HRV and EDA) to detect users emotion response to music, considering also the personality and music preferences.

As mentioned above, whatever stimulus is used to elicit an emotion, this is supposed to affect participants' cognitive, and consequently physiological status. To combine the users' perception of an emotional stimulus together with the physiological recordings, self-assessment questionnaires have been used in literature, such as the above-mentioned SAM [2]. However, the mentioned studies are mostly focused on the emotion classification, performed by extracting features to feed and test several ML algorithms. In order to obtain a high performance from such an automatic approach to emotion detection, a detailed analysis of the GSR measurement data properties is essential. Therefore, we propose a preliminary study to investigate the characteristics of the physiological signals in response to acoustic stimuli, namely by analysing the event-related changes in GSR curve morphology. Such signals are measured in real-life contexts, i.e. out of a lab, thanks to the use of the Empatica E4 device, which may open new possibilities in terms of exploitation of physiological information generated from wearable devices.

3 Materials and Methods

3.1 Measurement Device

Data was acquired using a single wearable device, called Empatica E4[1]: a multi-sensor wristband device designed for comfortable, real-time and continuous data acquisition in everyday life. According to the datasheet provided by the manufacturer [8], four sensors are embedded in such a device, namely a photoplethysmographic sensor (PPG), a 3-axial MEMS accelerometer (sampling frequency, $f_s = 32\,\text{Hz}$), an EDA sensor ($f_s = 4\,\text{Hz}$) and optical infrared thermometer ($f_s = 4\,\text{Hz}$).

This specific work was focused on the signal measured by the EDA sensor (see Table 1 for details). Regarding this sensor, the E4 device provides a way to measure the electrical conductance by passing a minuscule amount of current between two silver-coated electrodes in contact with the wrist skin, as they are located onto the device bracelet.

Table 1. Technical specification of the EDA sensor embedded in Empatica E4.

Specification	Value
Sampling frequency (f_s)	4 Hz
Resolution	900 pS
Range	0.01–100 µS
Alternating current (max 100 µA) frequency	8 Hz
Time needed for automatic calibration	15 s

[1] https://www.empatica.com/en-eu/research/e4/.

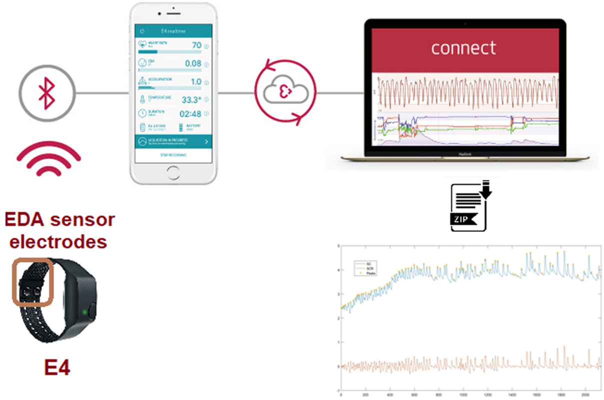

Fig. 1. Graphic representation of the IoT-enabled EDA measurements acquisition process. After the measuring session, data is retrieved through download from the Empatica cloud platform.

The E4 device can be used in two different modalities: streaming and recording mode, with the battery life declared as >20 h and >36 h, respectively. Herein, participants run the device in streaming mode allowing to monitor data in real-time from the mobile App (i.e., E4 realtime) over a Bluetooth Low Energy (BLE) connection. The EDA measurement and data acquisition process is graphically shown in Fig. 1. In order to access and download the recorded measurement data, the users shall create a personal account in the E4 Connect cloud-based repository, in which their own sessions are saved, including details about the duration, the device serial number, and the session date. Raw data can be downloaded as a compressed directory (.zip), containing one .csv file for each sensor and an additional file (named tags.csv) related to events marked during a session. Specifically, the EDA files are organised in single-column format, where the first row reports the starting time (t_0) of the data measurement process, the second shows the sampling rate, then measurement samples from the EDA sensor, giving skin conductance values in microSiemens (μS), are listed. Instead, in the tags.csv files each row represents the time instant in which the physical button located on the E4 has been pressed, expressed in UTC and synchronised with the acquisition start time t_0 specified in the other files, belonging to the same session.

3.2 Test Population and Data Collection

Seven healthy subjects, 2 males and 5 females of age (35.7 ± 17.9) years (mean ± standard deviation), were recruited. To gather their physiological measurement data, participants were submitted to six sessions of auditory stimulation: three sessions lasted 11 min and the remaining ones 12 min, as shown in Fig. 2. Specifically, in the first and last 5 min of each session, the subject's baseline (i.e., EDA data at resting condition) was acquired, while during the central minutes (i.e., 1 or 2 min) the physiological changes under acoustic stimuli were measured. In order to reduce possible distractions during sessions, the participants were left alone in their room, lying on a bed with closed eyes. The E4 was attached on the dominant wrist to acquire the skin electrical signal. Prior to signals registration, volunteers were asked to push the event-marker button of the wristband, at the start and at the end of the acoustic stimulus, thus allowing the real-time annotations of sessions.

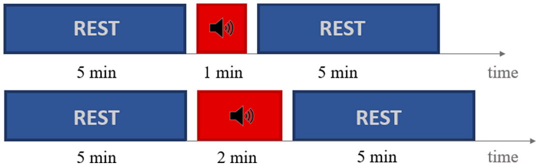

Fig. 2. Schematic representation of the temporal structure of the auditory stimulation sessions presented to the participants: 11 min (upper graph) and 12 min long (bottom graph).

To elicit emotions in volunteers, three audio clips were extracted from the IADS database, which includes a list of sounds categorised in terms of valence, arousal and dominance using the SAM scale. The three clips, lasting 6 s each, were selected considering the associated valence score: pleasant (no. 815: 'RockNRoll'), neutral (no. 722: 'Walking') and unpleasant (no. 275: 'Scream') sound. Table 2 lists the mean and standard deviation values of the three evaluation dimensions of each audio clip chosen from the IADS database, according to female and male subjects.

Table 2. Gender-based evaluation (mean ± standard deviation) of the stimuli (i.e. audio clips) chosen to elicit emotions in the volunteers, for each dimension.

Gender	Sound	Valence	Arousal	Dominance
Female	RockNRoll	8.13 ± 1.41	6.75 ± 2.28	6.99 ± 1.99
	Walking	5.02 ± 1.19	4.87 ± 1.86	4.85 ± 1.41
	Scream	1.65 ± 1.16	8.35 ± 1.32	2.11 ± 1.74
Male	RockNRoll	7.56 ± 1.65	7.00 ± 1.77	6.67 ± 2.00
	Walking	4.61 ± 1.22	5.08 ± 2.00	4.45 ± 1.56
	Scream	2.49 ± 1.94	7.96 ± 1.67	3.04 ± 2.19

Previous studies, such as Akdermir et al. [17], found that stimuli lasting from 2 to 4 min are useful to produce variations of physiological parameters, including the EDA. Therefore, in this study, two playlists with different length were created for each sound, to investigate the effect of the stimulus duration on the elicited physiological changes. Given the fact that audio clips in the IADS database are only 6 s long, in the first playlist the same clip was reproduced ten times, thus obtaining a 1 min-long stimulus, while in the second playlist the audio clip was repeated twenty times, in order to reach a total duration of 2 min. This way, the 2 min-long audio clip allowed to replicate the procedure used in [17]; the 1 min-long clip was added in order to check whether the repetition of the same sound may affect or not the subjects' reaction.

Based on the subjective assessment of sound, the presented audio tracks can elicit different emotions in different individuals. Hence, to measure the emotional response after each sound, participants were provided with the standardised SAM scale to identify themselves with the five different pictographs (scoring from 1 to 9) along the three dimensions. Such scores were compared with the standardised values provided by the IADS database, to investigate whether the experience from our participants was consistent or not with the standardised ranges.

4 Data Processing

In order to accurately analyse the SCR as a reaction to the stimulus, raw data were analysed in time domain, not by resorting to automatic tools (such as LedaLAB[2]) but following the standard procedure described by iMotions [12]. First of all, data from the first and last 4 s within the trials were discarded to remove the artefacts (e.g., transient noise due to the movement of the subjects during the recordings, mostly at the beginning and at the end of each session). Secondly, scanning each signal sample by sample, as in a sliding-window filter, the median EDA was computed for each sample and the surrounding samples in a window of 4 s, centred on the current sample. Such median filter allowed to decompose the phasic component from the EDA signal, and peak-related features were extracted [1,12]. In this sense, we use the phasic component as representing the signal physiological content, and the number of peaks as a meaningful feature to represent the effects of an external stimulus [18], and thus to compare the reaction to different stimuli of a same subject, or to the same stimulus by different people. According to literature [10], a peak-and-through detection algorithm has been developed to identify two thresholds of the SCR curve: the onsets at $TH_{on} = 0.01\ \mu$S and offset at $TH_{off} = 0\ \mu$S. Therefore, an onset was identified when SCR $> TH_{on}$ and an offset when SCR $< TH_{off}$. Then, back to the original EDA signal, for each onset-offset couple, the exact position of each peak was identified and counted as peak. An example is shown in Fig. 3.

[2] http://www.ledalab.de/.

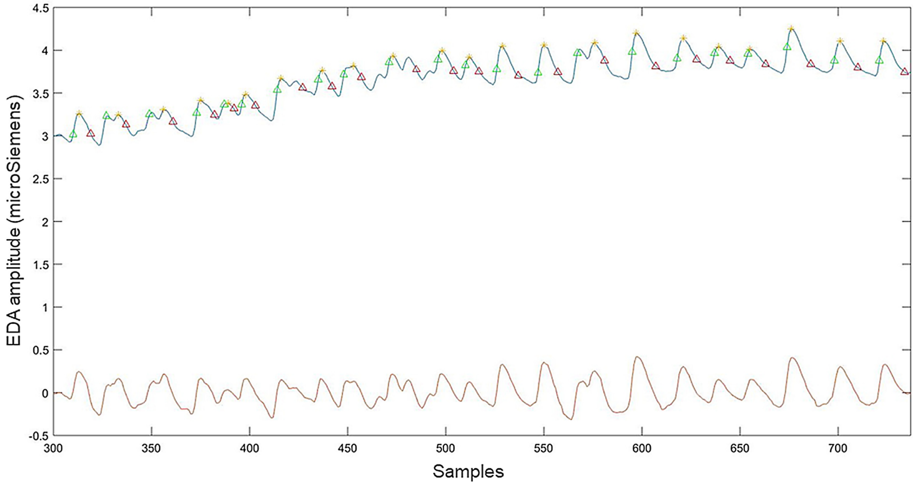

Fig. 3. Example of raw EDA signal (blue) with onsets (green), peaks (yellow) and offsets (red) marked. The SCR signal is in red. (Color figure online)

5 Results and Discussions

In the following sections, the findings from the proposed algorithm described in Sect. 4 are reported and discussed in detail, by comparing the results observed among the subjects involved and among the different acoustic stimuli.

5.1 Comparison Among Individuals

As explained in Sect. 3.2, each session was composed by three parts of different duration. For this reason, the number of EDA peaks per minute was defined (a kind of *peaks frequency*) as a representative metric and counted for each part, in order to understand how the peaks frequency changed during the music listening phase, and in the absence of acoustic stimuli phase, irrespective of the absolute time duration of each phase. Graphs in Fig. 4 show the results of the peaks frequency analysis, with values obtained by averaging the outcomes on the three sessions. For each subject, the orange bar represents the peaks frequency in the first 5 min of acquisition at rest (i.e., pre-stimulus); the yellow bar indicates the rate of EDA peaks in the phase of external stimulation (i.e., stimulus), while the green bar states the number of peaks per minute computed in the last minutes, following the end of the sound clip (i.e., post-stimulus).

By comparing the three columns and the two rows in Fig. 4, especially focusing on the middle phase of acquisition, it is evident that the reaction determined by listening to different sounds is subjective. For example, by examining how much the pleasant sound affects the physiological changes in EDA properties, it is possible to notice that while the subjects S3, S4 and S5 are more sensitive to

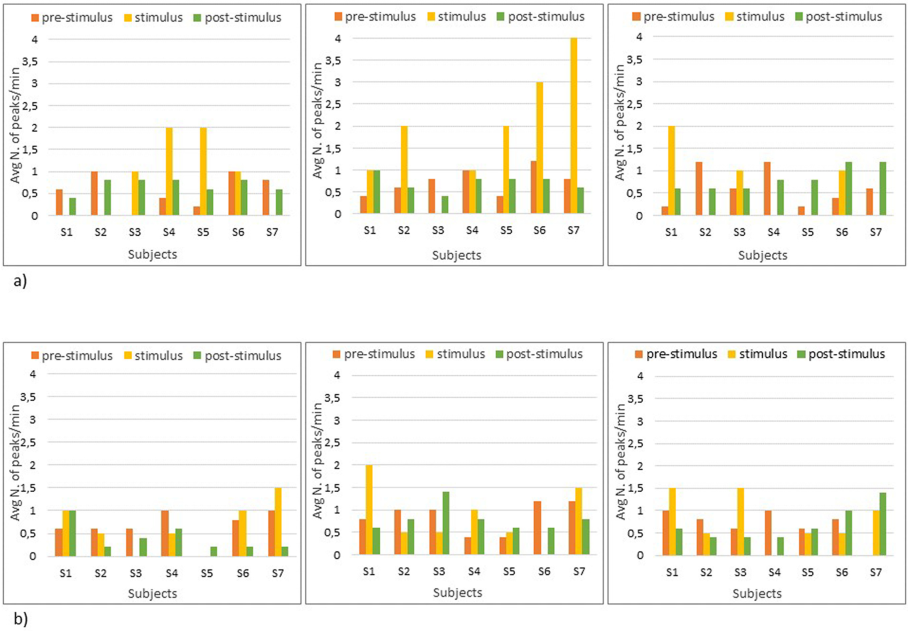

Fig. 4. Average number of peaks per minute recorded on signal acquired during the listening of pleasant (first column), unpleasant (second column) and neutral (third column) sound for each subject: a) one-minute-long sound clip, b) two-minute-long sound clip.

sound clips lasting one minute, the subjects S1, S2, S6 and S7 are more sensitive to pleasant sound two minutes long. Regarding the effect of the unpleasant sound on the EDA signals, in one-minute-long sound clips, six out of seven participants, except S3, show a number of peaks per minute greater or equal to the one recorded during the resting phase (i.e., $\geq$1). This illustrates an increase of the number of peaks per minute from the resting to the stimulating phase. However, when the stimulating period was longer (i.e., 2 min), the number of peaks per minute decreases drastically, even reaching zero for S4. Therefore the subjects S2, S5, S6 and S7 appear to be more sensitive to unpleasant sounds of short duration. Finally, the values obtained from the analysis of EDA signals measured during the listening to the neutral sound are interesting: four out of seven participants, namely S2, S4, S5 and S7, show an average peaks frequency that increases from 0 to higher values under longer stimuli. The opposite considerations can be applied to S6.

5.2 Comparison Among Different Acoustic Stimuli

In this section, the results obtained from the analysis of signals acquired during listening sessions of pleasant, neutral and unpleasant sounds are compared. In particular, the peaks rate was averaged over all the participants, in order to obtain a single value for each sound listened to, for both the sound clip lengths. Figure 5 displays the findings from acquisitions with the external stimuli lasting one minute (left side), and two minutes (right side).

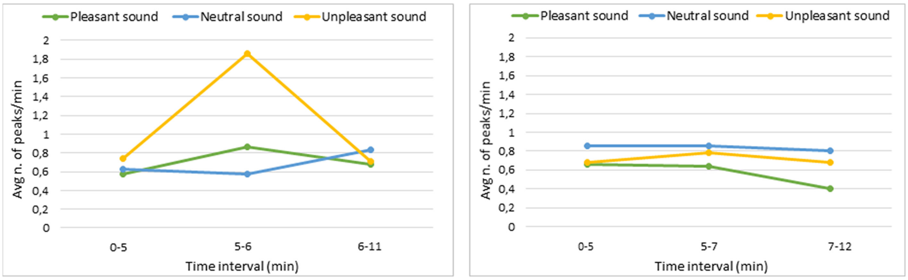

Fig. 5. Changes in average EDA peaks rate over all subjects: before, during and after the listening of pleasant (green line), neutral (blue line) and unpleasant (yellow line) sound clips, lasting one minute (left side) and two minutes (right side). (Color figure online)

According to the first analysis among the subjects, it is evident how the acoustic sounds produce different effects on the EDA signals of the listeners, depending on both the length and the valence score of the sound clip. Specifically, the unpleasant sound elicits a different effect depending on the time duration of the stimulus. Looking at the effects of unpleasant sound stimulus lasting one-minute, it is possible to see an increase of EDA peaks per minute during the period of sound listening, and then it returns close to starting values. However, slight changes and variations are observable in unpleasant sounds lasting two minutes, as well as when using neutral sounds as external stimulus.

In order to explore if the physiological response of the participants was somehow associated to the emotional experience, we compared the SAM scores declared by the participants, given in Table 3, and the number of peaks per minute counted from the EDA signals.

Table 3. Average scores of valence, arousal and dominance and related standard deviation for each sound clip listened, over all the tests participants.

	Valence	Arousal	Dominance
RockNRoll	7.1 ± 0.8	6.9 ± 0.7	6.5 ± 1.1
Walking	5.3 ± 0.5	4.0 ± 0.9	5.1 ± 1.5
Scream	2.3 ± 0.8	6.7 ± 0.9	3.1 ± 1.1

The values rated by subjects involved in our experimental test are comparable to the standardised scores in IADS database: the ‘RockNRoll’ and ‘Scream’ sounds were evaluated as arousing, while the 'Walking' as a relaxing sound. Even though both the pleasant and unpleasant sounds have a high and quite similar arousal score, 'Scream' was assessed with a low value of valence, that corresponds to an unhappy emotional state according to the SAM scale. Regarding the dominance and control dimensions, the 'Scream' elicited subjects feeling dominated and dependent on the sound, the 'RockNRoll' sound produces a sensation of maximum control in the situation, while the 'Walking' sound was rated as neutral.

6 Conclusion

EDA (or equivalenty GSR) is a biometric signal reflecting changes in the electrical properties of the skin, produced by external emotional stimuli [23]. In this work, the EDA signal was measured by using the E4 wristband and then processed in time domain, by evaluating the effects of different type and length of acoustic stimuli, in a small population. In particular, the number of peaks per minute of the EDA curve was counted, being the event-related feature, and then compared among the subjects and among the stimuli. Regarding the unpleasant sound, the same effect (i.e. an increase of EDA peaks per minute during the listening period) in almost all individuals was presented especially for short sound, probably due to the track played: an unexpected and well-known annoying sound (i.e., 'Scream'). Probably, the negative emotion was able to induce a high sweat reaction, and consequently evident physiological changes. However the same reaction, if the external stimulus is too long, can be affected by the habituation phenomenon, resulting in a lower number of peaks per minute in the EDA curve. Contrarily, the findings from the pleasant and neutral stimuli are more randomly distributed. Many subjects did not show any physiological reaction to 'Walking' and 'RockNRoll' sounds, especially when presented the one-minute-long tracks.

In general, the results confirm that the physiological changes in EDA are visible, but subjective. Even though different individuals can share some emotional status or mental perception of the same sound track (as declared in SAM scale scores), their physiological features can have significant differences. This statement is evident for pleasant sound, where high perception of affective valence and intensity corresponds to a small number of peaks during the stimulation. Contrarily, the low valence and high arousal of 'Scream' sound can be strictly associated to the bigger number of peaks during the elicitation of an unpleasant experience.

Although the results of this preliminary experiment are promising, some clear limitations rely in the use of a single audio clip per IADS category, the small population affected by gender imbalance, and the use of the time-domain peak detection approach alone. More accurate findings can be achieved by enrolling a wider and more heterogeneous population in terms of gender and age. For example, the different perception of an external stimulus (e.g. acoustic), and consequently the resulting EDA fluctuations can be compared among males and females of different ages. Additionally, also selecting more sound tracks of the same valence scores from the IADS database, can allow to obtain more generalised and reliable findings. These activities are foreseen as future developments of the research.

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