# Skin Conductance Under Acoustic Stimulation: Analysis by a Portable Device

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**Abstract.** Skin Conductance (SC) variations, or, alternatively, changes of the human skin resistance known as Galvanic Skin Response (GSR), allow to detect the physiological reactions of a subject to different stimuli, either physical, or emotional and cognitive. This paper presents the analysis of SC variations under acoustic stimulation, performed by using a low-cost portable device designed for experimental use, able to acquire the human skin resistance values, which can be easily converted into SC ones. Preliminary findings, despite not generalizable because of the small set of participants involved in experiments, suggest that the reaction to sounds perceived as not pleasant is quite clear to identify, while further investigations are needed for acoustic stimuli classified as pleasant.

**Keywords:** Skin conductance · Acoustic stimulation · Portable device · Emotional state recognition

## 1 Introduction

In recent years, several hardware technologies and signal processing techniques have been developed to integrate different physiological measures into single portable or wearable devices, often enabled with wireless connectivity (according to the Internet of Things paradigm), with the aim of acquiring a broad range of parameters to evaluate different dimensions of an individual's status, from the physical and health-related ones [11,32], to the cognitive and emotional ones [7,9,24].

Among the signals of interest to collect, the Skin Conductance (SC), also known as Galvanic Skin Response (GSR) or Electrodermal Activity (EDA), plays

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an important role, especially to investigate the relationship between physiological status and external stimuli, such as sensory, emotional, cognitive or physical ones [1,21,34]. The electrodermal activity reflects the changes in electrical conductance of the skin, which is modulated by sweat glands activity. An increase in sweating, mostly composed by water, increases the capability of the skin to conduct an electrical current. As all the eccrine sweat glands spread over the body skin are involved by emotion-evoked sweating, it is recognised that SC may provide a quantitative functional measure of the human symphatetic functions, such as cognitive or emotional arousal [17]. When a subject is exposed to some physical, emotional or cognitive events, the activity of the Autonomic Nervous System (ANS) affects the secretion of sweat glands, resulting in a variation of the EDA values [4].

Actually, the EDA signal consists of two main components, namely tonic and phasic levels. The tonic level, known as Skin Conductance Level (SCL), reflects slow changes in skin conductance, depending on skin dryness, hydration and automatic regulation. Instead, the phasic level or Skin Conductance Response (SCR) represents the dynamic changes associated to stimuli [4]. Hence, the SCRs induced by skin sweating are indicators of both psychological [5] and emotional status [38] of the considered individual.

Regarding the emotional status, acoustic stimulation is possible to induce emotional reaction and to affect physiological responses on humans. Three different types of audio stimuli are reported in the literature: (i) speech, (ii) music and (iii) general sounds, i.e., non-verbal and non-musical sounds [37]. In particular, music has the ability to regulate humans' emotions [25]; conversely, an individual's mood may affect preferences in music listening [12]. A possible mechanism behind the aforementioned regulation may be that music initiates brainstem responses, which successively modulate SC, as well heart rate, blood pressure, body temperature and muscle tension [6]. In addition to the brainstem responses, five more mechanisms, namely evaluative conditioning, emotional contagion, visual imaginary, episodic memory and musical expectancy are hypothesized to be involved in the musical induction of emotions [26]. The analysis of the above mechanisms is out of the scope of this work. As regards the humans' sense of hearing, the auditory nervous system is responsible for the conversion of the soundwave delivered at the entrance of the outer ear into information to the human brain. Sound reaches as soundwave (i.e., increase and increase of air molecules' pressure) at the entrance of the outer ear and, after passing the ear canal, it vibrates the tympanic membrane (i.e., transformed to mechanical energy). Following, within the cochlea, vibration is converted to electrical signal by the auditory hair cells, which in turn is delivered through the auditory nerve to the brainstem. [2,19].

As acoustic stimuli may elicit individuals' arousal, the acquisition of the corresponding EDA signals may support a quantitative evaluation of the generated effects. EDA signals may be collected in a so-called endosomatic fashion, meaning that no external source of electricity is used, or by an exosomatic approach, in which electrodes in direct contact with the skin allow to apply a constant current or voltage source. The second approach is far more common in wearable devices, as it does not require to collect the voltage between an active site and a relatively inactive one of the skin, despite the design of the corresponding acquisition device would be simpler in the former case. Using the exosomatic approach, the Ohm's law is exploited to compute the skin conductance (or conversely, its resistance) by measuring how the applied current or voltage is modulated by the electrodermal activity of the subject.

In this context, the aim of this work is to acquire SC signals through a portable low-cost device, and to analyse their variations under acoustic stimulation. The advantage of using a simple and low-cost portable device to collect SC signals relies in the possibility to run different types of experiments without the use of bulky equipment, and to have full control of the system settings [13]. Raw signal samples can be collected and processed by means of algorithms selected or designed on purpose, depending on the specific study targets [22]. In this work, the portable device was used to collect SC signals from six subjects, starting from their baseline EDA, then moving to the acquisition of their galvanic skin response as a result of different types of auditory stimulation, namely audio tracks of different genres. Acquisitions were performed out of laboratory settings, thus allowing a more realistic footprint of the subjects' reactions.

The paper is organized as follows. Section 2 describes the background studies on the effects of audio stimulation and on measurement devices for SC. Section 3 introduces the prototype components used for the experiments and explains the data collection procedure. Section 4 discusses the experimental results. Finally, Sect. 5 reports the conclusions.

## 2 Background

Many studies on the effects of the audio stimulation on human beings can be found in the literature. In particular, knowing how a particular audio stimulus can affect the listener is an important task for all the applications where a personalized listening experience is required. In [31], a genre-free model of five factors is introduced to classify the music preference of a subject in terms of emotional/affective responses. In [12,35], the audio equalization preference was investigated through subjective tests, that have proved the tendency of choosing a personalized equalization. In the last years, studies have aimed at finding a more objective evaluation of the perceived sound, comparing to the subjective self-reporting procedures. Furthermore, listening experience should be evaluated under real life, out-of-lab conditions and not through time-consuming, self-reporting, in-lab procedures. Thus, an alternative is the evaluation through physiological parameters measurements [29] collected by means of portable and easy-to-use devices.

In this context, the GSR signal has raised attention as a possible way to attain a more objective evaluation of the audio stimuli from the listeners' point of view, contrary to the mostly subjective self-reporting procedures. Additionally, a listener's GSR may be acquired during the process of auditory stimulation in a minimally invasive fashion, without interfering or interrupting the listening experience. This section reviews the works found in literature and related to GSR measurements under audio stimulation.

Several works aim at investigating the relationship between the GSR and the emotion induced on a listener by an audio stimuli. In recent works, the relationship between GSR and the pleasure induced on the listener [16,20,28], as well the arousal induced on the listener [16], considering the ground truth pleasure and arousal values taken by the IADS database [39], was investigated. In [36], the GSR measurement under music stimulation indicated that subjects not involved in music or not enjoying music gave little response of GSR. Moreover, GSR was used in [3] to measure the relaxation induced to individuals under the effect of binaural phenomena, in [30] to evaluate the effect of 3D sound on relaxation, and in [38] to test peoples' emotional responses to horror music. In [8], the effect of environmental noise on GSR was investigated. In [40], Zhang *et al.* presented the PMEmo dataset, which contains the perceived valence and arousal annotations of 794 songs along with the simultaneous GSR signals acquisitions. Except from the emotion, sound quality is another very important attribute to investigate. In fact, in [29], the correlation between the subjective assessment of perceived sound quality and the GSR was analyzed, however the meaningfulness of the specific physiological parameter for the sound quality evaluation was not able to be proven. Despite there is not, to the authors' best knowledge, a formal protocol for GSR acquisition under audio stimulation, it was observed that the aforementioned experimenters followed, some to a greater and others to a lesser extent, the following principles:

- The GSR of every participant is recorded during both, the presence and the absence (i.e.,"baseline" period) of audio stimulation. Different factors (e.g., skin dryness, nervousness, temperature) result to different "baseline" GSR among participants [3]. Thus, the knowledge of GSR under no audio stimuli is necessary for calibrating the acquisitions of each participant under audio stimuli.
- Any external stimulation, besides the audio under examination, should be avoided during the GSR acquisition. Thus, GSR acquisition has been mostly conducted under in-lab conditions, to avoid any other undesirable cognitive process that could affect the GSR, and eyes are required to be closed to avoid any visual interference.
- The audio stimuli duration is not too long, to avoid the habituation phenomenon (i.e., the familiarization of the participant with the stimuli).
- The audio stimuli order presentation should be randomized to avoid the ordering effect.

### 2.1 Commercial Portable Devices for SC Acquisition

Looking at the commercial portable devices for SC-based monitoring found in the market, it is relevant to notice how there is not a huge variety of choices available, and most of them are quite expensive. The different options are presented in the following paragraphs.

The *Empatica E4* is a clinically validated device (Class IIa Medical Device according to 93/42/EEC Directive), equipped with four monitoring sensors, namely a 3-axes accelerometer, a photoplethysmography (PPG) sensor, an optical thermometer and an SC sensor. In particular, the SC sensor detects the electrical conductance across the skin by passing a very small alternating current (8 Hz frequency, 100 μA peak-to-peak amplitude) between two dry electrodes located on the bracelet, in contact with the bottom wrist. SC signals are collected at a sampling frequency 4 Hz, with a dynamic range of 0.01–100 μS and a resolution of 900 pS. The device may operate either in streaming and recording mode, and comes with a desktop application (E4 Manager) to transfer data to a cloud repository; a web application (E4 Connect) to visualize and manage data; a mobile application (E4 RealTime) to stream (via Bluetooth Low Energy) and visualize data in real-time, on mobile devices. Since a few months, the device has been discontinued by the manufacturer, so in the future it will be not available anymore for research studies. The device has been used in research studies, to measure the impact of auditory emotional stimuli [28], or to recognize the user emotions while watching short videos [41].

The *Empatica Embrace* is equipped with four sensors, namely a 3-axial accelerometer, a thermometer, a 3-axial gyroscope and an SC sensor. The last one detects the SC with a dynamic range of 0–80 μS and a resolution of 900 fS, at a sampling frequency 4 Hz. Specifically, three electrodes located on the bracelet and in contact with either the ventral (inner) and dorsal (outer) wrist are passed by an alternating current 4 Hz maximum frequency. Data are continuously sent via Bluetooth, and analysed in real-time to identify unusual patterns in movement and skin conductance. In fact, the smartband has been mainly involved in studies for seizure tracking and epilepsy management.

The *Gobe2* smart band is equipped with four embedded sensors, namely a bioimpedance sensor, an accelerometer, a piezo sensor and an SC sensor. For what concerns the individual's emotion, the *Gobe2* detects a so-called emotional tension, strictly associated with feelings and mood, by analysing the changes in cutaneous sweating. After evaluating these changes, the smart band notifies the users about their emotional status, with a vibration and a message on the display. The manufacturer declares that *GoBe* can detect the human stress, by using derived measurements, namely heart rate, previous night's sleep quality and personal details (i.e., weight, height, sex and age). A fully charged *GoBe2* can transfer data, through BLE, to a dedicated app and work for up to 48 h. No further details about the SC sensor are available, to the best of authors' knowledge.

The *Moodmetric* is a ring device specialised for measuring the SC: it collects SC levels and converts them into a scale ranging from 1 to 100, where higher values indicate higher arousal that can have either positive (e.g., excitement) or negative valence (e.g., stress). Approximately, the scores in the range 1–20 reflect a state of deep relaxation (e.g., meditational state); from 21 to 40, a regular

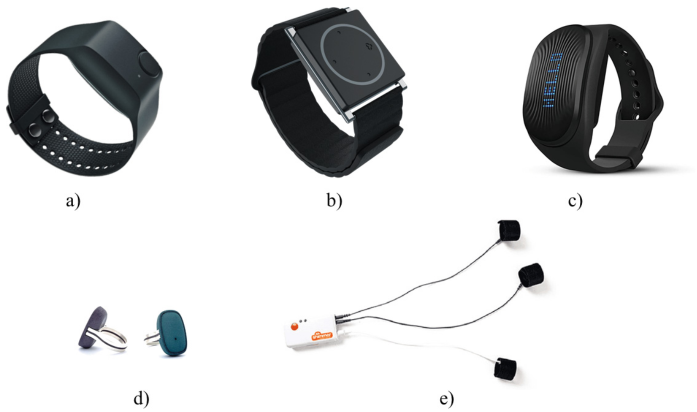


**Fig. 1.** SC-enabled portable devices available in the market: a) Empatica E4, b) Empatica Embrace, c) Gobe2, d) Moodmetric rings, e) Shimmer GSR+.

relaxation (e.g., walking); range 41–60 denotes mild activities (e.g., talking); 61–80, arousal during elevated activity (e.g., working under mild pressure); and 81–100, high arousal such as strong emotions. No details are available about the way these ranges are estimated from the raw data collected from the device, which is transferred by Bluetooth connection to a computer, for long term storage.

Finally, the *Shimmer3 GSR+* unit provides connections and pre-amplification for one channel of GSR data acquisition, and it is suitable for measuring the electrical characteristics or conductance of the skin, as well as jointly capturing an Optical Pulse/PPG signal to estimate heart rate, using the Shimmer ear clip or optical pulse probe. The collected samples are processed by a companion PC software, to compute different data features. The above mentioned devices are shown in Fig. 1.

As described above, specific algorithms for each device are able to process the collected raw data and provide the user with an output figure or index related to stress, or other conditions. Such processing typically takes place at the firmware level, or at the application level of a companion software, and related details are not available to users. This prevents the possibility to access the true signal samples, and to design or test different approaches to filtering or processing, e.g., for research purposes, as well as to evaluate precision and accuracy of the measured values. For this reason, it may be useful to setup a portable and low-cost device for SC that allows to collect unprocessed raw signal samples, for experimental usage.

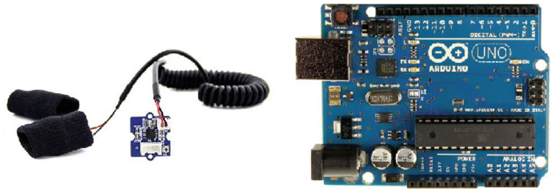


**Fig. 2.** The GSR-Grove sensor (left) and the Arduino UNO board (right).

## 3 Materials and Methods

### 3.1 Prototype Components

The prototype designed for the acquisition of the SC signal in this study is based on the Arduino UNO embedded platform, equipped with an ATmega328P microcontroller, and a GSR-Grove Sensor v1.2 [33], as shown in Fig. 2. The prototype collects samples of the skin resistance, thanks to two embedded Nickel electrodes worn in direct contact to the finger skin, applied through two small velcro bands. The GSR sensor operates at 3.3 V or 5 V, and its sensitivity may be adjusted via a potentiometer. A 4-wire cable is used to connect the GSR sensor to the Arduino UNO board. The signal acquired by the sensor is the skin resistance, encoded into an analogue voltage reading. To remove glitches, the code embedded into the firmware computes the average resistance value over 20 samples, in a 100 ms time interval. This way, resistance samples are acquired at a frequency 10 Hz. The analog skin resistance values are converted into 10-bit digital ones. It follows that the digital resistance values will range from a minimum of 0 to a maximum of 1023. By acting on the sensor potentiometer, the open circuit output (i.e., when the electrodes are not applied on fingers) may be set to 512, i.e., at the center of the output values range, to take advantage of the whole sensor dynamics. When using the device, power is preferably provided by an external supply, for better signal stability, and a USB cable connected to a PC allows to save data values into a file, for further processing.

### 3.2 Data Collection Protocol

In a first data collection session aimed at acquiring signals of relaxation state at rest condition, 2 young subjects (both 23 years old) were involved. Since fingers are among the most sensitive SC measurement sites and strongly respond to stimulation [27] (together with hand palms and foot soles) the sensor electrodes were placed on both index and middle fingers of the non-dominant hand with velcro stripes, as shown in Fig. 3. Following the open-circuit calibration of the device, the electrodes were suitably worn for ensuring the best adherence on the skin, and guaranteeing an accurate acquisition. As suggested in [23], prior to collecting data, the two individuals were instructed to breathe normally, keep limb movements to a minimum, try not to talk, and seat comfortably in a natural position. This procedure aimed to collect the subject's basal state and also to minimize artefacts.

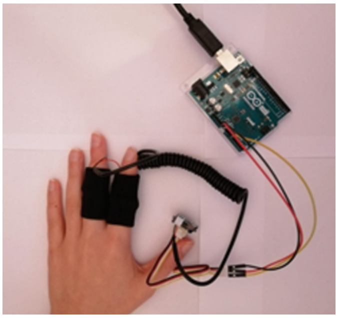

**Fig. 3.** Position of the wearable Arduino-based Grove GSR sensor.

GSR values were collected for 7 days, 3 times per day (i.e. after breakfast, after lunch, and after dinner) with a duration of 5 min per each acquisition. A total of 105 min of data, for each individual, was recorded in a week. Such data, acquired with the sampling frequency set 20 Hz, was transferred by directly connecting Arduino platform to a PC, saved in .txt files by using Coolterm software tool, and then analysed in Matlab environment.

Then, a data collection protocol was defined for experiments with acoustic stimulation. Six subjects, 5 females and 1 male, in the age range 20–51 years, were asked to lay supine on a bed, with arms at their sides, and to settle in a comfortable position. A bedroom was chosen as a recording environment, paying attention to have controlled ambient conditions to put the subjects at ease, and avoid light stimuli. Before connecting the equipment, some precautions were suggested to make the acquisitions more precise: it was asked to breathe normally, to relax and to avoid movements as much as possible, so as to minimize artifacts on the acquired data. The Arduino GSR sensor was applied with its power and ground electrodes respectively connected to the index and middle fingers of each subject's left hand, at approximately the height of the last phalanx, as shown in Fig. 3. As a last indication, subjects were asked to place the palm of their hand on the surface of the bed, to improve the coupling and reduce artifacts due to involuntary movements.

Performed acquisitions consisted of two phases: the former, lasting between 10 and 15 min, took place in the absence of audio stimuli to derive the subject's baseline GSR. In the latter phase, each subject listened to 5 audio tracks of different types and duration, played in a randomized order, then expressed how pleasant each listening was, with values from 0 (i.e. no liking at all) to 100 (i.e. extreme satisfaction). The audio tracks used as stimuli belong to the following genres: Track 1 - classical music, Track 2 - jazz music, Track 3 - white noise, Track

4 - rock music, and Track 5 - snoring noise. During both the sessions, subjects were provided with active noise canceling headphones, strongly recommended to improve listening quality and isolate from disturbances.

### 3.3 Data Processing

According to the Grove-GSR Sensor datasheet [33], the raw GSR data consist of time instants and the corresponding sensor values. Such data were firstly converted into human resistance (i.e. GSR) values, expressed in $\Omega$, according to Eq. (1):

$$GSR[\Omega] = ((1024 + 2 \times SPR) \times 100000)/(512 - SPR), \quad (1)$$

where $SPR$ stands for Serial Port Reading, i.e., the value displayed on the Serial Port (between 0 and 1023). From the skin resistance values output by the sensor, a conversion to skin conductance (given in µS) may be performed according to Eq. (2):

$$SC[\mu S] = 10^6 * (1/GSR[\Omega]) \quad (2)$$

Since the GSR signal (and the SC one as well) is an aggregate of two different components, the signals acquired were decomposed into tonic and phasic components. Inspired by the approach described in [23], the tonic component was obtained by applying the basic median filter to the entire signal. In particular, considering sample by sample, the median GSR was computed for each sample and the surrounding samples in the 4 s time interval centred on the current sample (i.e., 80 samples before and after the current one). The phasic component is obtained by subtracting the tonic one from the original GSR signal. Among the most common methods to analyse the phasic component, a classic one is the through-to-peak detection [10, 15], which is achieved by finding the onset and

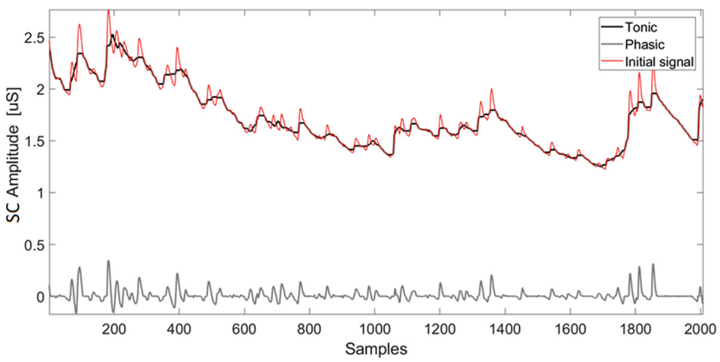


**Fig. 4.** A sample SC signal generated by processing the Arduino GSR sensor data, and its tonic and phasic components.

offset of signal's peaks. According to the physiological definition of the parameters of phasic electrodermal activity curve [4,23], the onset is generally set to the time point where the curve exceeds a minimum amplitude criterion. Hence, setting two thresholds (peak onset and offset, $TH_{ON}$ and $TH_{OFF}$) an onset is identified when the signal goes over $TH_{ON}$ and an offset when the signal gets below $TH_{OFF}$. Then, back to the unfiltered GSR data, the maximum GSR value within each pair of onset and offset is computed and labelled as a GSR peak. From these values, the GSR amplitude is obtained as the difference in signal magnitude at the onset and the peak value.

An example of an SC signal (derived from the GSR one, based on Eq. (2)), from which the phasic and tonic components have been extracted, is shown in Fig. 4.

To analyse the collected data under acoustic stimulation, following the conversion of the values displayed on the Serial Port by the Arduino GSR sensor into GSR (i.e., human resistance), according to Eq. (1), then the initial and the final 10 samples of each acquired signal were removed, to eliminate the transient error and select the GSR data of interest.

## 4 Results and Discussion

Since everyone has a specific physiological responsiveness at rest, the measured GSR is subjective, depending on the individual. Generally, an initial baseline measurement is carried out for a few minutes, followed by the GSR activity's recording. This procedure allows to identify the so-called *baseline*, that includes individual GSR features and the differences among physiological condition at rest. Moreover, it allows to avoid some issues related to dry skin or undesired environmental stimuli [18]. An example of different neutral baseline signals from two subjects is reported in Fig. 5.

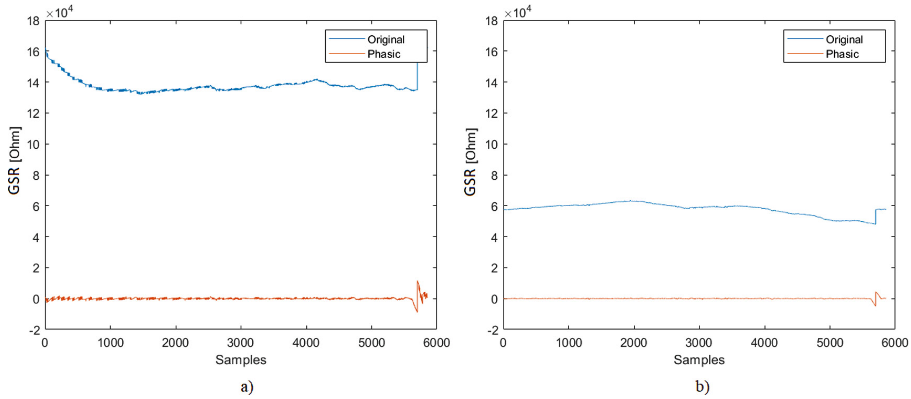


**Fig. 5.** Baseline of GSR data recorded for a) subject 1, and b) subject 2, during session 4.

**Table 1.** Number of peaks related to the GSR signals of subject 1.

| | Day 1 | Day 2 | Day 3 | Day 4 | Day 5 | Day 6 | Day 7 |
|---|---|---|---|---|---|---|---|
| Session 1 | 248 | **334** | 156 | **1538** | 396 | 429 | 389 |
| Session 2 | **259** | 283 | **449** | 432 | **402** | **464** | 381 |
| Session 3 | 128 | 251 | 401 | 320 | 356 | 438 | **396** |

**Table 2.** Number of peaks related to the GSR signals of subject 2.

| | Day 1 | Day 2 | Day 3 | Day 4 | Day 5 | Day 6 | Day 7 |
|---|---|---|---|---|---|---|---|
| Session 1 | 219 | 130 | 173 | 185 | 245 | 263 | 139 |
| Session 2 | 326 | **443** | 266 | 237 | 358 | **361** | 322 |
| Session 3 | **480** | 231 | **428** | **390** | **394** | 315 | **389** |

Tables 1 and 2 detail the results obtained in the first analysis of this experiment, respectively for the subject 1 and 2. More specifically, in this phase, the number of GSR peaks was counted for each recorded session (i.e., three times per day), and the highest number of peaks achieved in a day was highlighted.

The second analysis was focused on the computation of two statistical figures, namely the average peaks amplitude [$\mu_p$, in $\Omega$] and the corresponding standard deviation [$s_p$, in $\Omega$]. The weekly results related to the three sessions performed by the two subjects are summarized in Table 3.

In this study, we used the number of peaks on the phasic component as representing the signal physiological content, whereas the mean amplitude of peaks and the corresponding standard deviation metrics were considered for a quantitative analysis of the GSR signal variations.

As underlined in Tables 1 and 2, while the highest number of peaks for the second subject was mainly achieved in the evening sessions (i.e., Session 2), for the first subject it was achieved in the afternoon sessions (i.e., Session 3). Moreover, it is interesting to notice how the signals acquired by the first subject had a number of peaks several times exceeding those acquired by the second individual. The second part of experiment was focused on the evaluation and discussion of the highest average amplitude and standard deviation of peaks. As shown in Table 3, the highest values of average amplitude were reached in both Session 2 and 3, respectively for the subject 1 and for the subject 2. Moreover, almost in the overall sessions, it can be noticed the inverse proportion between the number of peaks and the average amplitude. This relation trend is much more evident in the second subject than in the first one. Indeed, considering the subject 1, the highest number of peaks may be associated to the shortest average amplitude in three out of seven days, while considering the subject 2, in six out of seven days the number of peaks increases where the average amplitude decreases. The values of standard deviation also confirm the high daily variability of the signal. However, a common trend may be observed in the majority of days. In fact, almost in the overall session, both the subjects showed the highest standard deviation in the morning acquisition. Contrarily,

**Table 3.** Average Amplitude ($\mu_p$, in $\Omega$) and Standard Deviation ($s_p$, in $\Omega$) of GSR peak values, related to both subject 1 (on the left) and subject 2 (on the right).

| Day | Session | $\mu_p$ [$\Omega$] | $s_p$ [$\Omega$] |
|---|---|---|---|
| Day 1 | Session 1 | 85.7 | 296.3 |
| | Session 2 | 40.4 | 441.5 |
| | Session 3 | 174.2 | 330.7 |
| Day 2 | Session 1 | 71.8 | 366.9 |
| | Session 2 | 17.2 | 79.8 |
| | Session 3 | 31.9 | 116.4 |
| Day 3 | Session 1 | 483.2 | $1.1 \times 10^3$ |
| | Session 2 | 22.3 | 168.2 |
| | Session 3 | 18.7 | 163.4 |
| Day 4 | Session 1 | 64.1 | 493.9 |
| | Session 2 | 7.0 | 144.8 |
| | Session 3 | 27.9 | 198.5 |
| Day 5 | Session 1 | 14.6 | 234.1 |
| | Session 2 | 30.5 | 205.8 |
| | Session 3 | 212.4 | $2.9 \times 10^3$ |
| Day 6 | Session 1 | 34.3 | 318.8 |
| | Session 2 | 42.5 | 417.2 |
| | Session 3 | 0 | 0 |
| Day 7 | Session 1 | 23.3 | 460.3 |
| | Session 2 | 22.1 | 162.6 |
| | Session 3 | 19.4 | 157.6 |

| Day | Session | $\mu_p$ [$\Omega$] | $s_p$ [$\Omega$] |
|---|---|---|---|
| Day 1 | Session 1 | 87.4 | 260.4 |
| | Session 2 | 11.1 | 98.3 |
| | Session 3 | 4.8 | 41.4 |
| Day 2 | Session 1 | 184.5 | 376.7 |
| | Session 2 | 8.1 | 130.3 |
| | Session 3 | 17.7 | 63.8 |
| Day 3 | Session 1 | 139.8 | 293.3 |
| | Session 2 | 19.2 | 83.3 |
| | Session 3 | 4.3 | 53.3 |
| Day 4 | Session 1 | 56.7 | 152.7 |
| | Session 2 | 141.6 | 370.8 |
| | Session 3 | 1.6 | 22.2 |
| Day 5 | Session 1 | 46.5 | 134.4 |
| | Session 2 | 19.4 | 114.4 |
| | Session 3 | 3.6 | 37.3 |
| Day 6 | Session 1 | 100.6 | 354.2 |
| | Session 2 | 11.7 | 65.5 |
| | Session 3 | 19.5 | 77.9 |
| Day 7 | Session 1 | 104.3 | 214.3 |
| | Session 2 | 13.6 | 89.8 |
| | Session 3 | 28.7 | 321.3 |

**Table 4.** Mean value ($\mu$) and standard deviation (s) of the GSR, and percent pleasure value (Ple.), for each track and subject.

| | Subject 1 | | | Subject 2 | | | Subject 3 | | | Subject 4 | | | Subject 5 | | | Subject 6 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | GSR $\mu$ [$\Omega$] | GSR s [$\Omega$] | Ple. [%] | GSR $\mu$ [$\Omega$] | GSR s [$\Omega$] | Ple. [%] | GSR $\mu$ [$\Omega$] | GSR s [$\Omega$] | Ple. [%] | GSR $\mu$ [$\Omega$] | GSR s [$\Omega$] | Ple. [%] | GSR $\mu$ [$\Omega$] | GSR s [$\Omega$] | Ple. [%] | GSR $\mu$ [$\Omega$] | GSR s [$\Omega$] | Ple [%] |
| Baseline | 493 | 8 | −− | 437 | 15 | – | 336 | 16 | – | 140 | 36 | – | 426 | 4 | – | 445 | 3 | – |
| Track 1 | 474 | 13 | 85 | 385 | 41 | 55 | 342 | 22 | 10 | 249 | 48 | 55 | 438 | 3 | 100 | 428 | 1 | 100 |
| Track 2 | 466 | 14 | 100 | 429 | 24 | 30 | 350 | 17 | 80 | 235 | 51 | 65 | 424 | 15 | 100 | 391 | 11 | 90 |
| Track 3 | 466 | 10 | 40 | 318 | 29 | 10 | 313 | 13 | 0 | 225 | 18 | 4 | 330 | 20 | 5 | 365 | 20 | 10 |
| Track 4 | 471 | 10 | 60 | 407 | 20 | 70 | 315 | 13 | 80 | 198 | 68 | 60 | 380 | 28 | 70 | 415 | 14 | 80 |
| Track 5 | 461 | 8 | 30 | 334 | 29 | 0 | 294 | 15 | 0 | 172 | 17 | 0 | 338 | 18 | 0 | 364 | 26 | 0 |

analysing the remaining standard deviation values, the subject 1 achieved the lowest values mainly in the session 2 while the subject 2 in the session 3. The outcomes confirm as the GSR is a daily changing signal, reflecting the variability in electrical resistance of the skin related to sweating.

For the analysis of the skin resistance variations due to acoustic stimulation, the mean and standard deviation values of the GSR were computed, for each acquired GSR data series corresponding to each subject, both in the baseline condition and during each audio track listening. Additionally, for each subject, the difference in absolute value between the mean GSR measured in the baseline, and

**Table 5.** Difference between the mean GSR value corresponding to the track listening ($\mu_t$) and the mean GSR value of the baseline ($\mu_b$), and percent pleasure value (Ple.) for the track, for all the subjects. The bold numbers correspond to the two highest mean GSR difference values, for each subject.

| Track | Subject 1 | | Subject 2 | | Subject 3 | | Subject 4 | | Subject 5 | | Subject 6 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $\mu_t - \mu_b$ [$\Omega$] | Ple. [%] | $\mu_t - \mu_b$ [$\Omega$] | Ple. [%] | $\mu_t - \mu_b$ [$\Omega$] | Ple. [%] | $\mu_t - \mu_b$ [$\Omega$] | Ple. [%] | $\mu_t - \mu_b$ [$\Omega$] | Ple. [%] | $\mu_t - \mu_b$ [$\Omega$] | Ple. [%] |
| Track 1 | 19 | 85 | 52 | 55 | 5 | 10 | **109** | 55 | 13 | 100 | 17 | 100 |
| Track 2 | **27** | 100 | 7 | 30 | 14 | 80 | **95** | 65 | 2 | 100 | 54 | 90 |
| Track 3 | **27** | 40 | **119** | 10 | **23** | 0 | 85 | 4 | **96** | 5 | **79** | 10 |
| Track 4 | 22 | 60 | 29 | 70 | 21 | 80 | 58 | 60 | 46 | 70 | 30 | 80 |
| Track 5 | **32** | 30 | **103** | 0 | **43** | 0 | 32 | 0 | **87** | 0 | **81** | 0 |

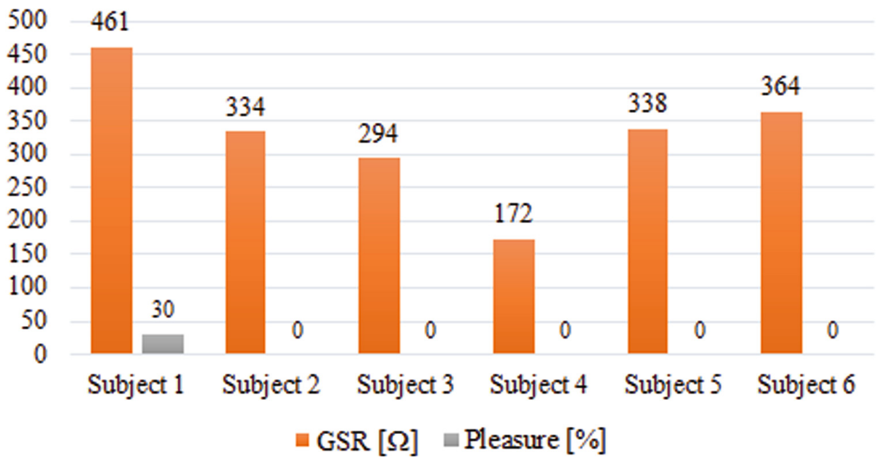


**Fig. 6.** Mean values of GSR, and percent pleasure during Track 5 reproduction, for the 6 subjects.

the mean GSR measured during acoustic stimulation, was computed, with the aim of evaluating the variations of the signal with respect to the reference condition.

Table 4 shows the experimental results in terms of mean value ($\mu$) and standard deviation ($s$) of the GSR for every track and every subject, compared to the values measured for each subject in the baseline. Table 5 shows the difference between the mean GSR during each track stimulation, and the mean GSR measured for the baseline. In both the tables, also the pleasure felt during the listening experience, and expressed in percent values, is provided, for each subject and audio track. As it can be seen in the tables, Track 3 and Track 5, that are white noise and snoring noise respectively, present the lowest scores pleasure. This result is reflected also in the difference values of Table 5. In fact, for Track 3 and Track 5 the difference is higher for every subject, except for subject 4. Moreover, Fig. 6 shows the mean values of the GSR and the pleasure scores for every subject reported in Table 4, but only for Track 5 (i.e., snoring noise), that is the track with the lowest pleasure scores, and for which a highest difference between mean GSR values is found in 5 subjects out of 6.

These results, despite not being generalizable because of the limited number of tests participants, show that the impact of the audio stimuli on a subject is more evident when unpleasant sounds (white noise and snoring noise, in the cases under study) are involved. On the contrary, there is no evident correlation between GSR values and pleasant tracks (with pleasure $> 80$). In fact, for some subjects a pleasure of 100% corresponds to a high difference on mean GSR (e.g., subject 1), while for other subjects it is related to a low difference on mean GSR (e.g., subject 5 and subject 6).

## 5 Conclusion

In order to investigate the individual GSR features, it is crucial to compare the individual baseline of GSR activity and the stimuli-evoked reactions. However, many studies omit the research of GSR in physical and mental rest conditions. For this reason, this work proposes an experimental approach that allows to explore the GSR data recorded at rest condition, by means of a portable low-cost and easy-to-use device.

Firstly, the analysis went through a qualitative approach, finding the relationship between the number of peaks and the trends of GSR signal recorded by two different subjects at rest. Since the GSR is a subjective signal and measurement, it is very difficult to perform a comparison between different subjects, especially due to their own skin resistance with individual basis threshold and peaks [14]. The findings of this study, despite not being generalizable because of the limited number of test participants, suggest that the impact of the acoustic stimuli on a subject is more evident when unpleasant sounds are involved. Additional research should be performed to clarify the effects associated to sounds perceived as pleasant.

The outcomes of our exploration can be considered promising for future analysis. Some developments might regard the extraction of GSR features to classify emotional response in reaction to external audio stimuli and compared to a self-assessment questionnaire. Moreover, future works should focus on expanding the validation and the reliability of the investigated experimental approach, involving a larger population.

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