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Article

Correlation analysis of different measurement places of Galvanic Skin Response in test groups facing valence and arousal changes.

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Abstract: The Galvanic Skin Response (GSR, also widely known as electrodermal activity EDA) is one of the signals related to this emotional reaction. Given the sparsity of studies related to and the variety of devices, we experimented at the Human Health Activity Laboratory with 17 healthy subjects. The goal is to know the variability of detection changes in the electrodermal activity among a test group with heterogeneous respondents in response to valence and arousal stimuli, correlating GSR biosignals measured from different body sites. We experiment with the right and left wrist, left fingers, the right foot's inner side using Shimmer3GSR, and Empatica E4 sensors. Results indicate as the most promising homogeneous GSR measure place the left fingers and right foot. Results suggest that due to a significantly strong correlation among the inner side of the right foot and left fingers and moderate correlations with the right and left wrist, the foot is a good place to measure EDA. This paper also contributes knowledge about some wearable sensor technologies available in the market. Shimmer3GSR sensor may be better reliable to homogenous detecting electrodermal activity changes, as these have fewer anomalies among the respondents. However, we found some anomalies in signals from the Empatica E4 sensor, which we discuss in this work.

Keywords: Stress; Wearable; Sensor; Physiological Signals; Galvanic Skin Response; GSR; Electrodermal activity; EDA; Valence and Arousal; Correlation.

1. Introduction

In recent decades thanks to the advance in data analytics techniques and sensor hardware development caused new research fields as activity recognition was born, taking advantage of technologies such as smartphones, wearable devices, the Internet of Things, and any device with sensors or embedded systems and digital storage or streaming capacity [1]. All this opened a Pandora box showing up a wide range of new application leading from Computer Science toward others fields as elderly independent living [2][3], cognitive diseases treatment [4], autism lifestyle [5], and care [6], in which this work is motivated. Human Activity Recognition (HAR) led to improving fields like these, supported by specialized research and development on emotion, posture, gesture, localization, and occupancy recognition [7].

Identify human emotion has been a study field historically related to sociology or psychology science field toward understanding the human behavior through techniques based on subjects observation, interview, spoken or written expression made traditionally by experts in the matter. Nevertheless, Computer Science has boosted this field's development capability by applying machine-learning techniques over video or physio-

logical data. Some literature, as [8] proposes three essential detection sources for emotion detection for a smart environment: Facial Emotion, Behavior Detection, and Valence/Arousal Detection.

This study focuses on study valence and arousal detection, through wearable devices. This technology may incorporate features as Electrocardiography (ECG), Electromyography (EMG), Electroencephalography (EEG), Galvanic Skin Response (GSR) Photoplethysmography (PPG), and Skin Temperature (ST) as many literature reports [9][10][11][12][13]. Although multimodal measures to improve emotion recognition performance are highly recommended [11], this study focuses on evaluating performance over GSR signals gathered from some wearables technology to improve autistic people's life quality. So simplicity and portability is part of the requirement for scenarios like these, where solutions should be as more transparent in individual daily life as possible.

People with Autism Spectrum Disorder (ASD) often have difficulties in social communication and interaction [14]. This condition frequently includes motor disturbance, which affects postures, gaits, hand workability, even speak, ignoring orders, swing or come and go movements, making moments difficult for parents and caretakers. This behavior is not always present in people with ADS' daily activities but could be triggered by stress sources [15]. This increasing emotion cannot be detected as the autistic person may be in an apparent calm but could have an unusually high resting heart rate [16], or its electrodermal activity can oscillate very fast [17]. Authors of this study consider it is essential to take preventive action to avoid trigger behaviors mentioned above, as some strategies have arisen like noise attenuating using headphones to reduce the probability of troublesome and distressing behaviors [18].

We focus on GSR biosignal as a measuring unit for positive or negative change in valence and arousal, as is one of the physiological changes present during an increasing stress moment in people with ADS; as mentions above, this is a common biosignal used in many stress-related studies [19]. Despite emotion recognition in autism through GSR signals have at least a decade documented in the scientific literature [20], recent advances in the last decade reports Machine Learning Techniques applied for Activity and Emotion Recognition. Also, by the miniaturization of hardware technologies, emotion recognition has received an impulse for researchers to think of new and disruptive solutions to address problems, as mentioned above in this work. A Quick view of scientific literature evidence that GSR sensor technology is a rising interest in development and research as Activity and Emotion Recognition does (see Figure 1). These trends reinforce the vision of authors from this work, to develop future concepts based on wearable technology that can measure levels of stress and alert the people around, or stream information to parents or caregivers about stress levels of people with ADS as literature highlight [21], or during therapy sessions [22], or classrooms specialized in children with ADS.

The recent work of Betancourt et al. [21] explore benefits, considerations, and implications of using GSR sensors for uses in-situ on children with ADS, discuss and propose some consideration for uses this technology in-situ as a wearable device. Authors highlight some behavioral challenges of autistic children for using this technology: Acclimatization to the biosensor before wearing them, development tolerance over the sensor over time, and the sensor location. As GSR biosignals can be measured in different body places, these authors found in an experimental intervention involving children with neurodevelopmental impairments that the sensor were better tolerated on the ankle than on the wrist by the children. For the researchers of the present work, this is our motivation, as now day exist various wearable devices capable of measuring GSR signal in different body place. As we seek to find better places to measure this stress-related signal for people with ADS, the goal in this study is to know the variability of different GSR measuring places in a test group in the detection of changes in the electrodermal activity, which may lead us to a suitable place for measuring stress-related signal.

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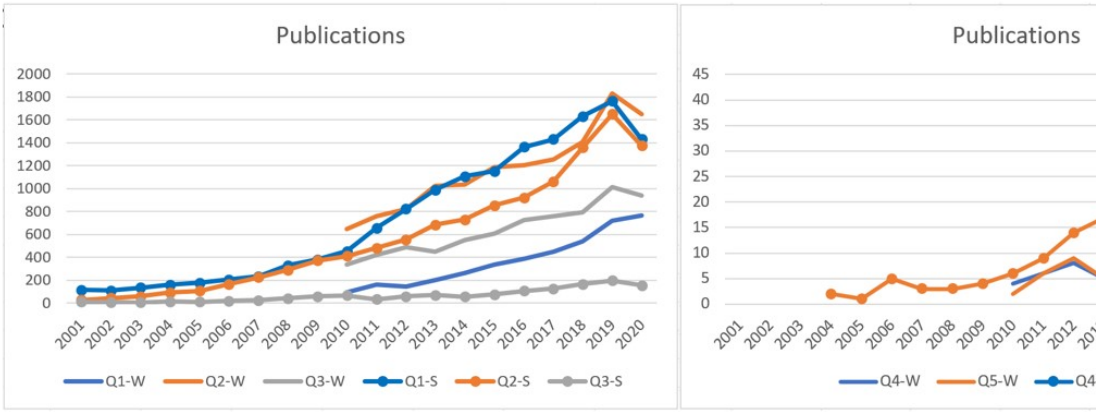

Query	Label	Web of Science Source
("Activity Recognition" OR HAR)	Q1	
(Emotion Recognition)	Q2	

Figure 1. Trends in the scientific literature of Emotion Recognition and GSR/EDA sensors.

Electrodermal behavior in autistic people in literature has been documented in some studies for better understanding of autistic condition using commercial wearables designed for research in general purposes [23][24][25][18]. Researchers in the computer sciences field have been investing efforts in developing wearable devices for autism spectrum disorder based on EDA measuring, some improving computing techniques [26][5], and others working on developing ad hoc hardware wearables for the autism population. Therefore, Westeyn et al. [27] propose a wireless sensor to measure electrodermal activity and acceleration called ActionGSR, positioning the electrodes ad sensor on the waist, advertising that location electrodes can influence the sensitivity of the readings. Fletcher et al. [28] present a wireless sensor platform and compact wearable sensor to measure EDA, skin temperature, and PPG biosignals, measuring EDA from the left and right wrists. The work of Gul Airija et al. [29] presents a prototype of a real-time embedded device to measure galvanic skin response (GSR) and heart rate (HR) to help adults preventing impending anxiety attacks in autistic children; the GSR electrodes were attached in the middle and ring fingers. Also, Krupa et al. [30] proposed a wearable wristband for children with autism by measuring GSR and HR using machine learning techniques to predict emotional states as neutral, happy, and involved. Oluwayemisi et al. [31] developed an e-Healthcare platform and a wearable for emotion detection called using electrodermal activity measured on ring and index finger, and speech recognition sensor.

As can be seen, find a better place to measure GSR biosignal is a valuable contribution for science and engineering to continue working on new technology for stress monitoring, seeking to improve better quality of life for both the autistic people and family and caregivers. The present study aims to find a suitable body place for measuring GSR signals among a non-homogenous population, using two correlations analysis workflow for four signals gathered in different places (right and left wrist, left fingers, and the inner side of the right foot). One analyzes each signal's correlation in the test group, the other the correlation between the respondents' GSR signals. We measured each signal with the same sensor in the same place in all respondents, using video clips with pleasant and unpleasant situations as a psychophysiological activating stimulus of valence and arousal changes. We used Pearson's method correlation to know which body place is more reliable for measuring valence and arousal changes in a test group, Rstudio as the data processing tool, and iMotion software to integrate and synchronize the data gathered by the sensors.

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The article is structured as follows. Section 2 provides an overview of related works of correlation studies of GSR signal and the sensor location. Section 3 explains the physiological signal measured and presents the sensors used and their body placement. Section 4 describes our experiment conducted and explain the method used in the present study. Section 5 present the results from two analysis approaches. Section 6 discusses the results and analyze some possible outliers. Section 7 gives the conclusions and future works.

2. Related Work

Correlation of GSR and other stress-related signals as heart rate, interbeat interval (IBI), and photoplethysmogram (PPG) are usually studied for detecting emotional arousal. Portable sensors for stress-related studies have hit the market, including these measurement functions, turning studies to a cost-effective and straightforward acceptance level, making popular these devices among the researcher [19]. As mentioned in the introduction, the variety of affordable wearable technology allows measuring the electrodermal activity parameter in different body places. Some studies investigate the effects of GSR biosignal measurement location using wearables during valence and arousal changes using visual-auditory stimuli. Others study the measurement location or similarity and correlation measurements of affordable wearables compared among well-calibrated or high-quality sensors, as Table 1 shows.

Table 1. A summary of the recent literature about GSR measure places studies and physiological sensors.

Research work	Focus Research	Devices used	Position measured	Comparison method
Anusha et al. [32]	Optimal dry electrodes location for EDA measurement.	Analog Devices®: Ag/AgCl, stainless steel, silver, brass, and gold electrodes	Ventral and dorsal surfaces of the wrist	Pearson's
Kushky et al. [33]	Correlation between palmar and non-palmar GSR measurement sites.	Flexcomp Infiniti physiological monitoring and data acquisition unit	Fingers, toes, and arch of the foot for skin conductance	Hierarchical linear model (random effect model)
Kappeler-Setz et al. [34]	Correlation between EDA measurements at feet with fingers.	Emotion Board	Index and middle finger, and the inner side of the foot	Pearson's linear correlation
Borrego et al. [35]	Reliability measures of galvanic skin response of a wristband against a laboratory-grade equipment	Empatica E4 and Refa System	Wrist and fingers	Spearman rank correlation coefficient
Kutt et al. [36]	Comparison of HR and GSR quality signals among wearable devices	Microsoft Band 2, Empatica E4, Health Sensor Platform, BITalino, and a (Polar H6) as a reference	Wrist and fingers	Pearson correlation coefficient
Sagl et al. [37]	Quantify the accuracy of low-cost wearables in comparison to high-quality laboratory sensors.	Wearables Zephyr BioHarness 3, Empatica E4, and VarioPort laboratory recorder bioelectric signals	hand palm vs. wrist	Pearson's r correlation, Maximal information coefficient (MIC), local time series similarities, Fréchet distance, and dynamic time warping (DTW).
Poh et al.	Study the continuous EDA measurement in different places outside of a laboratory setting	Flexcomp physiological monitoring, and a wrist-worn EDA sensor module developed by the authors	palmar and distal forearm	Pearson's correlation coefficients

Anusha et al. [32] focused on identifying the optimum configuration of dry electrodes for monitoring EDA from the wrist, as hypothetically electrodes designed for EDA detection are influenced by parameters like the anatomical location of measurement, interelectrode distance, and electrode material. Authors fabricated dry electrodes made from stainless steel, silver, brass, and gold material, geometrically and dimensionally similar to the commercially available standard wet electrodes. They used 16 dry electrode configurations with interelectrode separations of 2 cm and 4 cm, both on the wrist's ventral and dorsal surfaces at a 6 cm distance from the carpus. These configurations were systematically investigated, monitoring the electrodermal activity using a sensor unit Analog Devices®, to identify which position yielded the highest correlation with the standard wet electrodes using the Pearson correlation coefficient for comparing EDA signals. The silver electrodes worn on the wrist's dorsal surface with an interelectrode separation of 4 cm performed were consistently well on all subjects with an average Pearson correlation coefficient of r=0.899 ± 0.036.

Kushki et al. [33] conducted a study correlation among palmar and non-palmar measurement sites under cognitive and mental stressors from BVP and ADA signal characteristics. They measured cognitive and affective stimuli from three different body place (fingers, toes, and ear for BVP; fingers, toes, and arch of the foot for skin conductance). They evaluate these signals' correlation using a hierarchical linear model (random effect model), gathered from a Flexcomp Infinity physiological monitoring and data acquisition unit. In this model, the hand's signal features were used as the independent variable, and the alternative sites as the dependent variable. Results indicated a significant correlation among EDA signal features gathered from these different body places. Cognitive and affective stimuli changes at non-palmar sites were significant from baseline (fingers), suggesting these sites for affective computing and human-machine interface measures.

Kappeler-Setz et al. [34] envisioned a sensor system in the shoe or sock as a promising approach to long-term monitoring of the EDA signal. They investigated the correlation between EDA signal measured at the feet with measurements at the fingers (most established sensing site), using an action movie as psychophysiological activating stimulus and limbs' performance movement. EDA signals were recorded using an Emotion Board, attaching the electrodes to the index and middle finger's medial phalanxes, the medial side of the foot adjacent to the plantar surface and midway between them the first phalanx and a point beneath the ankle. The authors synchronized the two devices' SI-transformed level signals and calculated the Pearson linear correlation coefficient to compare the signals recorded at hand and the foot. This study showed changes in electrodermal activity 88% of the time at both sensing sites, but the foot's EDA reactivity is weaker than in hand. Authors of this study suggest foot recordings of EDA signals in daily life as a suitable location, as the moderate movement has low influence in measurement and has similar effects in both measurement sites.

Borrego et al. [35] conducted a study to compare the reliability of measures in the galvanic skin response of the Empatica E4 wristband against the Refa laboratory-grade system, facing emotional valence changes. The E4 is a wristband sensor with EDA electrodes located in the strap of the wristband sampling at 4 Hz in the wrist, and the Refa system consists of two Ag-AgCl sensors wired to an external amplifier sampling at 256 kHz on the fingers. The correlation was analyzed using the Spearman rank correlation coefficient; the α level was set at 0.05 (two-sided). The study showed low to moderate correlations for positive and negative images, while no significant correlation was found for neutral stimuli.

Kutt et al. [36] made a comparison of HR and GSR quality signals among four wearable devices (Microsoft Band 2, Empatica E4, Health Sensor Platform, and BITalino (r)evolution), and a professional fitness device used for HR tracking (Polar H6) as a reference. MS Band 2, eHealth, and the reference device Polar H6 provide direct HR measurements. E4 and BITalino do not provide direct HR information as they record blood

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volume pressure (BVP). To compare the devices, they used from the recorded signals the Pearson correlation coefficient. Authors suggest focusing on the BITalino combined with the MS Band 2 for future works in some cases. Correlation of HR signals was better between MS Band 2 and the data reference measured from Polar H6. Authors also comment that BITalino and Empatica E4 measures of GSR are sensitive to devise placement. The correlation factors for BITalino decreased with each experiment, most likely caused by ECG electrodes reusing, as they should be replaced more frequently. Authors also found a lower amplitude of skin conductance response from Empatica E4 than eHealth and BITalino may be caused by different sensor location (Empatica on the wrist, and eHealth and BITalino on fingers).

Sagl et al. [37] measured the physiological parameters: heart rate, inter-beat interval, galvanic skin response, and derived heart rate variability. It was done simultaneously in a high-quality laboratory recorder bioelectric signals (VarioPort) and two wearables (Zephyr BioHarness 3 and Empatica E4), while the participant was cycling on an ergometer. The study seeks to demonstrate an approach to quantify low-cost wearables' accuracy compared to high-quality laboratory sensors. In the study, the authors used Pearson's r correlation, Maximal information coefficient (MIC), local time series similarities, Fréchet distance, and dynamic time warping (DTW). Authors reported lower similarities in GSR correlation due to different measurement methods, placement of the sensors on hand palm vs. wrist, use of electrolyte gel or not for electrodes used with the VarioPort GSR measure, not with the other three devices.

Phitayakorn et al. [38] conducted a study to determine the practicality of the Bandu wristwatch (manufactured by Neumitra Inc., Boston, MA.), to measure galvanic skin response (GSR) in operating room team members during surgical simulations, wearing a sensor on the wrist and the ankle. They used the Pearson correlation to determine the relationship between sensor data from the wrist and the ankle. The study report a lack of correlation between ankle and wrist sensors. The study suggests that wrist sensors are more sensitive at measuring GSR fluctuations than the ankle sensor, which may be the anatomic variations in eccrine gland concentration around the ankle.

Poh et al. [39] developed a wrist-worn wearable device. They conducted a study of continuous EDA measurement at both palmar and distal forearm sites, on the long-term outside of a laboratory setting, during physical, cognitive, and emotional stressors. The study found that the distal forearms' ventral side is a viable alternative to the traditional palmar sites for EDA measurements. They calculates Pearson's correlation coefficients and the corresponding p-values as a measure of similarity between signals, recording GSR signals from the right fingers with the Flexcomp physiological monitoring and data acquisition unit. The wrist-worn EDA sensor module developed by the authors recorded the left fingers and right distal forearm using Ag/AgCl electrodes and the left distal forearm using conductive fabric electrodes.

In light of these, the literature review shows research interest in the measurement of stress-related signal location. From The Human Health and Activity Laboratory H2AL [40], we contribute to expanding the mass of knowledge about electrodermal behavior and wearable technologies available in the market, correlating stress-related biosignals from the right and the left forearm, and left fingers. The right foot's inner side was gathered from the wearable devices Shimmer3ECG, Shimmer3GSR, and Empatica E4. Thus, all these can keep using for designing multimodal strategies for emotion recognition in futures development.

3. Physiological Parameters and sensors

3.1. Galvanik Skin Response

Also known as Electrodermal Activity (EDA), the Galvanic Skin Response (GSR) is a measuring unit for the surface resistance skin or conductivity. It can be measured passing a microcurrent of electricity through a pair of electrodes located near each other, ampli-

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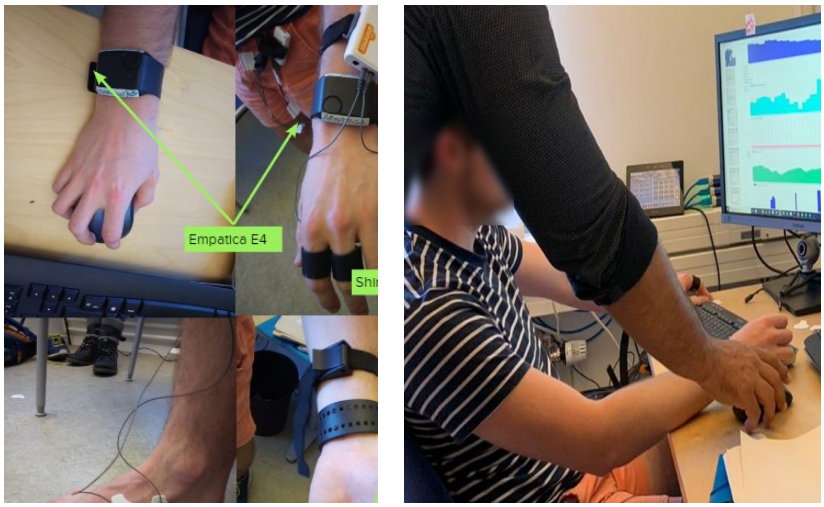
fying and registering current variation. This variation is possible as the skin resistance depends on skin humidity (sweating), the thickness of the outer layer of the skin (epidermis), vasoconstriction, and others [41]. The sweating behavior is sensitive to emotional stimulation due to the sweat glands controlled by the Autonomic Nervous System (ANS) [42], which controls others' body physiological responses like heart rate, temperature, and pupil diameter. The physiological response of the ANS can increase in the presence of stress stimuli and several stimuli [24]. The higher the sweet response, the higher the conductivity (μSiemens) and less the resistance (kOhm). This behavior of physiological response links the electrodermal activity to measures of emotional valence, facing pleasant stimuli (positive valence) or unpleasant stimuli (negative valence)[35][43].

3.2. GSR Sensors

We used four sensors for the present study, two Wearable Shimmer3GSR+, and two E4 Wristbands from Empatica. Both sensors' brands specially designed for physiological data streaming and visualization, widely known in the scientific field of physiological data analytics. Shimmer3GSR is a wearable sensor technology, which offers a variety of devices to measure different physiological parameters. The Shimmer3GSR+ measures the skin's electrical conductance using finger belt electrodes, or pre-gelled electrodes for the foot placing as the case in this study (http://www.shimmersensing.com/products/shimmer3-wireless-gsr-sensor). This sensor can record the raw data in SD memory cards and download data through desktop software. The wristband Empatica E4 is CE- medical certified in the United States, could save the raw data in a cloud-account, which plots the data every time the user connect the E4 to the desktop software or a mobile app (https://www.empatica.com/research/e4/). Table 2 shows signals gathered from each sensor used for the study, their units, sample rates, and body position for this study.

Table 2. Sampling characteristics of sensors and place of measurement.

Sensor	Unit	Sample Rate	Measure place
Shimmer GSR 1	μSiemens	128Hz	Left finger
Shimmer GSR 2	μSiemens	128 Hz	Right foot
Empatica 1	μSiemens	4 Hz	Left wrist
Empatica 2	μSiemens	4 Hz	Right wrist



(**a**) (**b**)

Figure 2. Placing the GSR sensors in a subject from the test group (a); checking streaming data in iMotion software (b).

We measured the GSR signals the signal from the usual sensor placing, figure 2(a) shows how this sensor was placed over the study subject. Both sensors can also be paired through a Bluetooth link—this hardware feature allowed synchronizing all the raw data through iMotion software. The video clip of pleasant and unpleasant sensations was configured as stimuli. iMotion software also gathered the data from the four sensors via Bluetooth, labeling the registers by signal, sensors, and time stamps each millisecond, according to each sensor's sample rate, the register had a value or not. The advantage is that iMotion stores all the raw data in one data-file per respondent per studies, and the timestamp marks the time series. Figure 2(b) shows the streaming data being gathered in iMotion software from all sensors during the setup study for one subject.

4. Material and Methods

4.1. Study Setup and Participants

Our study included 18 subjects comprised of 22% females within the age range of 30 to 39 years and 78% males within the age range of 23 to 53, recruited some via e-mails others just asking to participate in an experiment. We carried out the study out in the Department of Computer Science, Electrical and Space Engineering at Luleå Tekniska Universitet, approved by the ethics board. All participants provided informed written consent.

Each participant was cited for the study at different times. We gave general instructions to the respondents, explaining why and how the study will be and ask them to read and sign the informed written consent. After placing the sensors, we ask the participants to put on a headset and choose the best comfortable chair and establish a set point of comfortability for sitting in front of a screen, avoiding unnecessary movement during the experiment. Sound and video were tested, and data sensor acquisition was checked, asking the participant to be calm and then start the study over a confirmation in the Imotion software to start recording the data and ran the stimuli simultaneously. The staff was out of the room while the subject watches the video.

The video watched by the subjects was built based on several video clips available on the web, chosen carefully by the study team to influence pleasant and unpleasant emotions according to Russel's Circumflex Model of Affect [44]. The video clip started with a relaxing sound and video of a Caribbean beach as a pleasant stimulus, followed by a countback clip showing a danger or accident video clip as unpleasant stimuli, followed by tenders babies or puppies video clips as pleasant stimuli. Then another countback appears announcing an expectation, again the pattern of unpleased and pleasant stimuli, as Table 3 shows. The iMotion software finishes recording the data when the video stimuli finish.

Table 3. Stimuli descriptions of pleasant and unpleasant situation video clips.

Time slots	Emotion	Stimulus description
0 > 32	Pleasant	Intro Beach
33 > 34	-	Countback transition from pleasant to unpleasant
35 > 42	Unpleasant	Crash accident
43 > 58	Pleasant	Baby with lemon
59 > 1:00	-	Countback transition from pleasant to unpleasant
1:01 > 1:27	Unpleasant	Baby in windows building
1:28 > 1:49	Pleasant	Baby laughing
1:50 > 1:51	-	Countback transition from pleasant to unpleasant
1:52 > 2:52	Unpleasant	Baby jumping from a building
2:53 > 3:57	Pleasant	Puppies
3:58 > 3:59	-	Countback transition from pleasant to unpleasant
4:00 > 4:30	Unpleasant	Broking bones
4:31 > 4:41	Pleasant	Looney Tunes end
4:42 > 4:45	Pleasant	Credits

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4.2. Data pre-processing

We integrated and synchronized the data gathered by the sensors in the iMotion software. This software extracted all the experiment's raw data in one data-file per subject study with a timestamp per millisecond. The sensors stream the data since the sensors synchronize with the iMotion software, but they do not link in the same milliseconds. So the data is started to record since the respondent gives "start" on the screen (Timestamp cero), as the stimuli ran into de iMotion software. Therefore, this raw data returned by the software does not need any temporal alignment or transformation, as all sensors give a signal in µSiemens (Skin conductivity) and with the same format. The results are time series per signal with a resolution in 1 millisecond, in which the missing data should be due to differences in the sampling rates. So we filled these by spline interpolation used for correlations study of GSR signals [45][46]. For comparison purposes, the data was resampled at 250ms, starting for the timestamp 250 as the sensors' low sample rate was 4 Hz. As all signals were the same type, we work with these GSR datasets from this point, as Sagl et al. [37] do. Figure 3 shows the time series of respondents of each signal dataset.

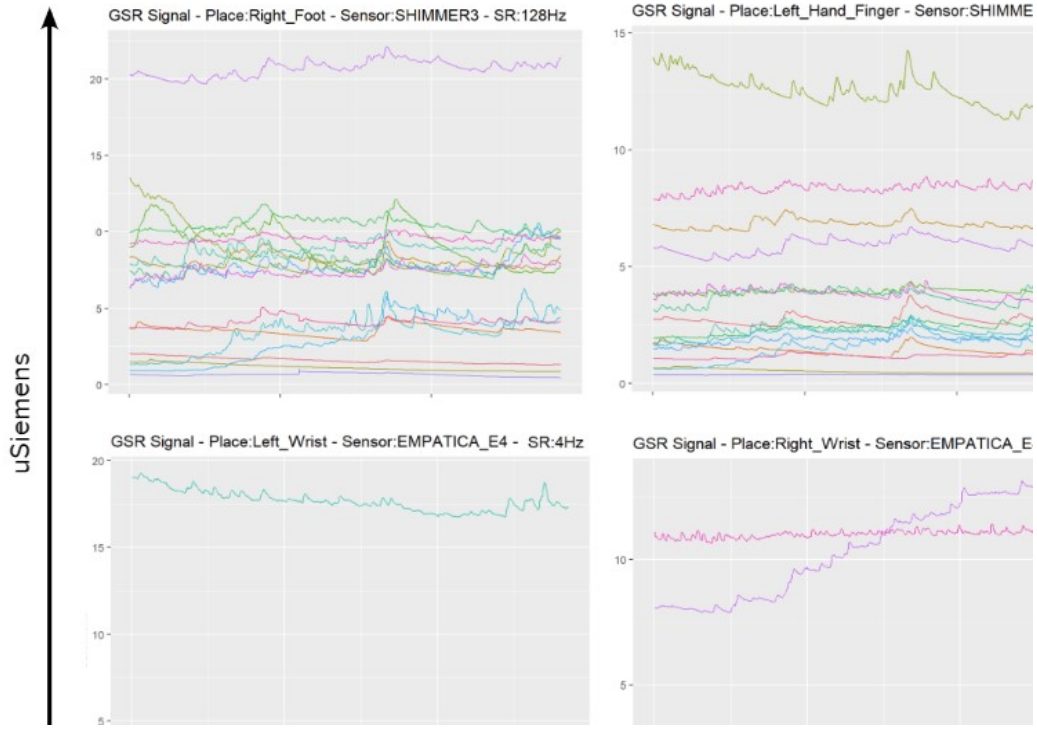

Figure 3. Time series of respondents of each signal dataset.

4.3. Statistical Signals Analysis

We conducted two analysis approaches. One analyzes the correlation each signal's correlation in the test group to know the signals' behavior in a heterogeneous test group, as any GSR signal-based stress detection system should work. The other approach analyzes the correlation between the signals measured in each respondent and compares them among the test group. Literature documents that Pearson's correlation method fit with time-series data analysis for physiological signals [47], so this was used for both workflows. We made all data processing and plots in the statistical computing software Rstudio. The analysis is based on a visual examination of the Pearson's correlation coefficient (r) using clustered correlograms, histograms, boxplots, and some statistical of dispersion as mean, standard deviation, and coefficient of variation as statistical estimates to variability in detection of changes in the electrodermal activity among a test group with heterogeneous respondents.

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5. Experimental Results

In this experiment, we measured GSR signals in 17 respondents with four sensors located in different parts of the body: right and left wrist, left fingers, and the inner side of the right foot gathered from the sensors Shimmer3GSR and Empatica E4. For each location of measure, one dataset was created, each one contains the data of the signal measured (μSiemens unit) in the same place in 17 different respondents, and every respondent dataset has 1142 registers of GSR measures from 258 seconds every 250ms (see section 4). Every respondent was stimulated with the same pleasant and unpleasant video to stimulate valence and arousal changes and, so, changes in electrodermal activity to measure the Galvanic Skin Response.

In this first analyzes approach, the Pearson coefficient (r) gives an associative measure between two respondents. We can determine if GSR measure locations have any association with other measure locations or between two respondents and measure this relationship's strength. This association indicates how much changes or variations occur in one respondent will also occur in the other. This association does not imply causality, could be a strong correlation between two signals and a linear response between each other, but one does not cause the other. So this experimental study is based on a relational hypothesis, how much correlation could have a GSR signal measured in specifics locations of the body in a heterogeneous test group? We use the Pearson correlation to compare each signal measured between every respondent as a paired comparison, generating a correlation matrix per GSR measure location. Each correlation matrix was plotted in a clustered correlogram using R functions hclust() for correlation plots (see Figure 4), giving a visual about how much a GSR signal from a particular measure place can be measured homogeneously in a test group, as any real stress or emotion recognition solution will work.

In the correlation matrix shown above, blue colors represent the positive correlations (Pearson's coefficient $1<r<0$), which means, if a signal in a respondent increase or decreases, the other will tend to increase or decrease, respectively. The red colors represent the negative correlations (Pearson's coefficient $0<r<-1$), which means that if in a respondent, a signal increases, the other signal will tend to decrease (and vice versa). Each cluster in the correlograms (black frame) agglomerate the respondent's group, which has more positive correlations between each other. A quick visual analysis lets us see that the GSR signal measured in the left fingers has a bigger group of respondents with a positive correlation, followed by the signal measured in the right wrist, left wrist, and right foot. However, it is visually remarkable that the left wrist has the strongest correlations in the group. The bigger the group means that the signal measured in that place may have a better chance to detect homogeneous changes in electrodermal activity in a heterogeneous test group. Nevertheless, groups with strong blue correlations could mean that the signal of that matrix has a better chance of being measured with similar increasing behavior.

Each signal measured from a particular measure place correlated among the 17 Respondents, giving a total of 136 correlations calculated for each GSR measurement site. The difference in the number of positives correlation was not too big in the four locations, 60% on average, which means GSR measures in writing wrist, left wrist, right foot, and left fingers could have approx. 60% probability of detecting increasing or decreasing in the electrodermal activity in a test group linearly. Nevertheless, the coefficient's magnitude indicates how strong or weak could be this linear relation of the signal between the test group. In order to know this, some statistics were calculated. Table 4 shows these statistics for each positive or negative correlation of each measure place.

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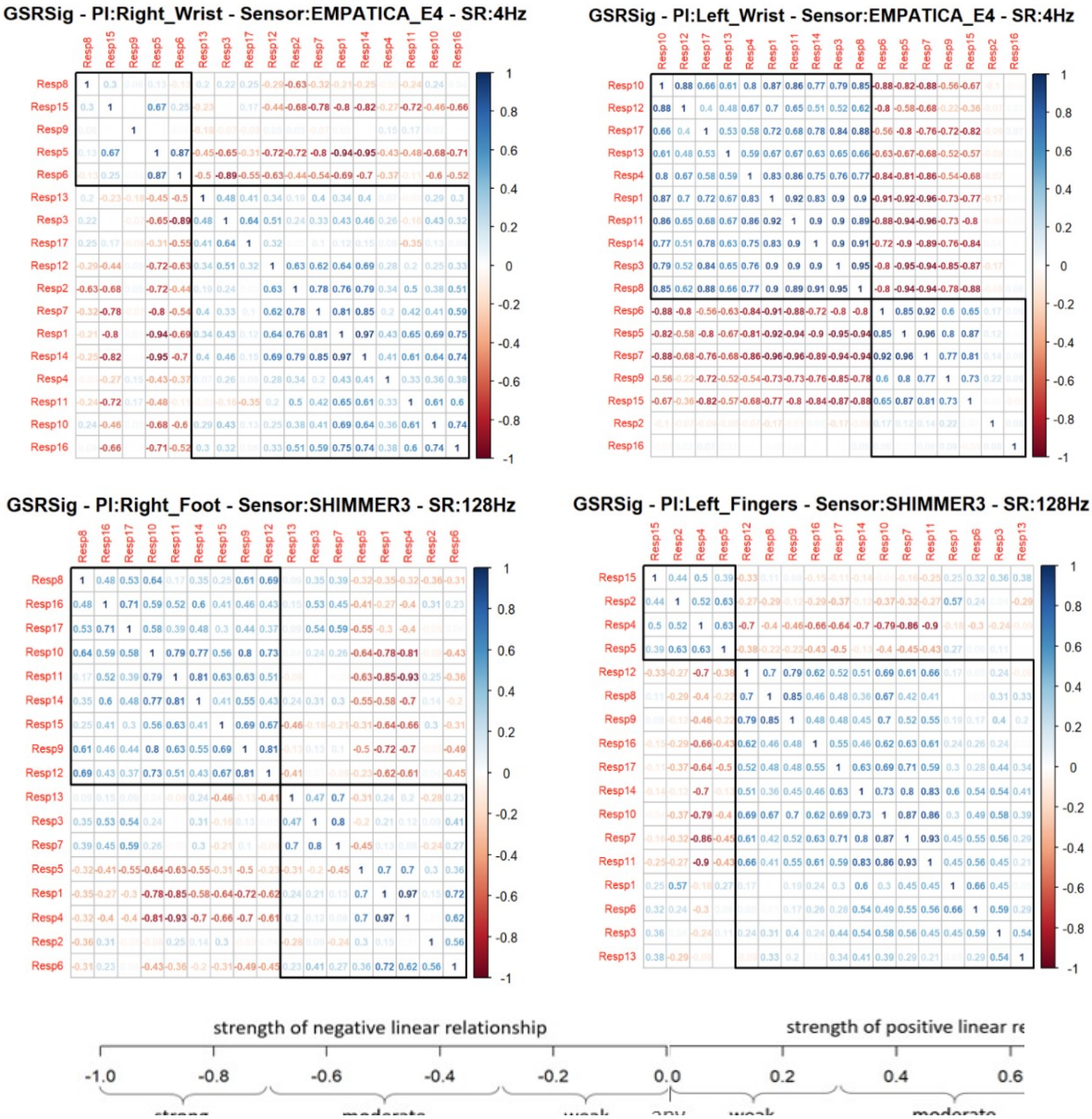

Figure 4. Correlation matrix of each GSR measuring place.

Table 4. Statistics of correlation matrices of each GSR signal.

Measure Place	Correlation (*r*)	%	p-value AS test	p-value K-S test	Mean (*r*)	SD (*r*)	CV (*r*)
Right_Wrist	Positive	61,8%	0,37	0,53	0,38	±0,25	0,65
	Negative	38,2%	0,53	0,52	-0,45	±0,27	0,61
Left_Wrist	Positive	52,9%	0,004	0,02	0,59	±0,31	0,53
	Negative	47,1%	0,005	0,01	-0,61	±0,32	0,52
Right_Foot	Positive	61,8%	0,59	0,64	0,42	±0,23	0,56
	Negative	38,2%	0,94	0,42	0,40	±0,23	0,57
Left_fingers	Positive	69,9%	0,87	0,90	0,45	±0,22	0,49
	Negative	30,1%	0,37	0,64	-0,34	±0,22	0,65

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We used the Anderson-Darling and Kolmogorov-Smirnov test (A-D and K-S test) as the goodness of fit tests to determine if each GSR measurement place's correlations follow a normal distribution. Correlations of GSR signal measured in the right wrist, right foot, and left fingers had a normal distribution in their positive correlations as the p-value (K-S test) is higher than 0,05 of statistical significance. Statistically, if measuring a GSR signal in a test group, there is a probability of 90% in the left fingers to have a positive linear correlation and a weak-moderate strength association, due to the Pearson coefficient could be between 0,23 and 0,67. A probability of 64% in the right foot has a positive linear correlation, and a weak-moderate strength association due to the Pearson coefficient could be between 0,18 and 0,65. A probability of 53% in the right wrist has a positive linear correlation, and a weak-moderate strength association due to the Pearson coefficient could be between 0,13 and 0,62. Although these three signals have a normal distribution in their negative correlations, we do not consider it in the analysis, as some physiological factors among respondents can cause a decrease in the GSR signal while others increase, which will be discussed in the next section.

The GSR measure on the left wrist also failed the goodness of fit test in negative and positives correlations. Its p-value is less than 0.05 (statistical significance), which means that these signals' positive linear relationship is not uniform in the test group. This measurement place has a very disperse correlation among the test group, so we can not get statistical inference as we did in the other three GSR measuring sites. A visual inspection to check the symmetry of the positive correlations to each signal (Figure 5) let us observe that unlike the GSR signals from the right wrist, right foot, and left fingers, the signal from the left wrist had a remarkable asymmetric distribution in its correlation among the test group. It has several correlations fitting in the different correlation scale, which does not imply a homogeneous behavior in this GSR measure place.

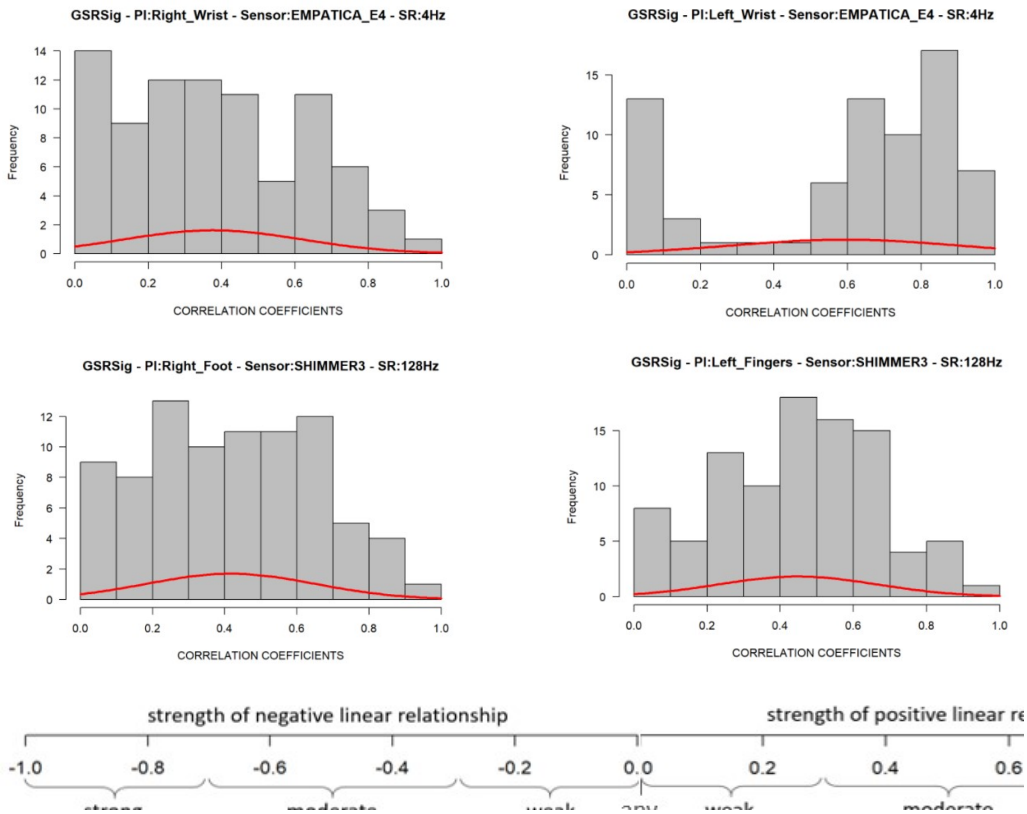

Figure 5. Distribution of positives correlations from the correlation matrices of each GSR signal. The bottom part is the strength of the association scale of Pearson's correlation coefficient.

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Despite GSR signals from the right wrist, right foot, and left fingers have all weak-moderate positive correlation, the mean of positives correlations of each measurement place gives a better idea about which could have better reliability about detecting increasing or decreasing electrodermal activity homogeneously in a test group. As shown in box plots in Figure 6, signals from the Left fingers and the right foot have better reliability than other signals as the mean and median are close, and both have certain symmetry in the standard deviation. The GSR signal from the Left fingers followed by the right foot are the ones that have better skewness, which means that there is a better probability that measures GSR in these sites has a moderate linear positive relation in a test group. The signal measured from the right wrist has a bigger dispersion than the two above mentioned, mean and median tends to a low-moderate positives correlation in the test group.

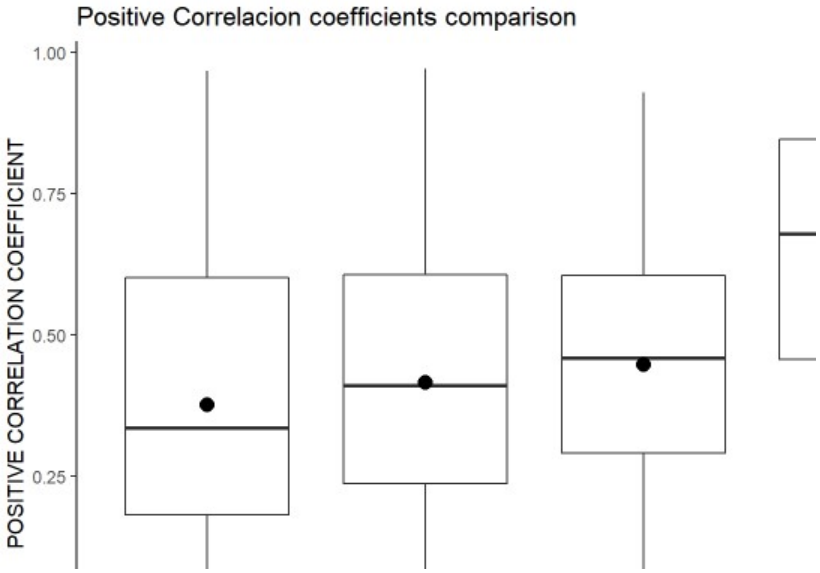

Figure 6. Box plot distributions of positives coefficient correlations from the correlation matrices of each GSR signal.

From Figure 6 above, despite whiskers of each signal denote dispersion of positives correlation in all the strength association scale, the statistical analysis did not denote any positive correlation outlier, the coefficient of variation (CV in Table 4)) gives a better understanding of which signals have less tend of dispersion in their positive correlation. Less dispersion means a better chance that GSR measures in a test group fit at a certain probability correlation of the strength correlation scale. The lower the coefficient of variation, the less the dispersion, the better the chance than if the electrodermal activity increases, and will do in another respondent simultaneously in a certain association strength interval. Statistics from Table 4, show the less correlation dispersion in the test group is in the signal from left fingers (CV=0,49), followed by right foot (CV=0,56) and then the right wrist (CV=0,65). The above has is a significant effect on reliability, giving some insights between these four-measure places. Despite the above, even based on Figure 6, the right wrist's GSR signal can not be taken as the strongest positive linear relation between the four measuring sites. As mentioned above, it has an asymmetric distribution in its positive correlations (Figure 5), and it does not meet a normal distribution (Table 4, the p-value is less than 0,05).

Although the statistical analysis pointed out no outliers of positive correlation, possible sources of correlation variability were inquired in order to see which errors or bias in the sampled data of each respondent may lead to a non-homogeneous response of electrodermal activity in a test group in that measure place, especially in the signal from

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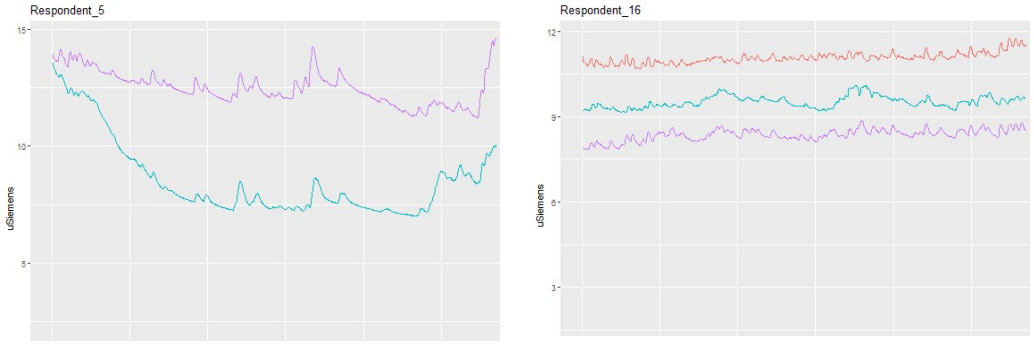
the left wrist. We conducted a visual inspection of the signals time plots of each respondent. To illustrate the finds, we only show some representative graphics from the experiment. The first impression was that GSR signals from the left wrist and right wrist both register electrodermal activities relatively small compared to GSR signals from the right foot and left fingers. The first two signals were measured with Empatica E4 sensors while the other two with Shimmer3GSR sensor (Figure 7a), so it's remarkable in this experiment these sensors tend to measure in a range of μSiemens higher than Empatica E4 (3 to 5 upper in most of the case). Also, 89% of the time, measures from the right foot is higher than the left fingers (Table 5).

Table 5. GSR measuring range of each measuring location.

EDA Measure range	Right wrist	Left wrist	Right foot	Left fingers
0 – 0,35 uS	88%			
0 – 0,75 uS		94%		
0,3 – 3 uS			29%	41%
3 – 10,7 uS			65%	53%



(**a**) (**b**)

Figure 7. Illustration of difference in GSR measuring range observed in the experiment. Case of difference between two types of sensors (a), case of difference in different types of sensor (b)

In order to see if differences in EDA magnitude reading could affect detection of increase or decrease electrodermal activity homogeneously in a test group in specific measures sites (as well other possible anomalies), we lean on the second analyses approach based on the correlation between the signals measuring sites in each respondent, and compare them among the test group. Figure 8 summarise the linear correlation among sensors of each respondent, both positive and negative relation, as in this case the comparison is between signals in the same respondent, and no factors should affect the measure in specific places but the respondent itself or the sensor used for, which is of interest in this study.

Both Empatica E4 sensors have a lower range of measure than the Shimmer3GSR sensors (Figure 7(a)); this is present in 82% of the test group. However, in 18% of the test group, one sensor Empatica E4 read a higher magnitude than the other Empatica E4 sensor (See Figure 7b). Respondent 9 in left wrist, Respondent 14 and 16 in right wrist measure from an Empatica E4 sensor were the higher magnitude signals than the other E4 sensor signal. Then, to investigate whether the measure's magnitude influences a better correlation between the test group, we made a paired comparison between correlations involving these signals with other respondents' anomalies (Figure 8), indicating no significant difference. So we can not affirm that higher magnitude reading causes better homogeneous reading among a test group, but we can affirm the type of sensor.

Based on the insight and previous results from the first correlation analysis approach, a quick horizontal view next in Figure 8, stand out that signals measured from

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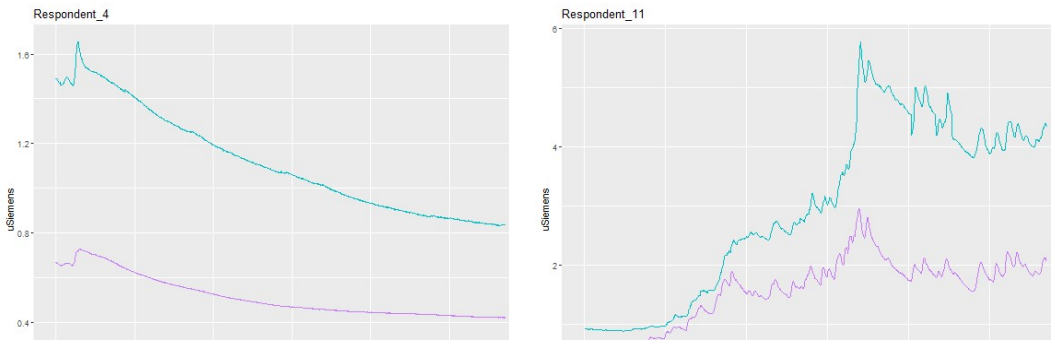
the right foot and Left fingers still having a homogeneous response in the test group, as they have the higher correlation mean, the less standard deviation and the lower coefficient of variation. Which mean that this two place of measure has a strong linear response in a test group, it means, independently of any factor from a heterogeneous group, in both place if one increase or decrease the electrodermal activity, the other measure place will tend to increase or decrease with a strong association. This association is about how much changes or variations co-occur in one respondent and will occur in the other.

SENSOR CORRELATIONS		MEASURE PLACE CORRELATIONS		Resp1	Resp2	Resp3	Resp4	Resp5	Resp6	Resp7	Resp8	Resp9	Resp10	Resp11	Resp12	Resp13	Resp14
Shim-GSR	Shim-GSR	Left finger	Right foot	-0,01	0,81	0,92	0,98	0,70	0,34	0,46	0,88	0,88	0,92	0,91	0,96	0,84	0,96
Shim-GSR	E4	Left finger	Left wrist	0,13	0,34	0,12	-0,75	0,62	0,19	-0,71	0,48	-0,08	0,60	0,79	0,90	-0,16	0,76
Shim-GSR	E4	Left finger	Right wrist	0,19	0,17	0,55	-0,42	0,64	-0,36	0,64	0,62	0,45	0,64	0,27	0,38	0,47	0,63
Shim-GSR	E4	Right foot	Right wrist	-0,94	0,60	0,36	-0,45	0,73	0,48	-0,20	0,66	0,35	0,75	0,45	0,26	0,40	0,69
Shim-GSR	E4	Right foot	Left wrist	-0,94	0,08	-0,14	-0,82	0,62	0,69	0,25	0,47	-0,38	0,78	0,92	0,92	-0,27	0,84
E4	E4	Left wrist	Right wrist	0,95	0,13	0,64	0,43	0,96	0,55	-0,78	0,01	0,27	0,88	0,71	0,17	0,33	0,94
		Sensors & Measure place															
		E4 Empatica - Right Wrist							FZ	FZ/AJ	AJ	FZ			AJ		
		E4 Empatica - Left Wrist			FZ												
		Shimmer3GSR - Right Foot		OD			OD									HV	
		Shimmer3GSR - Finger Left															

Figure 8. Correlation between signals in each respondent. In the bottom part, the anomalies detected related to each respondent, measure place, and sensor.

From the second correlation analysis approach (Figure 8 above), it can be appreciated not all respondents follow a positive linear relationship in the GSR signals measured in their bodies (Figure 8), which means that in a Respondent, not all GSR measures sites increase when others increase. We found two different cases about this negative correlation between sensors or measure sites in the same respondent (from now, opposite directions). In the first case of this opposites direction anomaly, some respondents have signals from some GSR measure sites increasing using one type of sensors, as others decrease measured by another type of sensors, For instance, Respondent 4 (figure 9a). Although the increasing signals of the Empatica E4 sensors cannot be appreciated, the negative correlations between these two types of sensors denote it (Figure 9). In this case, both signals from the right foot and Left fingers (from Shimmer3GSR sensors) decrease in almost perfect positive correlation (r=0,98, see Figure 8), while the signals from the left wrist and right wrist (from Empatica E4 sensors) increase both with a moderate positive linear relationship (r=0.43, see Figure 8).



(**a**) (**b**)

Figure 9. Illustration of opposite directions of GSR signals in the same respondent, case in different sensors. A respondent with negative correlations between different sensors (a), respondent with positive correlations between sensors (b).

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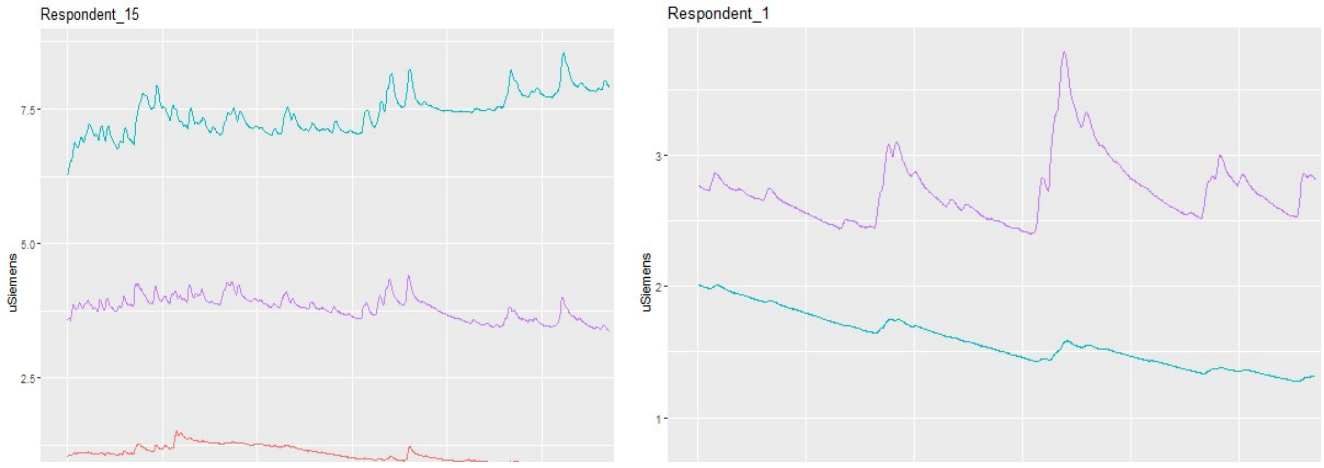
The second case is in Respondent 15 and Respondent 1, where the correlation between Shimmer3GSR sensors has a negative correlation (Figure 8). While a sensor measure increases, the signal from the other same type of sensor decreases, as Figure 10 shows. Despite the shimmer sensor being related in both cases, the right foot's signal is presented in this opposite behavior. It is easy to infer, as is this is the only signal measured with Shimmer sensors that present a negative correlation with both Empatica E4 sensors. Plus, a visual examination of the time signals plot of each respondent involved (Figure 10) indicate in this second case reported no tendency of increase or decrease, as the signal increase in one respondent while in other decreases. For this case we not take into account the negative correlation between Empatica E4 sensors in Respondent 7, as these correlations have some anomalies in the signal, which will be analyzed next.



(**a**) (**b**)

Figure 10. Illustration of opposite directions of GSR signals in the same respondent, case in the same sensor sensors. Respondents with negative correlations between the same type of sensors.

Besides the above anomaly, we highlight other anomaly findings in the GSR signals measured during the experiment: sudden falls to zero and abrupt jumps of magnitude, presents among the measures made with Empatica E4. Only one measure with one of the Shimmer3GSR presents a signal with held values for a relatively long time. The bottom of Figure 8 relates the respondent, measure place, type of sensors, and the respective correlation's anomalies. This type of error comes from the sensor and their use on the respondent, that the place of measure. From correlations in Figure 8, the first impression is that Empaticas E4 sensors have a higher rate with anomalies measure than Shimmer3GSR sensors. The second impression is that the anomalies of falls to zero (FZ) anomalies are the most frequent error in the Empaticas E4 sensors. First, it may think that the battery level may have been low during the experiment, but checking the raw data generated by iMotion software from both Empaticas E4 sensors, in which the battery level is also captured, did not show any pattern related to the anomalies.

Four of five signals with fall to zero anomalies have a positive linear relationship with the same type of sensor (Empatica E4), two of these has weak strength correlation and the other two moderate strength correlation, despite these signals have cero value almost half of the measuring time. Also, a visual examination shows up evidence that this anomaly haps when the electrodermal activity decreases (see Figure 11), as all the signals coming from Empatica E4 sensors have a decreasing electrodermal activity in different respondents. The above, plus the fact that Empatica E4 showed a lower range of GSR measure during this experiment, we can say that if the EDA measured range is below 0,6μS from an Empatica E4, the decreasing trends of the electrodermal activity might do this signals fall to zero suddenly, unlike other sensors. It may not be due to the measure

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place, but the type of sensor does, as the left wrist measure place also had a fall to zero anomaly, but with a different Empatica E4 sensor. Also, it cannot be said with certainty that anomaly of fall to zero influences low correlations, as the signals with this anomaly measured with the Empatica E4 sensor have higher or positive correlation than the other E4 sensor when this does not present anomalies.

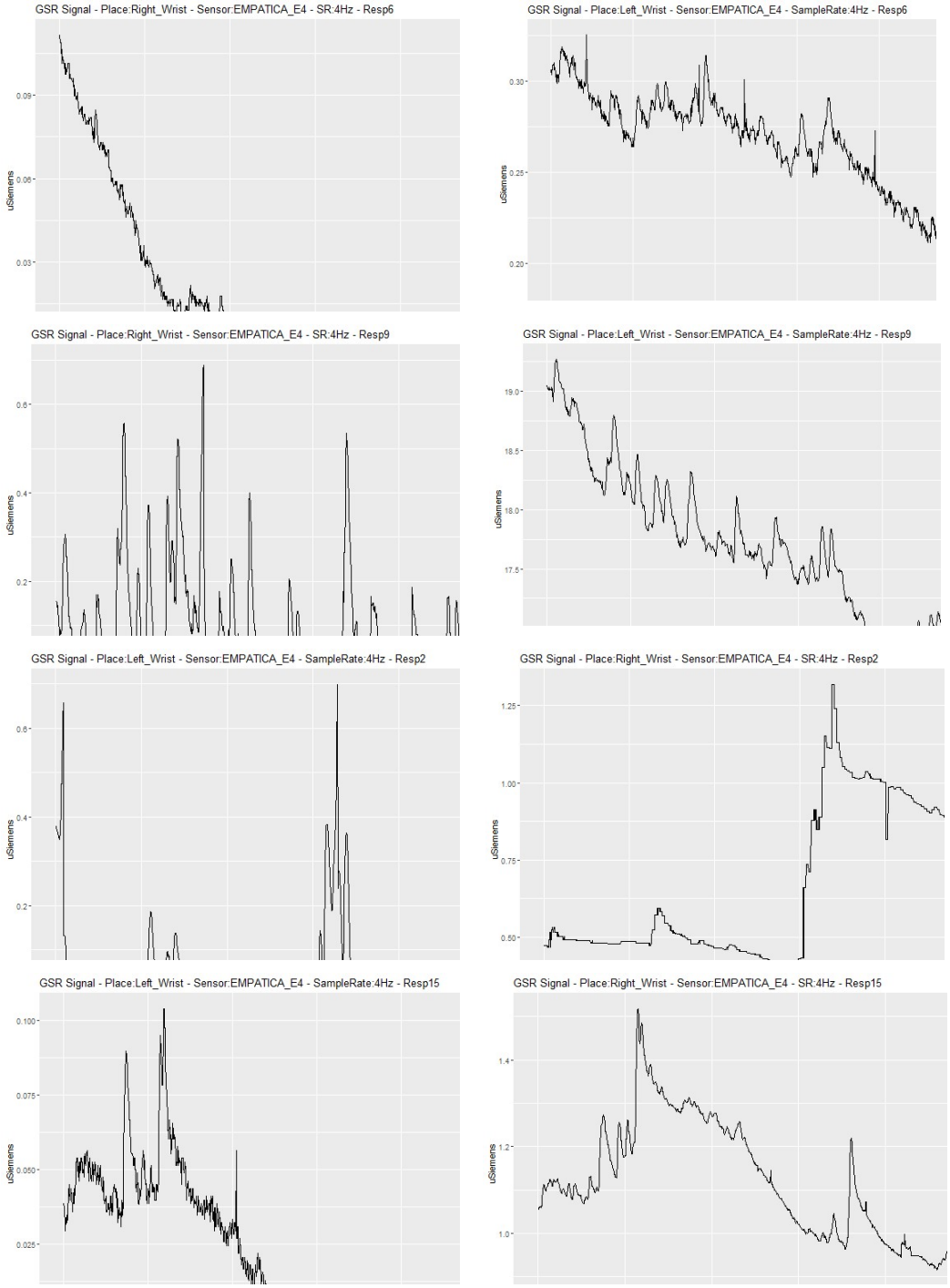

Figure 11. Illustration of cases with fall to zero anomalies detected. At left are the signal with anomalies, at right other signal measured in the same respondent with the same sensor type.

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We treat apart the fifth signal with a fall to zero anomalies, as this is the only signal with this anomaly that presents a negative correlation (E4-E4 in Respondent 7). We attribute this to a second anomaly in the signal, an abrupt jump (AJ), (see Figure 12), as correlations that just have abrupt jumps anomalies are the ones who present the lower correlation between Empatica E4 sensors (Figure 8). Nevertheless, the evidence is not enough to affirm that this anomaly may affect change detection homogeneously among a test group. There are correlations between signals with abrupt jump anomaly and other signals without it, which have a better correlation than those who do not have any anomaly in their signals (for instance, Respondent 7 Vs. Respondent 11). Neither can we attribute these abrupt changes too fast changes in the electrodermal activity, as this physiological parameter does not behave in this way. What haps is a sudden change of magnitude as can be seen in the right plots of Figure 12, where every dot is a GSR value measured in times of milliseconds, that unlike the left plots which came from the dataset sample rated in 250ms, the right plots come from the raw data.

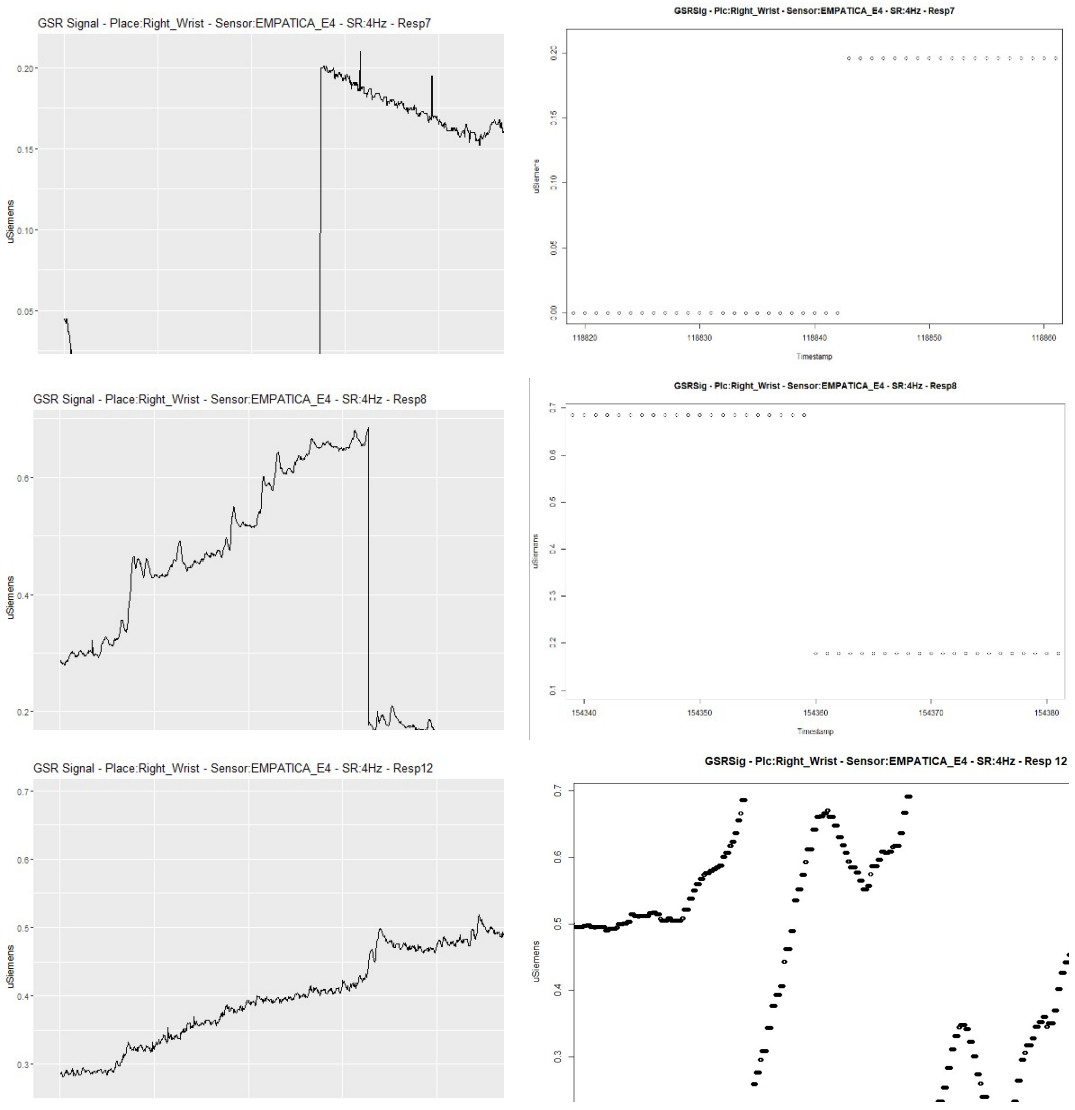

Figure 12. Illustration of cases of abrupt jump anomalies detected. At left are the signals with the anomaly graphed from the downsampled data, at right other signal measured in the same respondent with the same type of sensor, graphed from the raw data with time interval zoomed.

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The last anomaly detected on a Shimmer3GSR was a sustained measurement value for a relatively long period (Figure 13). The signal in Respondent 15 held a 0,67μS value during 120 seconds and then registered an abrupt change of magnitude held in specific values in several milliseconds. Despite this, the anomaly in the signal seems not to affect homogeneous detection of increasing or decreasing electrodermal activity in the test group, as in Figure 8 shows a really strong, almost perfect linear positive correlation between the pair of Shimmer Sensors.

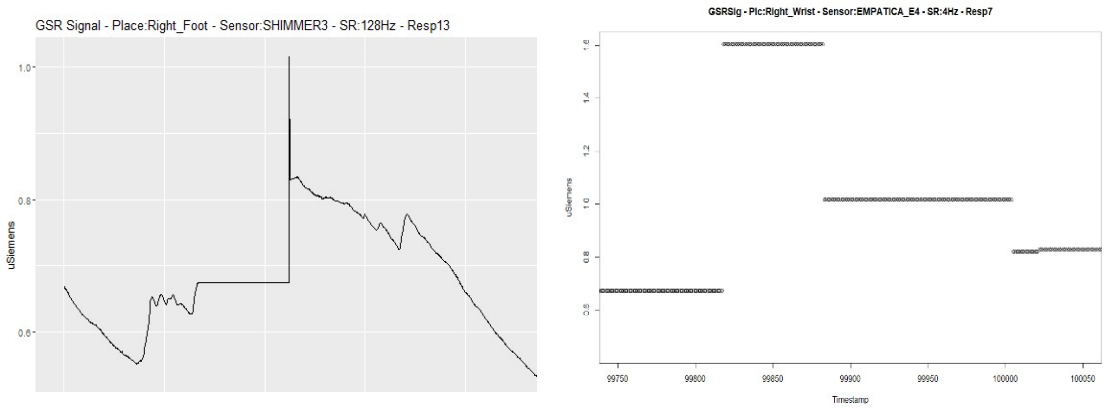

Figure 13. Illustration of held value anomaly detected. At left are the signals with the anomaly graphed from the downsampled data, at right other signal measured in the same respondent with the same type of sensor, graphed from the raw data with time interval zoomed.

Finally, this second correlation approach analysis highlights some insights from statistics in Figure 14. The test group's better homogeneous detection in this experiment was present in the signals from left fingers and right foot, measured both from Shimmer3GSR sensors. These statistics show that the second better mean correlation is from the right wrist and left wrist measured from Empatica E4 sensors. From the above, we can affirm that electrodermal activity changes can be measured homogeneously in a test group at least in two different sites with a strong positive linear correlation when using the same type of sensor (at least Shimme3GSR and Empatica E4). Compared to the above, as correlations of measure place which involve different sensors have, in general, a moderate positive correlation strength, we can affirm for this experiment that the type of sensor does not influence in a homogenous detection of EDA change among a test group—being Shimmer3GSR the one that gives better results.

The outliers in Figure 14 may be due to the anomalies previously analyzed, which caused negative correlations between sensors in each respondent, especially in the right foot and left wrist correlations, may due to anomalies in both measure sites, as well high dispersion detected in the first correlation analyze approach afore analyzed. This dispersion may pull the low strength of association with the correlation of the signal from the left Fingers. A comparison between the respondents with anomalies in their signals and those who do not have, indicated a certain affectation of the positives correlation between signals. However, a visual inspection to correlation respondents matrix of each signal (Figure 4) against anomalies in Figure 8, evidence some cases in which anomalies do affect the correlation between respondent, and other cases who do not, as low or negative correlation between respondents who do not have anomalies in their signals.

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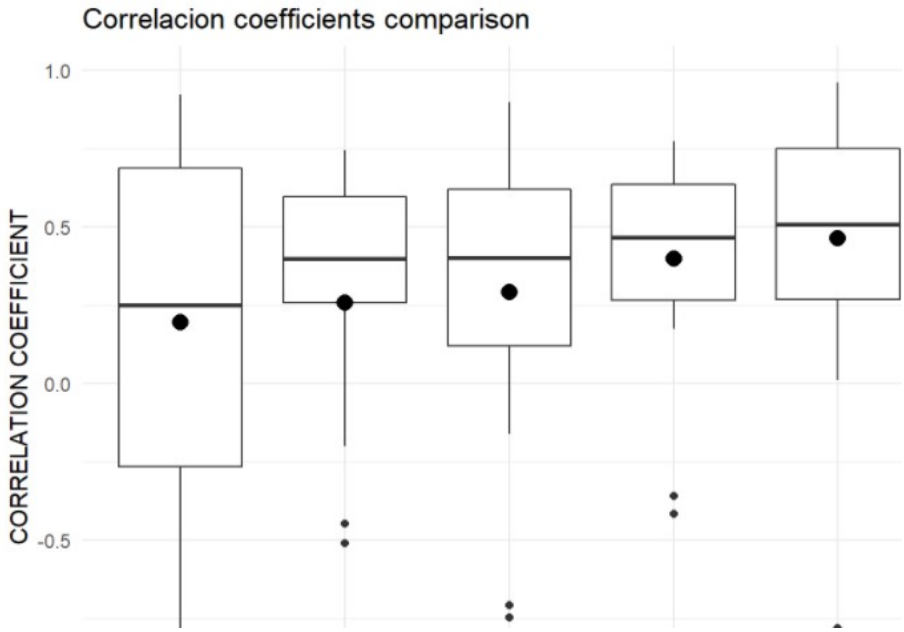

Figure 14. Box plot distributions of coefficient correlations from the correlation between signals.

6. Discussions

Wearable technology has led emotion recognition to a reasonable viability level due to hardware miniaturization and portability. Besides, computer science has improved data processing techniques to identify stress-related emotions. We seek to reduce the gap between real-life applications and people's quality of life with Autism Spectrum Disorder (ASD) their families and caregivers through this work. People with ADS are susceptible to stress, but their emotional reactions could be almost imperceptible in most cases, triggering difficulties in social communication and interaction. Galvanic skin response is one of the standard physiological biosignals for stress-related detection systems. There are several places to measure the response of the electrodermal activity. Using the Pearson correlation coefficient (r), we compare the signals measured from four wearable GSR sensors used in the right and left wrist, the fingers left, and the right foot, to investigate which place of measure could have a better homogenous response in a test group.

Our results from this first approach indicate four GSR measure places have, on average, a 60% probability of detecting increasing or decreasing in the electrodermal activity in a test group linearly (Table 4). GSR signal measured in the Left fingers has a bigger group of positives correlations, having a better chance among the four signals to detect homogeneous changes in electrodermal activity in a heterogeneous test group. They are followed by the right foot, right wrist, left wrist (Figure 4). There is a better probability of having a moderate linear positive relation in a test group when measure a GSR signal from the left fingers or the right foot, and these have better reliability than other measure sites as both have certain symmetry in the standard deviation and have better skewness in their correlations among the test group (Figure 6).

The signal measured from the right wrist has a more significant dispersion of positive correlation in the strength association scale. The mean and median of its positives correlation in the test group tends to a low-moderate strength (Figure 6). Statistically, there is a probability that GSR signals measured in the test group have a positive weak-moderate strength association of 90% in the left fingers, 64% in the right foot, and 53% in the right wrist. GSR signal from the left signal failed the goodness of fit test in the negative as in the positives correlations, and we were unable to make statistical inferential.

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The positive linear relationship of the GSR signal measured on the left wrist is not uniform in the test group. Its correlations fit in the high as the low strengths of positive association. However, it is visually remarkable that the left wrist has the strongest positives correlations between the signals matrix correlations; also, it has the highest mean. However, it also has the highest mean of negative correlations, which may be causing a remarkable asymmetric distribution in its positive correlation among the test group (Figure 5).

The analysis of the second approach yielded other conclusive results. We calculate the average per correlation between signals measured in each respondent to get a general impression of the correlation between signals in the test group. Initial evaluation revealed that signals measured from the right foot and Left fingers have a homogeneous detection of electrodermal activity changes in the test group, as well as in the first analysis approach. In average this two place of measure show a strong positive linear response between signals in respondents, it means, independently of any factor in a heterogeneous group, in both place if one increase or decrease the electrodermal activity, the other measure place will tend to increase or decrease respectively with a strong association. This association is about how much changes or variations occur in one respondent and will occur in the other.

However, this analysis also shows a negative correlation between signals in each respondent. It improves the approach of Phitayakorn et al. [38], who found no correlation of the GSR signals measured between the wrist and the ankle (a place close to the inner side of the right foot used in this experiment), due the ankle is less sensitive to GSR fluctuation—supported by Betancourt et al. [21]. They affirm that children with Neurodevelopmental Communication Impairments tolerated better biosensors secured with either an ankle wrap or socks than on the wrist. The bove turns green light to concept technologies for these potential sites of GSR measurement with electrodes held in sock-like against the skin proposed by Phitayakorn et al., idea boosted by technologies available as wireless skin-conformal bioelectronics sensors and electronics for continuous and portable stress monitoring in daily life as proposed by [48].

Looking for possible sources of negative correlations, we report anomalies in GSR signals' measures as sudden falls to zero, abrupt jumps of magnitude, opposite directions of GSR signals in the same respondent, and held value in a particular interval of time. We called opposite direction the anomaly founded in two cases. In the first case, a respondent has GSR signals measured in different sites, one increasing while using one type of sensors as other signals measured by another type of sensors decrease. In the other case, a signal goes in the opposites direction of another GSR signal measured with the same type of sensor (Figure 9 and Figure 10).

We trace this opposite direction anomaly to a wayward signal in the data from the right foot is the only one presenting this opposite behave, which is measured with a specific Shimmer3GSR sensor. This issue was also reported by Borrego et al. [35], which compares the reliability of two wristbands GSR, found that while the Empatica E4 detected an average increase of the EDA for unpleasant stimuli, the Refa system registered the opposite tendency. The authors give credits to the Refa systems as previous studies show them that Refa systems follow the good tendency for unpleasant stimuli. Furthermore, this decreasing electrodermal activity may be to lower skin temperatures at the right foot place as this causes the permeability of skin to water decreases [33][49]. We do not find tends to increasing or decreasing, as the signal increases in one respondent while decreasing in another. It is essential to evaluate this issue in the GSR measures further, as this should not be good for stress detection systems.

The above may be related to the fall to zero anomalies, present only in Empatica E4 sensors (Figure 11). We observe that if the EDA measured range is below 0,6μS from an Empatica E4, the decreasing tends of the electrodermal activity might make this signals fall to zero suddenly, unlike Shimmer3GSR sensors, which tend to measure in a range of μSiemens higher than Empatica E4 (3 to 5 upper in most of the case). We do not attribute

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this to the measure place, but evidence points to the Empatica E4 sensor as this haps in two different devices. Above is accorded with Kutt et al. [36], which reported that amplitude of skin conductance response from Empatica E4 is lower than other devices as eHealth and BITalino.

We could also observe that Shimmer3GSR sensors 89% of the time the right foot signals are higher than the left fingers (Table 5). Some suddenly abrupt jumps in the measured magnitude were present in the different respondent's signals, but the evidence is not enough to affirm that this anomaly may affect change detection homogeneously among a test group and cause negative correlations. Neither can we attribute these abrupt changes to fast changes in the electrodermal activity, as this physiological parameter does not behave in this way. What mayhaps is a sudden change of magnitude from one millisecond to another, as can be seen in the right plots of Figure 7. This issue was reported by Kutt et al. [36] with an Empatica E4 and MS Band. During movements, the contact between the body and the sensor was not constant, leading to sudden conductance changes, resulting in lower signal correlation.

Unlike the previous cases, which occurred throughout the experiment three times each in different respondents, we detected the held values anomaly only once. During the measuring, the signal start suddenly sustains the value of 0,67μS without any change during 120 seconds (Figure 13). Despite this, the anomaly in the signal seems not to affect homogeneous detection of increasing or decreasing electrodermal activity in the test group.

In this experiment, Empatica E4 sensors have a higher rate of anomalies registered than Shimmer3GSR sensors. Besides, the falls to zeros anomaly are the most frequent error in the Empatica E4 sensors. The battery level captured in the raw data in iMotion software did not show any pattern related to the anomalies. We did not take out the outliers for this study, as we want to observe the GSR signals' behavior among a test group as real-life will work. Also, we want to know how any outlier in the raw data captured may influence the increasing or decreasing detection of electrodermal activity in a test group, without any computation technique applied but the reconstruction of missing data. In this case, due to the downsampled and difference in timestamp synchronization, we use using spline interpolation [37]. Despite other studies attribute low correlation to the difference in the sample rate between devices [35], our results show that correlation between sensors with a significant difference in the sample rate (128 Hz for Shimme3GSR and 4 Hz for Empatica E4), after applying spline interpolation and downsample de dataset to 4 Hz, devices have moderate positive correlations.

The anomalies detected tend to pull the signals to low positives and negatives correlations between some participants. In contrast, other participants demonstrate opposites, so in this experiment, there is not enough evidence to affirm that these anomalies may affect the detection of changes in electrodermal activity homogeneously among a test group. A possible contributing factor may be related habituation of respondents to the stimuli used in this study could lead to a marked drop in arousal level [33]. We clarify that these are inferences from the experiment carried out and should not be taken as a fact in the acquisition of physiological GSR signals. More detailed studies about these anomalies, their causes and consequences must be studied more in-depth, according to the measuring devices.

Recurring assertions during the whole analysis may suggest the left fingers and potentially right wrist can provide homogeneous detecting changes of electrodermal activity in a test group. The four GSR measure places have significant tends to have a moderate-strong correlation. Outstand the hidden potential might be in the left wrist signal, which despite the dispersion present in its positive correlations, from Figure 6 and 14 may infer that without any outlier affecting the correlation, this signal could be a high potential strong correlated GSR measure places among the test group. Anyhow, specifics studies should be conducted to determine if the influence is on the Empatica E4 sensor or in the left wrist electrodermal activity.

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The use of iMotion software to integrate and synchronizes the data gathered by the sensors was valuable. Regarding the experiment, there are some limitations. The use of other wearable sensors to reduce cause factors of detecting suitable place to measure EDA as not all GSR wearable can detect peaks that may reflect in low correlation, and their location can cause that [36]. Another limitation is no assessment of the valence and arousal from the participants during the experiment as respondent sensitivity factor to pleasant or unpleasant stimuli can affect correlation analysis among a test group. In addition, the local skin condition may influence the reliability of the measurements and quality signals. These have to be included in an in-depth correlation study looking for potentially affecting factors like different measurement methods (sticky electrodes vs. plate electrode) [37], sensor movement [33], skin temperature, skin thickness, water content, body posture, and the density of sweat glands [33][50].

It is essential to complement this study with in-depth correlation analysis with datasets of GSR signals from all respondents per pleasant or unpleasant stimuli. As well as correlations comparison using different techniques of smoothing and low/high filters and the downsampled raw data, according to [37] that low-cost wearable sensors may tend to be producing datasets with reduced data quality, and noise in GSR signals gathered from wearable may variate [36].

7. Conclusions and Future works

This paper contributes to the literature reporting results about the correlation of measurement places of GSR signals with wearable sensors in valence and arousal changes, giving new information and comparing them with some existing findings through this experiment. These results also serve as the input of the next development stage for applications in our program research in the Human Health Activity Lab (H2AL). Although there have been a few studies related, there is still a need to find and prove correlation among different measuring places and compare them with other studies about negative correlation issues. Seventeen respondents participated in this experiment using four GSR sensors simultaneously while watching a video clip with pleasant and unpleasant scenes for 285 seconds to simulate valence and arousal changes. The experiment had a two-correlation analysis approach. One analyzed the correlation between the 17 respondents of each signal. The other analyzes the correlation between signals on each respondent. Both approaches use some statistical estimates and visual inspection of time plots to get insights about the homogeneity of detection electrodermal activity in a test group.

The experiment results show the better GSR measures place for a homogeneous detection in the test group is present in signals from left fingers and right foot measured both from Shimmer3GSR sensors. These statistics show that the second better correlation is from the right wrist and left wrist measured from Empatica E4 sensors. In general, from this experiment, we affirm that electrodermal activity changes can be measured homogeneously in a test group at least in two body sites with a strong positive linear correlation when using the same type of sensor. The type of sensor does not influence a homogenous detection of electrodermal activity changes among a test group, but there are some sensors as Shimmer3GSR that may give better results.

Our analysis indirectly shows that the Shimmer3GSR sensor may present better reliability to homogenous detecting electrodermal activity changes, as these have fewer anomalies among the respondent. However, the difference in the sense of the GSR signal should be paid attention to, as in this experiment in one respondent shows GSR signals from the right foot increasing while the rest of the signals tend to decrease. Our results show that correlations between sensors with significant differences in the sample rate (128 Hz for Shimme3GSR and 4 Hz for Empatica E4) have positives moderate correlations, at least after applying spline interpolation and downsample de dataset to 4 Hz.

Our analysis also demonstrates that the right foot's inner side is a promising place to measure EDA, as it is strongly correlated with GSR measures from the fingers left, at least when using the same type of GSR sensor. The right foot is also positively correlated with a moderate strength of association with the rest of the measure sites. The magnitude of the measure, regardless of the type of sensor, does not influence better correlations between the test groups. We do not found strong evidence that signal anomalies detected in this study influence low correlations. However, they were indirectly investigated in this study. Our future works will further evaluate more influence of factors for negative correlation as sensors movements, local skin conditions, type of electrodes, respondent sensitivity factor to pleasant or unpleasant stimuli, technical specifications of wearable sensors, and quality signal. Thus, the use of robust methods to describe the variation of signal correlation in the test group as the design of experiment (DOE) to understand the further behave of signals from different measure sites.

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