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Towards Continuous Monitoring of Well-Being

Anneloes L. MEIJER [a][1], Lukas P.A. ARTS [a], Randy GOMEZ [b], and Egon L. VAN DEN BROEK [a]

[a] *Department of Information and Computing Sciences, Utrecht University, Utrecht, The Netherlands*

[b] *Honda Research Institute, 8-1 Honcho, Wako-shi, Saitama 351-0188, Japan*

Abstract. When linked to wearable biosensors, Intelligent Environments could play a pivotal role in continuously monitoring and securing people's well-being. We explored the value of one such biosensor that records Electrodermal Activity (EDA) by assessing its correlation with participants' simultaneously, continuously, self-reported arousal. EDA's frequency and amplitude of 'non-specific' Skin Conductance Responses in low, mid to high, or high levels of arousal were determined. When participants were in mid/high and high arousal situations, self-reports showed significant correlations ($p < .001$) with both EDA characteristics. With low arousal, no significant correlations were found. So, in cases of elevated stress, EDA shows the potential of being a reliable signal stress and, hence, also monitor of people's well-being over time. Follow-up studies should further investigate and validate the utility of EDA monitoring as part of a comprehensive health monitoring strategy and its effectiveness in enhancing well-being.

Keywords. Intelligent Environments, well-being, ElectroDermal Activity (EDA), continuous monitoring, stress, biosensors

1. Introduction

In the past ten years, there has been an increasing awareness of prolonged stress and its relation to burnout, especially in work settings. Burnout is a condition characterized by prolonged and excessive stress, leading to physical, and mental exhaustion [1,2]. It can negatively affect individuals in different professions, causing a significant impact on their overall well-being. More generally, stress experienced over longer periods of time can negatively influence our well-being, like experienced in bad moods and disorders [3].

It is suggested that Intelligent Environments (IE) can aid in improving well-being, by monitoring and enabling early detection of long-term stress. IE is defined as any space in our surroundings in which different aspects of the environment are controlled and adapted by intelligent agents, enhancing individuals' experiences [4]. More specifically, wearable sensors can be used to monitor one's physiology and behavior continuously without causing discomfort to the wearer. As such, users are still able to interact with their environment intuitively and naturally, while also gaining valuable insights into

[1]Corresponding Author: a.l.meijer@uu.nl

their health and well-being. A practical application of this technology is a Body Area Network (BAN): a wireless network of multiple wearable sensors placed on the human body. BANs are designed to collect and transmit physiological and environmental data to other devices and systems to monitor and improve health [5]. Over the past few decades, advances in wearable technology made sensors smaller, lighter, and more wearable [6,7]. However, for BANs to work correctly, it is crucial to ensure that measurements are accurate, both in terms of the physiological and mental state.

Validation of EDA as a long-term stress indicator is a vital first step towards the continuous monitoring of stress. However, validation is difficult as self-reported annotation and EDA-based annotations often work on different time scales. EDA-based annotations are real-time, while self-reported annotations are often post-hoc. In this paper, we present a study that compares real-time self-reported annotations and EDA-based annotations using an unique annotation dataset. As such, validity of EDA as a real-time stress-indicator is assessed. Additionally, we showcase the possibility of indicating stress on a continuous scale, rather than in discrete states. Stress is often assessed by asking whether an individual is stressed or not, rather than how much stress they are experiencing on a continuous scale. This research could contribute to the development of more accurate and sensitive continuous measures of well-being, enabling better management of stress-related health issues over time [8].

Next, we discuss some background knowledge in Section 2, followed by an explanation of the methodology used in Section 3. The results are presented in Section 4. Section 5 provides a discussion of the results, their implications, and future research directions as well as a conclusion.

2. Background

First, we discuss the challenge of obtaining a ground truth of well-being. Second, we discuss the pros and cons of different forms of continuous monitoring of well-being. Third and last, we discuss ElectroDermal Activity (EDA), as promising biosignal for this continuous monitoring of well-being.

2.1. Annotation of the Internal State

Generally, self-reported annotation is used to gain insight into the mental state (i.e. subjective experience) of individuals. Common annotation methods include: self-report [9], behavioral coding [10], and experience sampling [11]. Each method has its strengths and limitations.

Generally, self-reported annotation is used to gain insight into the subjective experience of individuals. As mentioned, there are several common annotation methods: self-report, behavioral coding, experience sampling, and physiological measures. As a method, self-report relies on individuals to report their own thoughts, feelings, and behaviors. Limitations include: social desirability bias, accurate recall difficulties, limited insight into our own thoughts and feelings, and cultural differences like social norms [9]. Behavioral coding is a method used to systematically observe and record behaviors or interactions between individuals or groups. Here, limitations occur like observer bias, limited context, it is time consuming, and it can be intrusive which can alter behavior [10].

Experience sampling is a research method that involves collecting data, typically through the use of mobile devices or other technology, to collect data on multiple moments. Limitations include: time consuming which can lead to participant fatigue or dropout, and again accurate recall difficulties [11].

We can conclude that traditional annotation faces difficulties. Continuous, unobtrusive annotation of an individuals internal state can be a solution. Being able to continuously annotate a person's internal state can create real-time insight. Consequently, alternatives have been developed, including several in relation to stress [8,12]. It allows to better understand pattern, in this case health patterns, over time. Electrodermal Activity (EDA) could be such an alternative, as it allows unbiased, real-time annotation. EDA signals can be measured unobtrusively in wearable devices and are, unlike other physiological measures, solely affected by our bodies' stress system; the sympathetic nervous system [9]. As such, EDA has the potential to be a long-term indicator of stress enabling the continuous and unobtrusive annotation of stress without self-report.

2.2. Continuous Well-Being Monitoring

To monitor one's health and well-being, we need accurate measurements of the mental and physiological state. Physiologically, well-being can be monitored by evaluating one's biosignals. Existing research has shown the possibilities of this continuous measuring of biosignals in the health domain [13,14,15]. However, most of this work uses biosensors in clinical or lab settings, with a few exceptions [16,17] and even comparisons between lab and real-life settings [18,19]. However, the biosensors used are often discomforting for the user and there is a growing interest in monitoring well-being in everyday life.

The last two decades, researchers have been investigating the development of unobtrusive biosensors and the use of other sources, such as smartphone usage and context monitoring. In this regard, different modalities are currently used to monitor well-being, including audio-based, vision-based, text, blood samples, interaction-based, questionnaires, interviews, and wearable biosensors [12]. Among these modalities, wearable biosensors are becoming increasingly popular due to their unobtrusive sensing methods. Furthermore, the development of smart textile technology and flexible, stretchable, and printable electronics has provided new opportunities for monitoring well-being [6].

2.3. ElectroDermal Activity (EDA)

Since EDA was first measured, psycho-physiological research studied the relationship between emotional states and EDA on both a subjective and physiological level [9,20]. EDA measures the skin conductance as a result of sweat glance activity. More specifically, when sweat glance activity increases, conductivity increases due to the sweat acting as a conductor of electricity. Where other peripheral measures are influenced by both sympathetic and parasympathetic nervous system activity, sweat glance activity is directly coupled to the sympathetic nervous system. Hence, EDA offers a cheap and effective way of measuring sympathetic nervous system activity [9,21].

Emotions and stress are closely related. Both positive and negative experienced stress result in intense emotional responses, which are both present in EDA signals [21]. Overall, EDA provides a valuable physiological measure of stress that can be easily and non-invasively monitored over extended periods of time, making it a promising tool for long-term monitoring of stress and related outcomes.

3. Methodology

First, we introduce the Continuously Annotated Signals of Emotion (CASE) dataset [22] used (see also [23]). Next, we explain how we processed CASE's self-reported annotations. Last, we describe the EDA processing (see Figure 1).

3.1. CASE dataset

The CASE dataset is a publicly available dataset resulting from an experiment where participants continuously annotated their affect in a valence and arousal space while watching short movie clips. Several biosignals, including EDA, were measured during the experiment. Although designed with emotions (i.e. a short-term affect) in mind, the data set is still usable for analysis on larger time scales because of its long measurements. More importantly, the continuous annotation on arousal allows us to research the relation between physiological stress and self-reported arousal on a continuous basis. By analyzing both the continuous arousal annotation and the EDA signal, researchers aim to investigate how well EDA scales to a reliable continuous annotation for arousal. For more details on the experimental set up, we refer to [22,23].

The experiment followed a within-subject design, where participants were shown a sequence of eight different movie clips with different effects on valence and arousal. Looking only at the arousal domain, three types of stimuli are identified: low, mid to high, and high arousal effect. Between each stimuli, a two-minute blue screen was shown, allowing for a 'reset' and rest between annotations [22,23]. The dataset includes physiological signals and continuous annotations from 30 participants, resulting in 240 recordings.

3.2. Annotation processing

The joystick-based (sample rate; 20Hz) self-reported annotations are represented in Cartesian coordinates, where the x and y-axis represent *valence* and *arousal*, respectively. Here, only the arousal signal (i.e., the y-position of the joystick) was used.

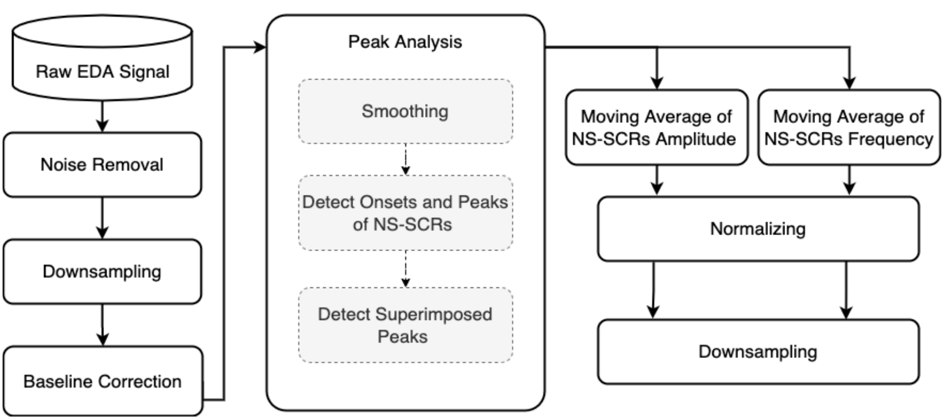

Figure 1. The ElectroDermal Activity (EDA) signal processing pipeline. NS-SCRs denotes non-specific Skin Conductance Responses.

The arousal signal ranges between 0.5 and 9.5. As such, the signal was first transformed by subtracting 5 to align the signal's center at 0. Then, the normalized signal a_n was obtained to correct for inter-personal variance among participants [20], as follows:

$$a_n = \frac{a}{a_{max}}, \tag{1}$$

where a contains annotations taking all videos of one participant into account and a_{max} the maximum a [20]. This normalization is used since it allows for positive arousal to remain positive interval of $[0,1]$ and negative arousal normalizes to an interval of $[-1,0]$.

3.3. ElectroDermal Activity (EDA) processing

The information in EDA signals is typically divided into tonic (i.e., underlying EDA) and phasic activity (i.e., Skin Conductance Responses, SCR). Tonic activity is measured in two ways: by calculating the Skin Conductance Level (SCL) and by analyzing the 'non-specific' SCRs (NS-SCRs). An NS-SCR is any emerging SCR that is not linked to internal or external stimuli. The frequency of these NS-SCRs is a widely used tonic measure, also in relation to arousal, stress, and emotions [21]. Although not widely applied, the mean amplitude of NS-SCRs also suffices as tonic measures and allows us to determine the total amount of 'non-specific' changes in EDA [21]. EDA signal processing is applied to extract this information (see Figure 1), which includes:

- *Noise Removal & Downsampling.* A 0.03s median filter is applied to remove noise. Subsequently, we downsampled from 1000Hz to 200Hz, to increase computational efficiency. This is allowed as EDA's energy is in the low-frequency range.
- *Baseline Correction.* To correct for personal differences and differences in the experimental set-up, the trend during the videos is removed by fitting and subtracting a linear function. The resulting signal only shows the effect of the stimuli around the average EDA.
- *Peak Analysis.* First, the signal is smoothed using a 1s moving average filter. The window was extended by repeating the boundary values to counteract boundary effects [24]. Then, NS-SCRs were detected, using a slope threshold [21]. NS-SCR onset is marked when the slope exceeds 0.0004μS/s. The peak must last for at least 0.5s for it to be considered a valid NS-SCR. The offset is denoted by the first value that has a smaller derivative than 0.0001μS/s. Subsequently, superimposed peaks (i.e., peaks that overlap because the previous peak had no time to recover) are split into two separate NS-SCRs [25].
- *Moving Averages* The average number of NS-SCRs and the average amplitude of NS-SCRs are counted within a sliding window of 30s. This is done by applying a 30s moving average filter to the number and amplitude of NS-SCRs.
- *Normalizing & Downsampling.* Both the frequency and amplitude signals are normalized using Eq. (1). Consequently, the EDA features are in the same interval as the annotation data. Finally, the signals are down-sampled to 20Hz, the sample rate of the annotation data.

where a threshold of 0.1μS was set, which represents the minimum EDA change to count as an elicited NS-SCR [9]. Additionally, a 1–5s window from the start of the stimulus is not considered, here the signal is influenced by the onset of the stimuli [9,21].

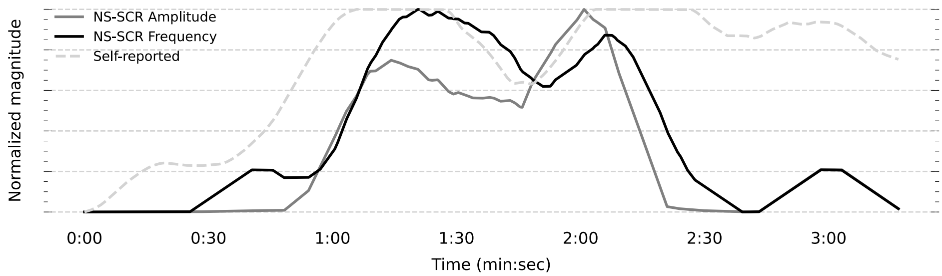

Figure 2. Example self-reported arousal against NS-SCR frequency and amplitude, given over the duration of one video with a high arousal context.

4. Results

To determine whether or not EDA is a reliable continuous stress indicator, a Pearon correlation test is performed on each video per participant. We hypothesise a positive correlation between the continuously self-reported arousal and NS-SCRs' frequency and amplitude: An increase in NS-SCRs' frequency and amplitude is expected to relate to an increase in self-reported arousal. Here, we distinct three types of videos, intended to elicit low, mid/high, and high arousal [22,23]. An example of the correlation between self-reported annotation and both EDA features on a high arousal video is shown in Figure 2.

A one-sampled t-test is used to test the significance of the findings against the null hypothesis. Here the null hypothesis is no correlation between NS-SCRs and self-reported arousal. Hence, a correlation coefficient of zero. The analysis is done on both frequency and amplitude of NS-SCRs with self-reported arousal.

4.1. Average correlation

NS-SCRs frequency & Self-Reported Arousal. The average correlations in the low, mid/high, and high arousal contexts are -0.04, 0.29, and 0.51 respectively (see also Figure 3). When arousal is low, the null hypothesis is not rejected, as evidenced by a relatively high p-value, $t(96) = -1.010, p = .315$. However, for cases of mid to high arousal and high arousal, the null hypothesis is rejected, as evidenced by very low p-values: $t(53) = 6.042, p < .001$ and $t(58) = 14.051, p < .001$, respectively. With these results the null hypotheses can be confidently rejected.

NS-SCRs amplitude & Self-Reported Arousal. The average correlations in the low, mid/high, and high arousal contexts are -0.05, 0.20, and 0.50 respectively (see also Figure 3). When arousal is low, the null hypothesis is not rejected, as evidenced by a relatively high p-value, $t(96) = -1.083, p = .282$. However, for cases of mid to high arousal and high arousal, the null hypothesis is rejected, as evidenced by very low p-values, $t(53) = 3.741, p < .001, t(58) = 15.236, p < .001$, respectively. With these results, the null hypotheses can be confidently rejected.

4.2. Personal Differences

Each individual has unique physiological and psychological traits that results in variations in their biosignals, including EDA [9]. These personal differences have significant

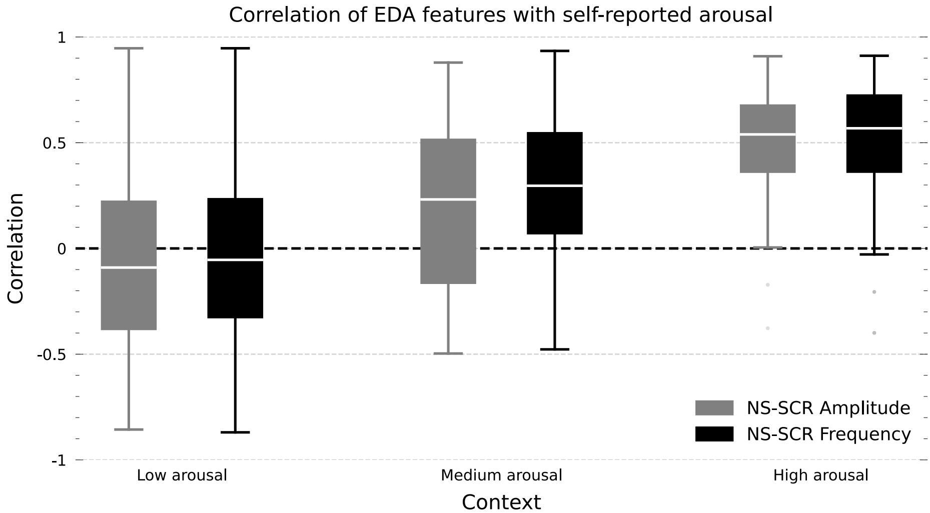

Figure 3. Distribution of correlation coefficients for frequency and amplitude of 'non-specific' Skin Conductance Responses (NS-SCRs) with self-reported arousal. Distribution is given on three different contexts: low, medium and high levels of arousal.

implications when monitoring and analyzing biosignals. As such, we calculated correlations across all participants on each of the three levels of arousal. Results are shown in Figure 4.

Correlations between self-reported arousal and both NS-SCR features varies greatly between participants. Despite these differences, a trend still emerges across the different contexts. Specifically, Figure 4 shows that correlations increases and the distribution clusters when the a higher level of arousal is experienced.

5. Discussion

Significant correlations between EDA and self-reported arousal were found whenever medium or high levels of arousal were experienced. The results suggest that situations that elicit high levels of arousal increase NS-SCRs in frequency and amplitude. Interestingly, the correlation coefficient dropped when low levels of arousal are experienced. In that case, no significant correlation was found. This suggests the presence of a threshold, where arousal above a certain level is directly reflected in physiology. Hence, the level of expected arousal is important when using of NS-SCRs frequency and amplitude as annotations.

Reviewing the correlations of EDA features and self-reported arousal across participants showed the importance of considering individual differences when using biosignals. One of the reasons for this individual difference is the difference of number of sweat glands across populations [20].

Schachter and Singer's two-factor theory of emotion suggests that emotions are the result of both physiological and cognitive interpretation of a given situation [26]. Physiological arousal alone is not enough to explain emotions; rather, it is the cognitive interpretation of that arousal that leads to the experience of affect. The positive correla-

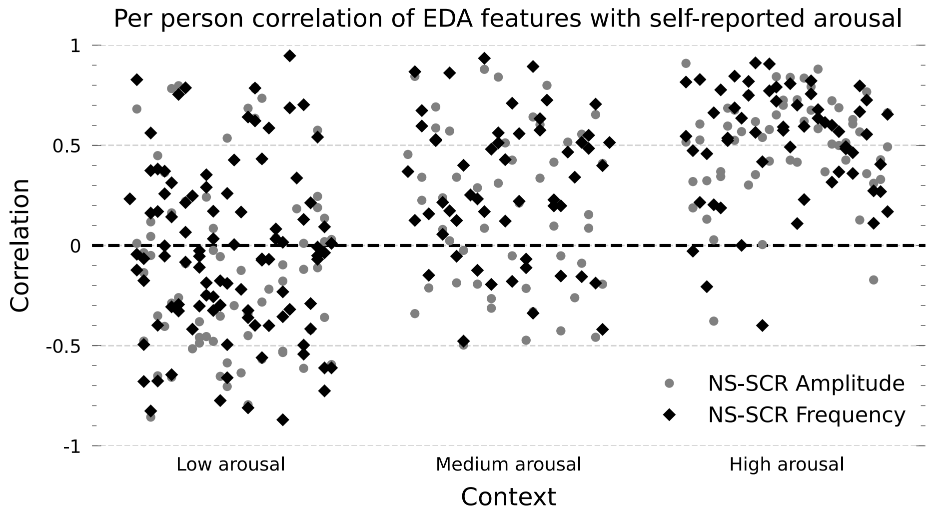

Figure 4. Mean correlation coefficients for frequency and amplitude of Non-Specific Skin Conductance Responses (NS-SCRs) with self-reported arousal. Distribution is given on three different contexts: low, medium and high levels of arousal.

tion between self-reported arousal and NS-SCRs characteristics over time may support this theory by suggesting that our physiological response and emotional experience are not separate. People experience physiological arousal and express this together with the context to an affective state accordingly, here arousal. As such, it supports the idea that physiological arousal plays a role in shaping our affective experience and that the two are intertwined.

If arousal levels increase to at least mid to high levels, EDA showed to be promising as a long-term continuous stress indicator. This allows a refined and precise measurement compared to discrete states. It also allows for increased sensitivity and can detect small changes. This is particularly important when measuring variables that exhibit gradual changes over time or that may be affected by subtle factors, like arousal (e.g., see Figure 2). This shows its ability as a long-term stress monitor, as opposed to its commonly used application for short-term event analysis and detection.

Interestingly, we found very low correlation for contexts of low levels of arousal. Evaluating this outcome showed that people generally annotated negative arousal in these cases. In some cases the frequency of NS-SCRs were zero for the entire duration of the video. Hence, one of the variables remained constant, resulting in no correlation coefficient. Here an interesting discussion point arises: if there are no NS-SCRs, is this not the most calm and neutral physiological state your body can express? So can you even have a negative level of arousal? If this is the case, then individuals should not have been given the opportunity to annotation negative arousal. Hence, findings no correlation in these situation can be expected.

There are limitations to the findings in this paper. For one, the nature of the dataset limits the long-term conclusions we can make on the analysis. Here, we are analysing time-windows with an average duration of 159 seconds. This research showcases the potential of EDA and a continuous measure on theses windows; however, further research is needed to validate these outcomes on longer time-windows (cf. [3]. This dataset allowed to analyse three different contexts of arousal, as a result of a lab study. However, these contexts do not approximate the complexity of real-world situations. Currently our findings do not provide an answer on how to deal with low states of arousal, limiting the direct translation to real-world applications. Further research with wearable devices is needed to show how well these findings generalise to real-world situations. It can allow us to conclude how EDA can fully attribute to Intelligent Environments (IE).

Concluding, this research has shown the possibilities of EDA as a continuous long-term monitor of stress, and ultimately well-being. EDA can support Intelligent Environments (IE) with the use of wearable devices and function as an indicator of individual subjective stress [18,19]. This can allow for an adaptation of the environment and create early opportunities to remedy stress levels [3]. Ultimately, the aim is to prevent the prolonged duration of stress, which has been a cause of burnout and a general decrease in mood and well-being. Future research can show the utility of EDA monitoring in IE and its effectiveness in enhancing well-being.

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