DETECTION OF PHOBIAS FROM ELECTRODERMAL ACTIVITY SIGNAL

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Abstract

This article is focused on the preliminary study of detecting different types of phobias from the electrodermal activity signal. Electrodermal activity is independent of parasympathetic activity; therefore, it is an ideal indicator of phobias. An automatic algorithm was created for the detection of phobias, which evaluates the presence of a stress reaction to a stimulus in the form of an image sequence representing the given phobia. The results obtained using the proposed algorithm were confronted with the data provided by individual respondents in the questionnaire. By comparison, it was found that the proposed algorithm detected a greater number of phobias than reported by the respondents. According to the achieved results, we can state that electrodermal activity can serve as a means of objectifying the presence of phobias in individuals.

Keywords

electrodermal activity, phobia, stress

Introduction

For many people, stress is a daily part of life. Stress can be defined as a non-specific alarm and defense mechanism that occurs as a result of a violation of homeostasis due to the effect of a stressor. The causes of stress are various, and the body reacts to stress by changes in the cardiovascular, musculoskeletal, gastrointestinal, nervous, and endocrine systems [1]. A phobia is an acute stress, which is defined as an irrational panic fear or anxiety about some objects, situations, or persons, which is objectively not proportional to the real danger. The most common cause of a phobia is surviving a stressful situation, such as an insect bite or an unpleasant experience at the dentist. This experience is stored in the brain and later recalled in a similar situation. A phobia in a person is most often manifested by a feeling of anxiety or panic, abnormal breathing, sweating, rapid heartbeat, a feeling of suffocation, pain or tension in the chest, the urge to vomit, nausea, dizziness, hot flushes or chills, high blood pressure or body tremors [2]. During stress, there is an increase in heart rate, accelerated breathing, vasoconstriction, involuntary contractions of facial muscles, and others. Based on the above manifestations, we can detect stress from signals such as ECG, EMG, or PPG. The most appropriate indicator of the presence of stress is electrodermal activity (EDA), the only one that does not depend on parasympathetic activity. EDA refers to changes in the electrical properties of the skin (i.e., electrical conductivity) caused by the activity of sweat glands controlled by the sympathetic part of the nervous system. The EDA signal (Fig. 1) consists of the tonic component SCL (Skin Conductance Level) and the phasic component SCR (Skin Conductance Response).

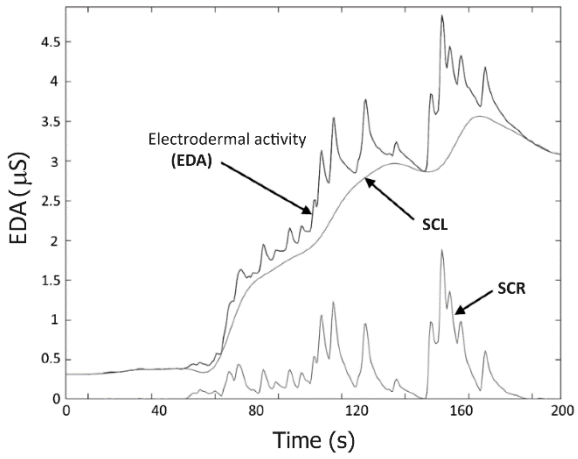

Fig. 1: Signal of electrodermal activity and its components – SCL and SCR. Adjusted according to [3].

The SCL component represents the basal activity of the sympathetic part of the autonomic nervous system and is related to slower signal changes. On the other

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hand, the SCR component corresponds to faster signal changes that arise from the activation of the sudomotor nerve, which acts on the activation of the sweat glands and is related to the emotional state of the person. In general, we can say that the EDA signal is formed by a fast-changing SCR signal modulated by a slow SCL signal. Both components can be separated by various methods, e.g., signal deconvolution. The frequency range of the EDA signal is approximately up to 1.5 Hz. [4, 5]

The aim of this article is to introduce a method for detecting the most common phobias from the EDA signal.

Materials and Methods

For EDA sensing, we used the Biopac MP36 device (Biopac Systems, Inc., CA, USA) together with the SS57LA cable set, which is designed specifically for this type of measurement. Silver/Silver Chloride gel electrodes were placed on the second joint of the index and middle fingers of the left proband's hand (Fig. 2).

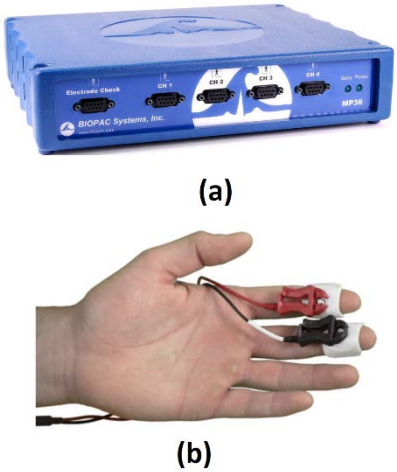

Fig. 2: Biopac MP36 (a), placement of electrodes on fingers (b).

The EDA signal was recorded with a sampling frequency of 1 kHz. The signal was pre-processed by applying a low-pass FIR filter with a cut-off frequency of 2.4 Hz, which suppressed disturbing artifacts that were outside the useful frequency range of the EDA signal. Furthermore, the signal was subsampled to speed up further signal processing.

Stress was detected from the SCR signal, which was extracted from the EDA signal using the deconvolution method presented in [6]. The separation of the EDA signal components is not the topic of this paper, so we will not discuss it in more detail. To detect stress, it is essential to define the parameters of the SCR curve and determine their threshold values, the crossing of which indicates stress. The typical parameters of the SCR signal are illustrated in Fig. 3. Latency is the time from applying the stimulus to the first significant deviation. The recovery time represents the time span when the SCR signal drops by 63% of its value. The half recovery time represents the time span when the SCR signal drops by 50% of its maximum value. According to [1, 7], the most significant features in stress detection are SCR amplitude, SCR rise time, and SCR 50% recovery time. In addition to the parameters depicted in the Fig. 3, the slope of the response is another important signal feature. Response's slope can be expressed as the ratio of the amplitude and rise time. A more stressful event is represented by a steeper slope, and vice versa.

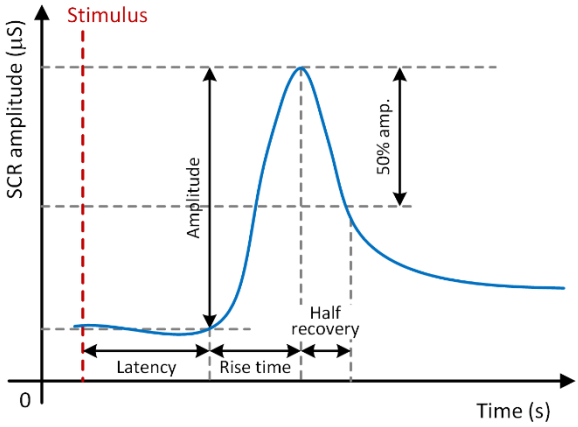

Fig. 3: A typical SCR response.

The above-mentioned signal's features are involved in our algorithm for phobia detection and are summarized in Table 1.

Table 1: SCR features used in phobia detection algorithm.

Feature	Limit value
Response slope	> 9
Latency	(0.5–10) s
Latency + Rise time + Half recovery	< 4 s

The values and its limits in Table 1 were determined based on experiments and research papers [1, 8]. According to the parameters in Table 1, we created a decision tree algorithm that detects stress if all the conditions are fulfilled.

Using the seven most common phobia types, we validated the suggested algorithm for phobia (stress) detection (Fig. 4). The investigated phobias include arachnophobia (fear of spiders), ophidiophobia (fear of snakes), entomophobia (fear of insects), trypanophobia (fear of needles), coulrophobia (fear of clowns), musophobia (fear of mice) and acrophobia (fear of height/depth). All mentioned phobias were part of a video in which each phobia was presented with a series of images lasting 15 seconds in total. Between

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phobias, there was a 15-second pause in the form of a black screen, which served to calm the subject down and stabilize the EDA signal. The onset of the phobia (stimulus) was marked in the EDA recording using a function key by the experimenter.

Fig. 4: Phobias used in the experiment.

The EDA records were analyzed in the MATLAB (Mathworks, Inc., MA, USA) programming language. For this purpose, a graphical user interface (GUI) was created, which allows the loading of the required record, automatic data preprocessing, and stress detection. The interface and the result of stress detection for a specific record can be seen in Fig. 5. Stimuli are indicated by red vertical lines. The result is represented in the form of the text POS or NEG under the label of the stimulus (e.g., Event 1). The inscription POS means capturing a stress reaction to a stimulus, and the inscription NEG means that the conditions for detecting a stressful event were not met. The GUI in Fig. 5 is intended for stress detection using various algorithms as selected from the panel on the right. In this article, only the decision tree algorithm according to the criteria mentioned above is presented.

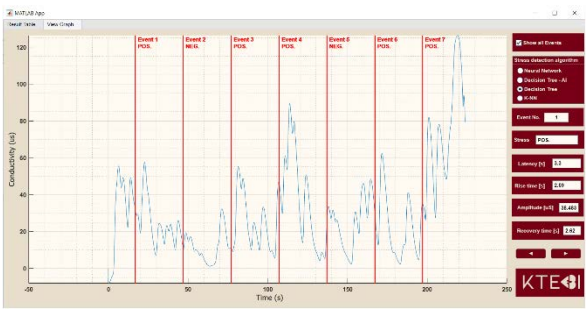

Fig. 5: GUI for EDA analysis and graphical interpretation of results.

Results

Thirty subjects (16 men and 14 women) participated in the experiment. The average age of the subjects was 30.73 years, with the youngest being 13 and the oldest 74. The informed consent was obtained from all participants before the experiment. Following the experiment, the participant completed a questionnaire indicating which phobias he had as well as his age and gender.

Based on experiments, we found that the most represented phobia among respondents is arachnophobia (fear of spiders), and the least represented is musophobia (fear of mice). Fig. 6 shows the proportion of the occurrence of phobias among respondents, taking into account their gender. Based on our results, we can say that more phobias occurred in women than in men.

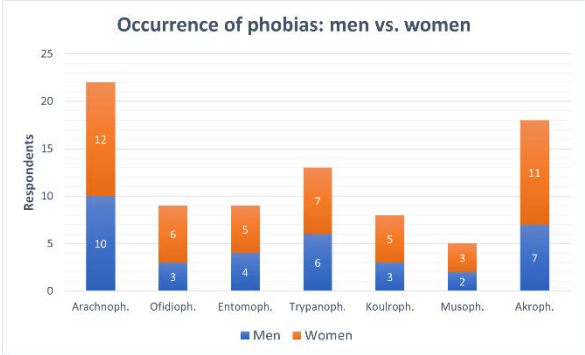

Fig. 6: Occurrence of phobias among respondents according to the proposed decision tree algorithm.

Next, we compared the automatic algorithm for detecting phobias and the data provided in the questionnaire. The comparison of the number of detected phobias is shown in Fig. 7.

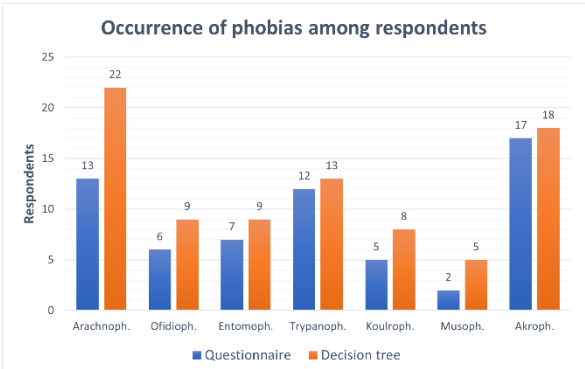

Fig. 7: Comparison of the occurrence of phobias in respondents according to the questionnaire and proposed algorithm (decision tree).

The results in Fig. 7 show that the number of phobias detected using the algorithm is higher compared to the number of phobias indicated by the respondents in the

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questionnaires. Most often, the subject did not mark the phobia in the questionnaire, and the algorithm detected it. This case occurred in 51.1% of cases—False Positive. A less frequent phenomenon was if the subject marked a phobia in the questionnaire and the phobia was not confirmed by the algorithm (16.15% of cases—False Negative).

Discussion

The proposed algorithm shows the ability to detect phobia from an EDA signal. According to the results in Fig. 7, we found that the proposed algorithm detected a greater number of phobias than reported by the respondents in the questionnaire. The occurrence of a phobia, which was detected even though the respondent did not indicate it in the questionnaire, could be caused by various reasons. Some participants may have felt stress from the measurement, which may have been reflected in the results. Furthermore, it could also be caused by a subconscious fear that they are either not aware of or do not want to admit. Another factor may be a suprathreshold stress trigger, even if the phobia does not normally occur. For example, climbing a tree does not show fear of heights, but looking down from a skyscraper does show fear. On the other hand, those who had a match between the detected phobia and their questionnaire statement have a good basis for coping with the given phobia. It is necessary to be aware of the stressful situations that a person is exposed to learn how to manage stress effectively. People who indicated that they had a given phobia and had no response measured may have learned to defend against that phobia, or the stimuli in the video were at a subliminal level.

The results show that the choice of image sequence for a given phobia is very important. Images that are too extreme can trigger a stress response even if the individual does not suffer from the phobia. A possible solution to determine a stress response or phobia is to increase the stress stimulus in the picture sequence. For example, for a person who suffers from an arachnophobia, an image sequence may contain images of small spiders to large spiders showing details that may be significantly repulsive. The formation of an appropriate image sequence is crucial to accurately determine the phobia and requires further investigation and experimentation.

Conclusion

The article aimed to investigate whether it is possible to detect selected types of phobias based on the measurement of the EDA signal. Based on the experiments carried out, we can say that the EDA signal is indicative in the detection of phobias and can help to objectify their presence in individuals. To confirm this statement, it would be necessary to include more respondents and specify more precisely the stimuli that trigger the phobia.

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