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Electrodermal activity measurements for detection of emotional arousal

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Abstract. In this article, we present a comprehensive measurement system to determine the level of user emotional arousal by the analysis of electrodermal activity (EDA). A number of EDA measurements were collected, while emotions were elicited using specially selected movie sequences. Data collected from 16 participants of the experiment, in conjunction with those from personal questionnaires, were used to determine a large number of 20 features of the EDA, to assess the emotional state of a user. Feature selection was performed using signal processing and analysis methods, while considering user declarations. The suitability of the designed system for detecting the level of emotional arousal was fully confirmed, throughout the number of experiments. The average classification accuracy for two classes of the least and the most stimulating movies varies within the range of 61–72%.

Key words: electrodermal activity (EDA), galvanic skin response (GSR), skin conductance response (SCR), feature selection, arousal, valence, classification, regression.

1. Introduction

Automatic emotion detection can improve human communication with the computer, can be used in psychology and medicine for diagnosis of a user's mental state and in neuromarketing [1–3]. To read the emotional state of a man, you can use a whole range of methods, including pulse measurement, ECG analysis, EEG analysis, facial expressions, pupil size and electrodermal activity (EDA) [4–6]. Also, a fusion of data, collected from different sources, can be used. Unfortunately, each of these methods has some weaknesses, and the effectiveness of the known solutions is still not satisfactory [7]. EDA is commonly used in the field of human-computer interaction [8]. Effective use of the EDA signal in recognizing the level of emotional arousal would offer better communication between human and computer, leading to affective computing [9–11].

Electrodermal activity (EDA) is the property of the human body that causes continuous variation in the electrical characteristics of the skin. In the past, by a number of authors, EDA has been identified with skin conductance (SC), galvanic skin response (GSR), electrodermal response (EDR), psychogalvanic reflex (PGR), skin conductance level (SCL), skin conductance response (SCR) and sympathetic skin response (SSR). The long history of research into the electrical properties of the skin by a variety of disciplines has resulted in an excess of names, now standardized to electrodermal activity (EDA). But the older names are still in use. So Thus, we can say that EDA is the one of the earliest known methods for measuring the level of emotional excitement [8, 12]. In a large number of articles, the concept of EDA is identified with only the measurement of skin resistance/conductance [13–16]. The biggest advantage of this method is its simplicity. In contrast, its disadvantage is a disturbed signal influenced by a number of factors [8, 17]. Proper selection of features, extracted from an EDA signal, can make the detection of the user's level of emotional arousal more effective.

As demonstrated in many studies, the nervous system is strongly connected with the sweat glands on the human skin [18]. The changes in the level of sweat secretion in response to emotional stimuli change the value of skin resistance. The two components of skin conductance (SC) can be separated: slow-variable (skin conductance level – SCL) and fast-variable (skin conductance response – SCR) [19]. In the literature, you can also find the terms: tonic component of skin conductance, specifying slow-variable component, and phasic component of skin conductance, specifying fast-variable component [20]. The tonic component is related to the level of emotional excitation of a user [13], but as it is changing very slowly, the measurement intervals have to be long (from tens of seconds to minutes).

For example, spontaneous fluctuations in this component occur 1–3 times per minute.

The use of skin conductance (SC) for the purpose of detecting the level of emotional arousal has been mentioned in many works. Furthermore, autonomic activity such as EEG or heart rate (HR) are also used to assess the internal emotional state of the subject [21]. In the paper [22] GSR for emotion recognition was used. Ten features of GSR were extracted: average signal value, signal variance, standard deviation, the number of local maxima, the number of local minima, the mean conductivity difference for each consecutive pair of local minimum-maximum, the global maximum, the global minimum, the difference

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of them, the ratio between the number of maxima and stimuli duration (peaks/time). These features allowed, at best, to classify 3 classes of emotions (positive, negative and neutral) with an accuracy of 77.33%. Lang et al. [20, 22] discovered that the mean value of the GSR is related to the level of arousal. Several GSR signal features have been proposed in the research (mean and standard deviation of skin resistance, mean of derivative, mean of absolute of derivative, mean of derivative for negative values only, proportion of negative samples in the derivative vs. all samples, spectral power in the bands 0–0.1 Hz, 0.1–0.2 Hz, 0.2–0.3 Hz, 0.3–0.4 Hz). But the selection of those features was not described well enough. Also, the significance of the features for the emotion recognition was not presented. In the work [23] EEG, GSR and respiratory signals were recorded. The following GSR signal features were proposed: mean skin resistance, mean of derivative over the whole trial, average GSR variation, mean of derivative for negative values only, average decrease rate, proportion of negative samples in the derivative vs. all samples. However, also no results of the usefulness of these features for the emotion recognition were presented. Paper [24] presents the use of GSR signal in attempt to determine the boredom, engagement and anxiety as indicators in computer games. There were applied features such as: mean skin resistance, mean of derivative, mean of derivative for negative values only, proportion of negative samples in the derivative vs. all samples. The authors indicate that all these features of the GSR signal were useful. In the work [25] affective characterization of movie scenes, based on multimedia content analysis and user's physiological emotional responses to them, are presented. GSR signal features such as average skin resistance, average of derivative, mean of derivative for negative values only, proportion of negative samples in the derivative were used. The authors showed that the highest correlations (of GSR and participant's self-assessments) was for the feature "GSR standard deviation" (0.55) for arousal and for the feature "average of GSR derivative" (–0.45) for valence. In the paper [26] multimodal emotion recognition in response to videos is presented. Physiological signals including ECG, EEG (32 channels), galvanic skin response (GSR), respiration amplitude and skin temperature were recorded while the videos were shown to the participants. Unfortunately, the authors do not show how they used GSR signals to recognize emotions. Summing up, in many works, the authors register GSR signals, calculate complicated GSR signal features and do not use them or use them in a limited extent to recognize emotions.

In this article, we present feature extraction and selection techniques of EDA for the automatic detection of the level of emotional arousal. We measure skin conductance, in an indirect way, by measuring the resistance between the two electrodes located on the subject's body [27], passing low-intensity current through the skin and measuring the voltage drop. To measure skin resistance in practice, electrodes are placed on the index finger and the middle finger of the non-dominant hand [28]. Novelty in our research is an examination of a wide range of twenty EDA signal features. The aim of the research was to indicate the most significant features for estimation of level of emotional arousal. In existing literature, studies have usually been performed only for several EDA signal features [13]. We did not find any works comparing such a large number of features, in terms of their significance, with the exception of [29, 30].

2. Materials

The experiment was attended by 22 men, students of the Warsaw University of Technology, aged 20±2 years. Prior to signal registration, volunteers were informed of the purpose of the experiment. Acquisition always started at the same time in the morning. The lighting conditions were uniform for all the participants. Movies were presented with stereo sound. The volume was always set at the same level (thereby ensuring the subject's comfort). The video was presented on a 27-inch LCD monitor. The user's eye distance from the center of the screen was approximately 60 cm. During the experiment, the person was seated in a comfortable armchair with a backrest and a palm rest. On the left-hand fingers (index and middle), electrodes were attached, from which an electrical signal proportional to the change in the skin conductance (SC) was acquired. For signal recording, a specially designed electronic circuit was used. The SC signal registration rate was 10 S/s. After instructing a user about the course of the experiment, the experiment supervisor left the room. The program created by the authors enabled synchronous video presentation and SC signal acquisition according to the sequence shown in Fig. 1.

A user was asked to watch all (21) movies in each session. A random movie order was established. The total recording time was 8 min and 10 s. Thereafter, the supervisor returned to the room and asked about the participant's comfort. After a short break, the SC signal was re-recorded with a random sequence of video presentations – second session. The registered SC signal was subjected to a preliminary visual assessment. The signal was recorded correctly for 16 people.

To elicit emotions in users, multimedia material in the form of short movies was prepared. Table 1 presents some of the characteristics of the prepared movies. Before and after each

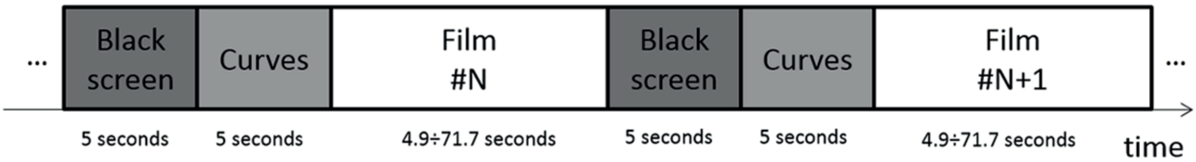

Fig. 1. Schematic representation of the video sequence presented to a user

Table 1
A compilation of movies used to elicit emotions

No.	Mark	Movie description	Duration [s]
1	Birds	A scene of birds flying against the sky, relaxing music in the background	10.13
2	Girl1	A scene of dancing, scantily dressed girl with rhythmic music	14.96
3	Highway	A scene presenting the loops of the motorways from the bird's eye view, with calm music	5.02
4	Horror1	A fragment of Sinister movie with a terrifying face and sound effects	9.11
5	Saw1	A fragment of Saw movie with scenes of blood faces and screams	10.07
6	Attack	A scene showing a boy, after leaving the camera the boy turns out to be an assailant	4.97
7	Refugees	A scene presenting an attempt to push a barricade on the border with screams	10.02
8	Slap	A fragment of Lynx advertising, a sneaking man gives a slap to his girlfriend's mother	11.08
9	Funeral1	A fragment of funeral, with calm music	14.95
10	Dentist	A fragment of a movie showing the tooth extraction	9.94
11	Flag	A fragment of a movie showing the man eating the metal pins with the flag.	5.00
12	Girl2	A scene of dancing, scantily dressed girl with rhythmic music	12.94
13	Beating	A scene showing the beating of a girl by a man	10.01
14	Weather	A scene presenting the lake among the mountains with calm music	9.94
15	Saw2	A fragment of the movie Saw with scenes of blood faces and screams	9.99
16	Funeral2	A fragment of funeral, with calm music	18.05
17	Horror2	A fragment of Lights Out movie with a terrifying face and sound effects	9.99
18	Weather	A scene with a man presenting a weather forecast	9.97
19	Vegetarian	A fragment of Lynx advertising depicting a man reacting to a woman's words	10.54
20	Amputation	A fragment of a movie showing finger amputation	9.97
21	Button	A fragment of the movie containing elements of surprise and rhythmic music	71.14

movie, a 5 s black screen was added along with a 5 s movie showing "colored curves." Such a gap between movies, lasting a total of 10 s, was dictated by the delay of the EDA response to a stimulus, at the same time the subject got some time to calm their emotions before the next presentation [13].

The presented movies did not have to elicit the desired emotions in all the participants. The way in which a stimulus is perceived by a user depends on a number of factors, such as cultural determinants, age, sex, life experience, and the psychophysical state of a user at the time of the experiment. Our experiments were carried out for a homogeneous group of people (22 men, students of the Warsaw University of Technology, aged 20±2 years). The selection of such a group of people allowed a more controlled evocation of emotions. Furthermore, the EDA signal and its features do not allow very precise determination of the degree of emotion in all subjects. Such accuracy is probably determined by the technical and physiological artifacts of the EDA signal. It can also be of great importance that each person reacts differently to the presented movies (even in such a homogeneous group). For that reason, there is no certainty that the calculated features will be just as useful for a differently defined group (e.g., women, or men of a different age).

The key issue was the proper choice of materials for the selected group. We were considering evoking emotions using the IAPS [31], IADS [32], NAPS [33] databases. However, we finally decided to use movies. We were hoping that movies could evoke stronger, more diverse emotional feelings [34]. We have chosen 50 publicly available movies on the Internet. In order to select the best of them, movies were shown to 3 people from the group taking part in the experiment. Based on their subjective assessment, 21 movies were selected which were then presented to the rest of the group. Despite this, the presented movies did not have to cause the same emotions in each person. Therefore, we created, based on the works [35], [36], a questionnaire to help to determine the evoked emotions. Right after the second registration session, each subject was asked to fill out a questionnaire with two questions about the emotions triggered by each movie:

3. "Evaluate the type of emotions you experienced while watching a movie on a scale of −4 (negative) to +4 (positive)".
4. "Rate the intensity of the emotions you experienced while watching a movie on a scale of 1 (low stimulating) to 9 (very stimulating)".

To make it easier for the subject to evaluate a movie, he could re-watch each of the presented videos while filling out the questionnaire. Thus, the questionnaires, covering 21 presented movies, were filled out by all users. The results of the subjective questionnaires (valence and arousal) about the emotions experienced while watching movies are presented in Table 2. This was an objective assessment and may not be honest or even fully aware. The distribution of the subjective evaluations (medians) in the valence-arousal space, for all movies, is presented in Fig. 2.

Table 2
Results of the evaluation of emotions for all users (valence and arousal), No.-film number, μ-mean, σ-standard deviation, Me-median

	Arousal			Valence		
No.	μ	σ	Me	μ	σ	Me
1	2.67	2.20	2.0	1.72	1.36	1.0
2	7.33	1.85	8.0	3.11	1.53	4.0
3	1.94	1.30	1.0	0.56	1.42	0.0
4	5.89	2.40	6.0	–0.72	1.99	–1.0
5	5.89	2.14	6.0	–0.94	2.31	–2.0
6	3.72	1.67	4.0	1.83	1.10	2.0
7	4.61	2.17	5.0	–0.78	1.83	–1.0
8	6.11	1.75	6.0	2.89	0.76	3.0
9	3.72	2.24	3.0	–1.06	1.59	–1.0
10	6.11	2.49	7.0	–1.28	2.14	–1.5
11	3.06	1.80	3.0	1.11	1.45	1.0
12	7.22	2.16	7.5	2.89	1.41	3.5
13	6.61	2.06	6.5	–2.22	2.21	–3.0
14	2.78	2.21	2.0	1.56	1.50	1.0
15	5.72	2.22	6.0	–0.61	2.15	–1.0
16	3.50	2.43	2.5	–1.11	1.68	–1.0
17	6.00	1.68	6.5	–0.94	1.80	–1.5
18	1.33	1.03	1.0	–0.17	0.79	0.0
19	5.22	2.16	5.0	2.67	0.77	2.5
20	6.44	2.31	7.0	–1.72	2.44	–2.5
21	6.00	2.17	6.0	2.22	1.52	2.0

Despite our attempt to select movies in such a way that they were found in every quarter of the valence/arousal space, the distribution was not even and was arranged in the shape of the letter "V". Similar distributions were obtained in other works [35]. This shape of distribution means that the most positive and negative movies were at the same time highly stimulating.

However, using movies as stimuli has its drawbacks. As movies were of relatively long duration, they could introduce a source of variation in emotions. Also the opportunity to watch movies two times could be a problem, because the feelings could not be the same as at the first time.

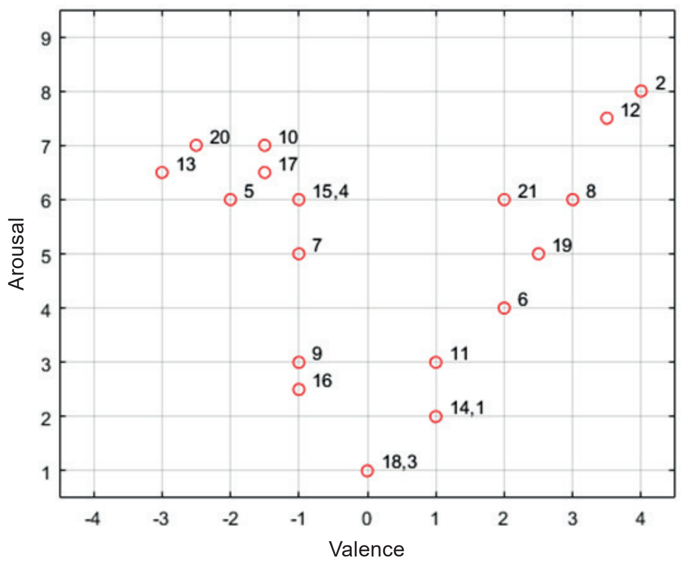

Fig. 2. Distribution of the median of the valence and the arousal for all the movies

5. Methods

A block diagram of the skin resistance measurement system is shown in Fig. 3. This system consists of electrodes, a measurement circuit (an amplifier with RC filters), an ATmega328P microcontroller (including an A/D converter), and a personal computer. During the experiments, elastic bands with Ag/AgCl electrodes (8 mm diameter) were used to ensure good electrode–skin contact. A schematic representation of the measurement system is shown in Fig. 4.

The circuit is powered from a source VCC of 5 V. A 2.5 V supply voltage from the R1/R2 divider is applied to the bridge arms. In one branch of the bridge are the R4 resistor and the P5 potentiometer, and in the other are the R3 resistor and the measured resistance connected via electrodes to the terminals E−/E+. The differential amplifier circuit is based on three operational amplifiers. Two of them, labeled as IC1A and IC1B, operate as high-input resistance that do not load the bridge. The

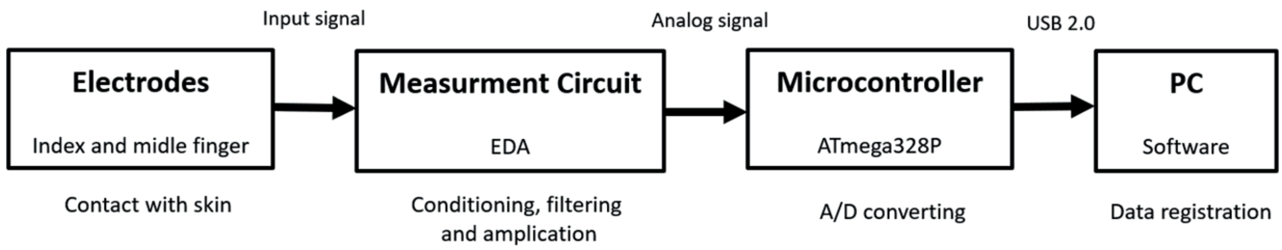

Fig. 3. Block diagram of the EDA measurement system

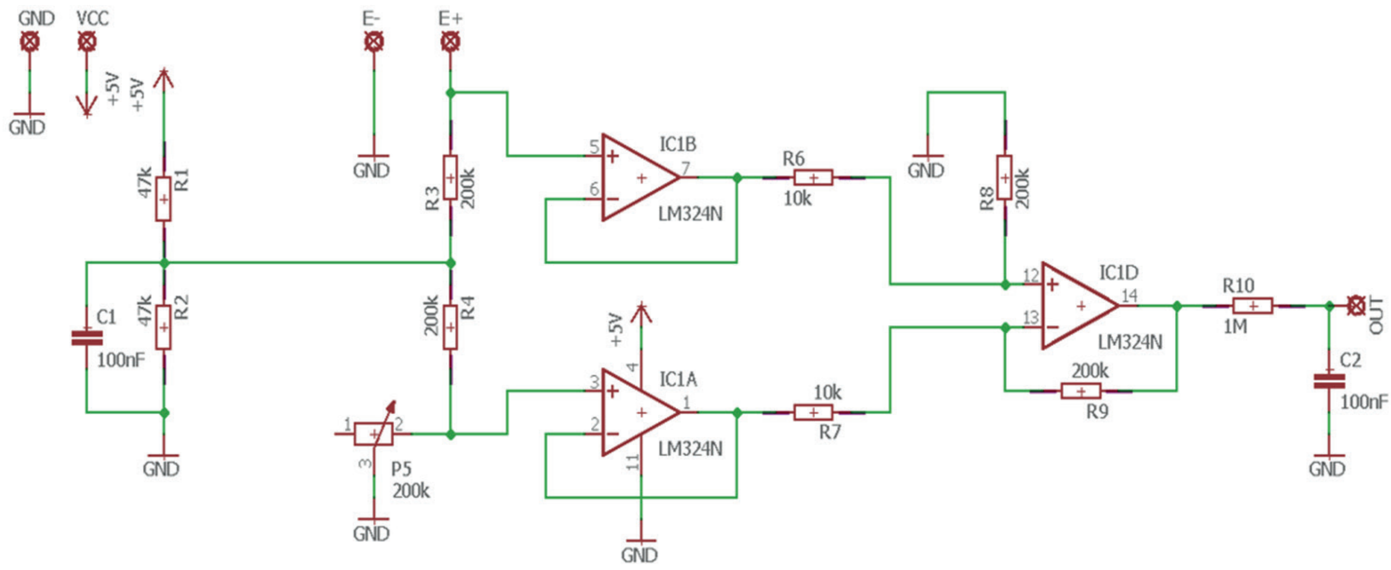

Fig. 4. Schematic representation of the skin resistance measurement circuit

output amplifier, designated as IC1D, operates in the differential mode with the gain $k_u = \text{R9}/\text{R7} = 200\ \text{k}\Omega/10\ \text{k}\Omega = 20$. The output signal is filtered through a passive RC filter (R1 = 1 MΩ, C2 = 100 nF, cutoff frequency = 0.16 Hz).

The amplified and filtered signal is further processed in the ATmega328P microcontroller (16 MHz clock). The microcontroller includes a 10-bit A/D converter with a processing speed of 6 kS/s. Next, the signal is averaged in the windows containing 600 samples, which reduces the recording speed to 10 S/s. These data are sent via a USB link to a personal computer. At the same time, an application (in C#) with a synchronous presentation of movies is launched on the same computer.

In the first step, the built-in electronic circuit was calibrated to read out the voltage at the output for the resistance applied to the input. To do this, resistors R_k of known resistance were applied to the measuring electrodes and the output level of the A/D converter was read. The results of the laboratory tests are provided in Table 3.

Table 3
Results of the laboratory tests for calibrating the measurement system

Input resistance value Rk [kΩ]	ADC levels
150	11
390	142
750	248
1000	289
2000	357
3000	383
4000	397
5000	405
6000	411

The rational model was used to approximate the measured characteristic (*Numerator degree* = 4, *Denominator degree* = 3), which was described by equation [37]:

$$R = \frac{p_1 x^4 + p_2 x^3 + p_3 x^2 + p_4 x + p_5}{x^3 + q_1 x^2 + q_2 x + q_3} \tag{1}$$

where x denotes the recorded voltage value (0–1023) and R represents the approximated value of the resistance in kilo-ohms. The calculated model coefficients were as follows: $p_1 = 2.894$, $p_2 = -2702$, $p_3 = 7.547\times10^5$, $p_4 = 1.733\times10^4$, $p_5 = 8648$, $q_1 = -1129$, $q_2 = 3.043\times10^5$, and $q_3 = -4091$.

The registered signal was subjected to pre-processing to identify the phasic component and then we extract features that enable us to describe a user's emotions (arousal level). A block diagram of the skin resistance pre-processing is shown in Fig. 5.

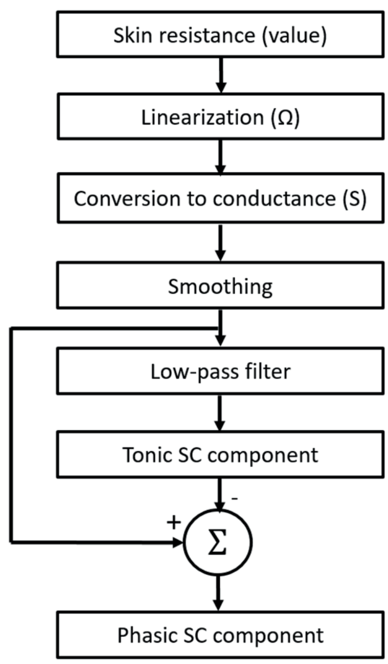

Fig. 5. Functional diagram of the measurement signal processing

Data from the 10-bit A/D converter were subjected to conditioning and linearization (Linearization) and then, converted to the conductance value (Conversion to conductance) expressed in siemens [S]. To get rid of the potential noise, the signal in the 250 sample windows was averaged (Smoothing). An important part of the signal processing was the use of a Butterworth low-pass filter (0.05 Hz) to extract the tonic component. Removing the tonic component from the registered signal enabled us to obtain the phasic component. This phasic component was subjected to the normalization process followed by feature extraction. An example of the phasic component is shown in Fig. 6. (0.05 Hz) to extract the tonic component [38]. Removing the tonic component from the registered signal enabled us to obtain the phasic component. This phasic component was subjected to the normalization process followed by feature extraction. An example of the phasic component is shown in Fig. 6.

For analysis, the EDA signals registered from the beginning of the movie to 4s after its completion was taken. We focused on the characteristic local extremes, as suggested in the existing literature [13]. The notation $Ap_{k,r}$ can be understood as the amplitude of the k-th local extreme, located at the position of the r-th sample. Usually, a few local extremes are registered and we do not know which of them are associated with the user's reaction to a stimulus. Therefore, often, certain statistical measures of the recorded extrema are used as features. In this study, we examined several known measures and proposed new ones (Table 4).

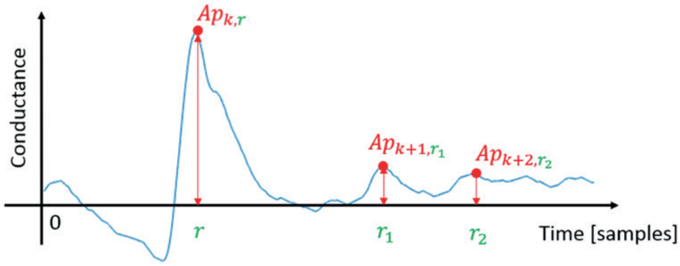

Fig. 6. Typical phasic component

Table 4
A summary of all the features of the phasic SC component

No.	Name	Movie description
1	*FrequencyPeak*	Frequency of occurrence of local extremes
2	*MaxAmpPeak*	The highest value of the determined maxima
3	*VarAmpPeak*	Variance of amplitude values calculated for local extremes
4	*StdAmpPeak*	Standard deviation calculated for local extremes
5	*SkewnessAmpPeak*	Skewness calculated for amplitudes of local extremes
6	*KurtosisAmpPeak*	Kurtosis calculated for amplitudes of local extremes
7	*MaxAbsAmpPeak*	Maximum value of modules of amplitudes of local extremes
8	*VarSC*	Variance calculated for SC signal samples
9	*StdSC*	Standard deviation calculated for SC signal samples
10	*SkewnessSC*	Skewness calculated for SC signal samples
11	*KurtosisSC*	Kurtosis calculated for SC signal samples
12	*SumPosDiffSC*	Sum of positive values of the first derivative of the SC signal
13	*SumNegDiffSC*	Sum of negative values of the first derivative of the SC signal
14	*FDSC*	Fractal dimension calculated using Box-counting method [37, 38]
15	*MaxDeltaForward*	The maximum value of the difference between the amplitudes of the local extrema and the amplitude values of the signal samples measured a second later
16	*MaxDeltaBack*	The maximum value of the difference between the amplitudes of the local extrema and the amplitude values of the signal samples measured a second earlier
17	*SlopeSC*	The measure of the rise or fall of the slope of the SC curve: calculated using the minimized squared error for the linear equation
18	*ActivitySC*	Hjorth activity that represents the signal power (the variance of a time function) [38]
19	*MobilitySC*	Hjorth mobility determined as the square root of the ratio of the variance of the first derivative of the signal to the signal [38]
20	*ComplexitySC*	Hjorth a complexity as an estimate of the bandwidth of the signal, which indicates the similarity of the shape of the signal to a pure sine wave [39]

In order to assess the usability of features, we used the Spearman correlation and classifiers. Spearman's correlation assesses monotonic relationships (whether linear or not) [39]. We also tested a range of well-known classifiers [40, 41]:

- SVM with a linear kernel (*SVM-LINEAR*),
- SVM with a quadratic kernel (*SVM-QUADRATIC*),
- SVM with a polynomial kernel (*SVM-POLYNOMINAL*),
- SVM with an MLP kernel (*SVM-MLP)*,
- SVM with an RBF kernel (*SVM-RBF*),
- LDA (*LDA-LINEAR*),
- QDA (*LDA-QUADRATIC*), and
- K-NN (1-*NN*, 3-*NN*, and 5-*NN*).

6. Results

To estimate which features are most associated with emotions Spearman's correlation between the determined features and the values of valence and arousal, declared in the user questionnaires, was calculated [42]. The minimum, maximum, and average values and the standard deviation of the calculated Spearman's correlations (for all the movies and all the users for session I) are given in Tables 5 and 6.

The obtained results show low or moderate absolute values of correlation of features with user's declarations [43]. In some cases, these values of the correlation are above 0.5. This proves that for some people the values of calculated features are correlated with the results of the questionnaires. Low values of these correlations show that the EDA signal is not an exact measure indicating emotions. However, similar to our study, small values of EDA signal features correlation with questionnaires can be found in other works, for example [25, 44]. Anyway, on the basis of results in the Tables 5 and 6, we are able to indicate worse and better features.

To indicate features associated with valence and arousal, we chose users for whom the mean correlation value was at least 0.2, and the value of the correlation between the determined features and the values declared in the surveys for at least one user were greater than 0.5. Consequently, we did not find even one feature, satisfying these criteria, for correlation with valence. However, such features for arousal were found. The features that meet the above criterion were as follows: *MaxAmpPeak* (0.26), *VarAmpPeak* (0.24), *StdAmpPeak* (0.24), *MaxAbsAmpPeak* (0.21), *VarSC* (0.25), *StdSC* (0.24) and *ActivitySC* (0.24).

We also use the t-statistic to select the best features. This allowed us to rank features from the best to the worst. The ranked features are listed in Table 7. The highest t-value ($t > 3$) were obtained for the following features: *MaxAmpPeak*, *MaxDeltaForward*, *MaxDeltaBack*, *MaxAbsAmpPeak*, *KurtosisAmpPeak*, and *StdSC* (boldfaced text in Table 7).

The obtained results indicate that the most useful features for the identification and classification of emotional excitation

Table 5
Statistics of Spearman's correlation between the valence values declared in the surveys and the values of the determined features

Feature No.	Min	Max	Mean	Std
1	–0.57	0.20	–0.12	0.22
2	–0.44	0.57	0.17	0.28
3	–0.36	0.43	0.02	0.16
4	–0.36	0.43	0.02	0.16
5	–0.36	0.38	0.06	0.23
6	–0.55	0.18	–0.05	0.17
7	–0.40	0.61	0.18	0.28
8	–0.51	0.63	0.14	0.29
9	–0.51	0.63	0.14	0.29
10	–0.46	0.54	–0.04	0.24
11	–0.49	0.24	–0.03	0.18
12	–0.48	0.44	0.11	0.26
13	–0.55	0.55	0.13	0.31
14	–0.44	0.28	–0.06	0.23
15	–0.42	0.60	0.17	0.28
16	–0.43	0.61	0.17	0.30
17	–0.25	0.40	0.05	0.21
18	–0.51	0.63	0.14	0.29
19	–0.44	0.70	0	0.24
20	–0.45	0.41	–0.11	0.19

Table 6
Statistics of Spearman's correlation between the arousal values declared in the surveys and the values of the determined features

Feature No.	Min	Max	Mean	Std
1	–0.48	0.33	–0.08	0.23
2	–0.36	0.60	0.13	0.29
3	–0.55	0.24	0.03	0.22
4	–0.55	0.24	0.03	0.22
5	–0.33	0.50	0.08	0.21
6	–0.34	0.36	0.02	0.17
7	–0.55	0.58	0.11	0.29
8	–0.48	0.62	0.06	0.29
9	–0.48	0.62	0.06	0.29
10	–0.44	0.56	–0.02	0.23
11	–0.35	0.18	–0.04	0.16
12	–0.42	0.38	0.01	0.24
13	–0.55	0.62	0.07	0.32
14	–0.43	0.29	–0.03	0.23
15	–0.50	0.57	0.11	0.29
16	–0.43	0.57	0.11	0.29
17	–0.36	0.45	0.03	0.23
18	–0.48	0.62	0.06	0.29
19	–0.5	0.42	–0.04	0.25
20	–0.42	0.36	–0.06	0.21

Table 7
List of features ordered according to the *t*-value

Feature No.	t-value	Feature No.	t-value
2	4.32	4	2.12
15	3.76	12	2.10
16	3.64	17	1.60
7	3.61	20	1.34
6	3.26	11	1.27
9	3.12	1	1.23
10	2.29	19	1.06
8	2.24	5	0.72
18	2.24	3	0.56
13	2.13	14	0.17

are those calculated for the local extremes in the phasic SC component. The results obtained are consistent with the results of the psychological research presented in the existing literature [45, 46].

The classification accuracy was used to assess the performance of the classifiers [47]. To use the data efficiently, a 10-fold cross-validation (CV) test was used in our experiment. For emotion classification CV tests were used in works [48–52]. In *k*-fold cross-validation, the original set is randomly partitioned into *k* equal sized subsets. Of the *k* subsets, a single subset is retained as the validation data for testing the model, and the remaining (*k*−1) subsets are used as training data. The cross-validation process is then repeated *k* times (*k*-folds), with each of the *k* subsets used exactly once as the validation data. The *k* results from the folds are then averaged to produce a single estimation [53].

We evaluated the suitability of the calculated features for the classification of high- and low-stimulating movies (according to the arousal parameter). For this purpose, the two most and the two least stimulating movies were selected. The questionnaires indicated, that the most stimulating movies were #2 and #12 (the median in the declarations was 8 and 7.5) and the least stimulating movies were #3 and #18 (the median in the declarations was 1 in both cases). The classification accuracies for a selected feature (and for the 10-CV test) are presented in Table 8.

The obtained results allowed us to conclude that for the "extreme" movies, there is a possibility of distinguishing strong and low emotions with an average classification accuracy of 61–72% (max = 75%). Similar results of emotion recognition, using the EDA changes, were reported in [54–56]. The best classification results (Table 8) we obtained for the *SVM-LINEAR* classifier (72%) and *LDA-QUADRATIC* classifier (70%). The best average accuracy of classification were obtained for features: *SkewnessAmpPeak* (71%), *MaxAbsAmpPeak* (71%), *MaxAmpPeak* (69%), *KurtosisAmpPeak* (69%), *MaxAbsAmpPeak* (69%).

The authors also carried out leave-one-subject-out tests for two classes: high- and low-stimulating movies selected as previously [53]. In this case only *SVM-LINEAR* classifier was used. The results of classification accuracy are presented in Table 9.

Table 8
Classification accuracies [%] (for the 10-CV test) for two classes: high- and low-stimulating movies

Feature No.	SVM-LINEAR	SVM-MLP	SVM-QUADRATIC	SVM-POLYNOMINAL	SVM-RBF	LDA-LIENAR	LDA-QUADRATIC	KNN-1	KNN-3	KNN-5	Mean
1	69	64	69	69	69	68	68	69	71	67	68
2	69	57	72	74	71	69	69	67	69	68	69
3	69	67	72	71	69	69	67	61	65	63	67
4	69	63	72	67	69	69	67	54	57	61	65
5	74	71	75	67	68	71	74	67	71	74	71
6	75	63	76	60	68	71	72	60	78	72	69
7	75	64	69	67	65	71	71	61	74	69	69
8	74	56	71	63	64	71	71	64	72	71	68
9	74	60	71	61	65	71	72	64	68	72	68
10	75	58	68	67	61	71	71	67	71	76	68
11	75	53	72	57	65	69	71	72	71	75	68
12	72	57	72	61	64	69	69	72	68	76	68
13	67	57	67	58	61	69	72	69	72	71	66
14	65	54	63	61	57	69	68	64	71	69	64
15	68	56	57	67	54	69	69	67	67	67	64
16	74	67	64	68	57	69	69	67	72	69	68
17	74	63	58	61	57	68	69	67	68	67	65
18	71	68	61	60	47	67	69	64	65	65	64
19	79	65	63	57	47	67	71	67	67	64	65
20	75	63	56	64	42	67	71	65	64	68	63
μ	72	61	67	64	61	69	70	65	69	69	

Table 9
Classifiation accuriacies (for leave-one-subject-out test) for two classes: high- and low-stimulating movies

Feature No.	Accuracy [%]	Feature No.	Accuracy [%]
1	75.0	11	73.6
2	73.6	12	73.6
3	76.3	13	73.2
4	73.6	14	73.6
5	76.3	15	73.6
6	73.8	16	73.6
7	73.0	17	73.1
8	72.2	18	73.6
9	76.4	19	73.6
10	73.6	20	73.2

The leave-one-subject-out test with *SVM-LINEAR* classifier was also performed for all 20 features altogether. In this case, a classification accuracy was 79%. Summed up for all users confusion matrix is presented in Table 10.

Table 10
Confusion matrix (for leave-one-subject-out test) for two classes: high- and low-stimulating movies

		True class	
		High-arousal	Low-arousal
Predicted	High-arousal	58	16
	Low-arousal	17	56

7. Discussion

An example of skin resistance recorded using the measuring circuit presented above, is shown in Fig. 7. The vertical dashed lines indicate the moments of change in the displayed stimuli.

There are several ways to separate the SC signal into tonic and phasic components. Barry et al. [57] attempted to correct the baseline by subtracting each phasic component from an extension of the preceding phasic component using graphical tools. Lim et al. [58] proposed a model based on a response function made of 4–8 parameters optimized for each single response to obtain a response-by-response variation in the SCR shape. This method required visual inspection to select the best model. Alexander et al. [59] estimated of the sudomotor nerve activity (SMNA) using a model where the SC is the result of a convolution between discrete bursting episodes of the SMNA and a biexponential impulse response function (IRF) assumed known a priori and time invariant. Benedek and Kaernbach [60] criticized some aspects of Alexander's model and developed two new models in which the LTI (linear time-invariant) assumption was modified to take into account the variability in SCR shape. These methods are known as nonnegative deconvolution [60] and continuous deconvolution analysis (CDA) [61]. Both models split the SMNA into two parts, one describing the phasic activity and the other representing EDA variations of different origins (e.g., noise). The above models assume a pharmacokinetic model of the dynamic law of diffusion of sweat. Recently, Bach presented the SCRalyze toolbox (now incorporated into PsPM), which comprises several models that assume a LTI system [62]. These models use a heuristic IRF which parameters have been optimized on large datasets. SCR analyze algorithms try to estimate the model input (SMNA) or parameters that best explain the observed SC data based on optimization methods. Moreover, they include a noise term, which also accounts for possible violations of the assumption of time invariance. In the work [63] the cvxEDA algorithm was proposed. The proposed model describes SC as the sum of three terms: the phasic component, the tonic component, and an additive white Gaussian noise term incorporating model prediction errors as well as measurement errors and artifacts. This model is physiologically inspired and fully explains EDA through a rigorous methodology based on Bayesian statistics, mathematical convex optimization, and sparsity. The simplest approach is to use a digital filter. Based on the literature, the cut-off frequency of the high-pass filter should be up to 0.05 Hz [38].

We conducted preliminary experiments using the Ledalab tools, the cvxDEA toolbox and the use of the IIR filter for EDA decomposing into the tonic and phasic components. We can

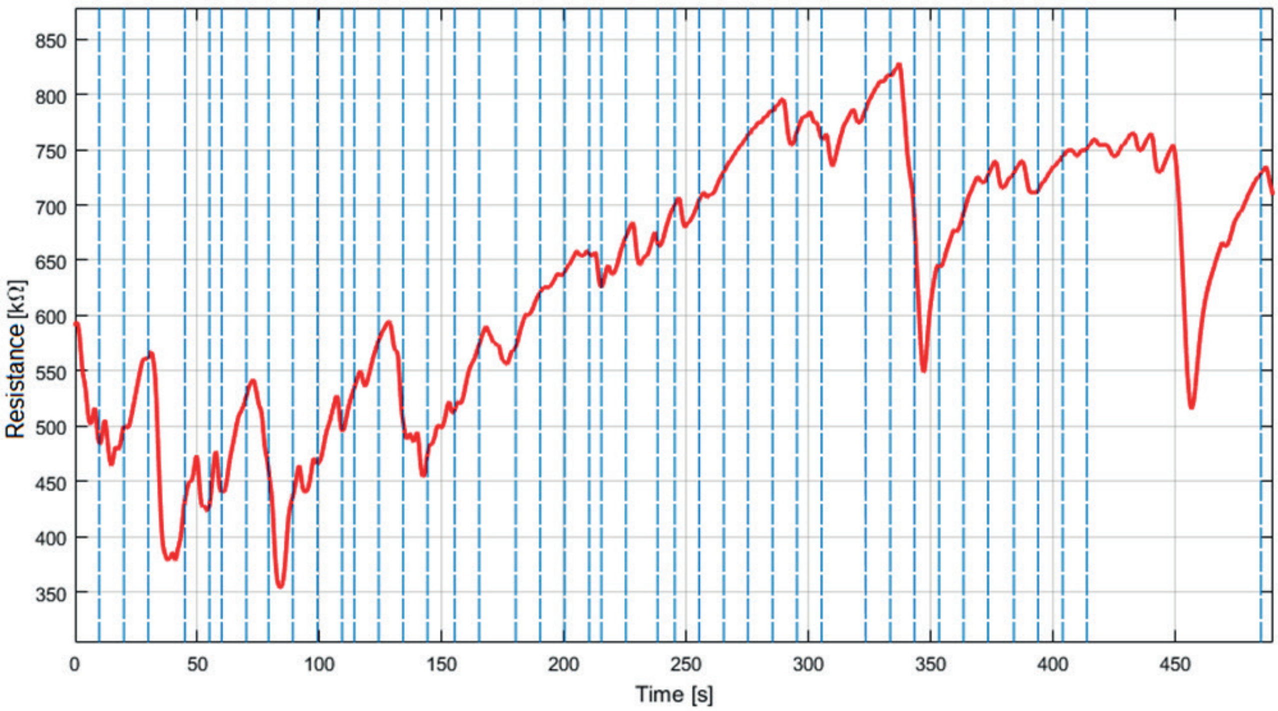

Fig. 7. An example of the registered SC signal

observe slight differences in the shape of this component for various types of decomposition algorithms (Fig. 8). Considering the obtained results, we decided to implement a second-order Butterworth low-pass filter, with a cutoff frequency of 0.05 Hz. An example result of SC signal decomposition using this filter is shown in Fig. 9.

We also wanted to check whether using the proposed set of EDA features, you can determine (approximate) the values

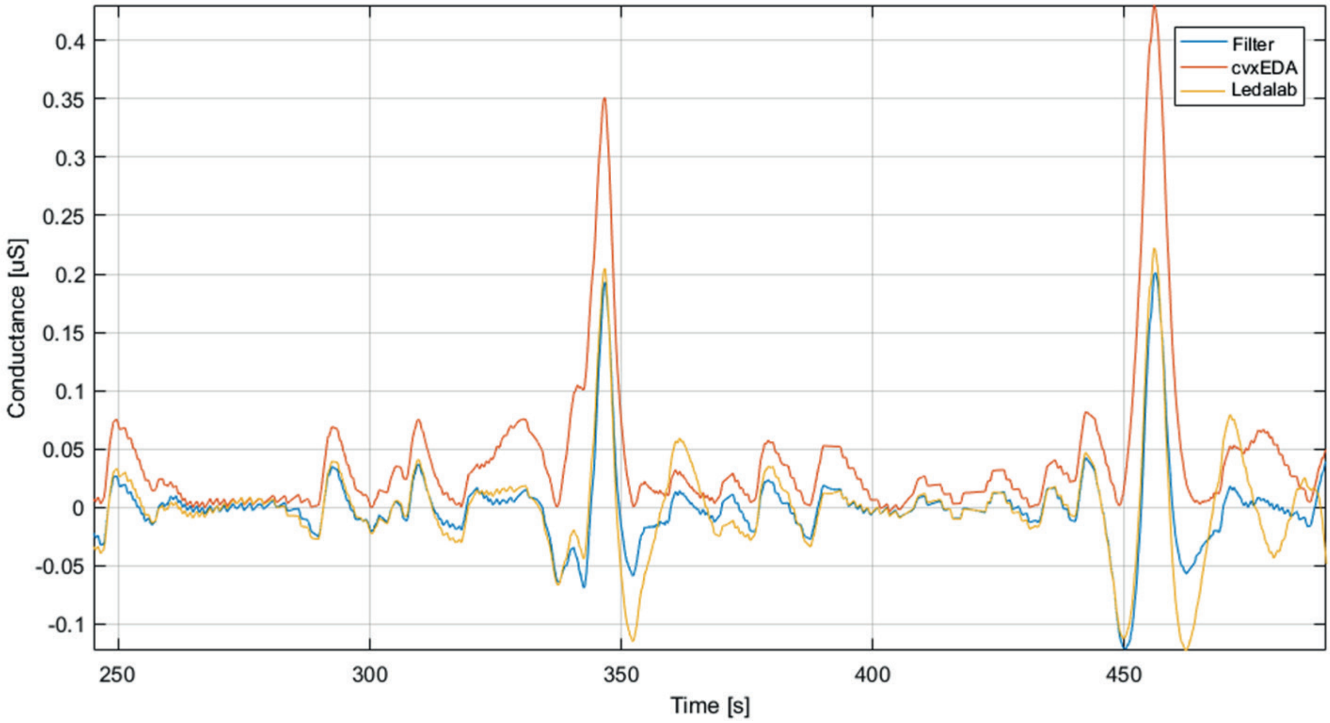

Fig. 8. Separated phasic component with the use of different algorithms

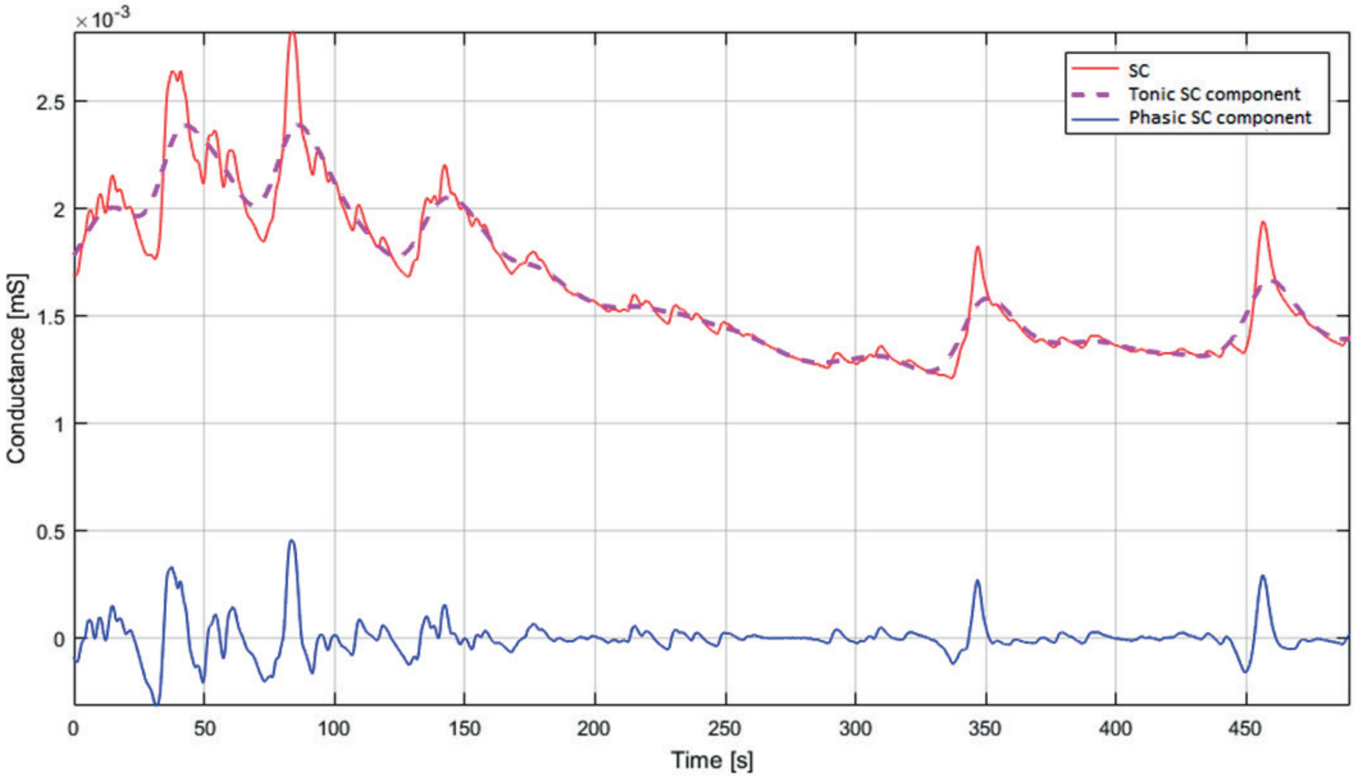

Fig. 9. SC signal decomposition into slow-variable and fast-variable components using IIR filter

of arousal. Based on all the calculated features of the SC signal, we tried to estimate the arousal value for a user. Thus, we could compare the level of stimulation declared by a user in the questionnaire with the real, measured value. For the estimation of the arousal value, linear regression was applied. The declarations collected for the least stimulating (#3) and the most stimulating (#2) movies were used. The estimated level of arousal and the declared value in the questionnaires for all the users (for all the features) are shown in Fig. 10.

The presented regression results (Fig. 10) indicate a slight deviation between the value declared by a user (Declaration) and the approximated value (Regression). Thus, it seems to be sensible to say that the proposed EDA features are suitable not only in the task of classification but also in the task of determining the level of arousal.

The classification results for individual features presented in Table 8 allow to indicate features that are important in determining the level of emotional arousal. We did not carry out research indicating the best sets of features. The use of several features could improve the classification results. We obtained the best average classification result 72% for the SVM-LINEAR classifier. The obtained classification results are hard to directly compare with the results presented in other works. To evoke emotions, stimuli are used in the form of photos, movies and sounds. In addition, each group of people taking part in experiments had different experiences and was less or more susceptible to the presented stimuli [35]. Therefore, in the literature, one can find results indicating the different accuracies of the classification of emotions. In the work [64], International Affective Digitized Sound System database was used to evoke emotions. The stimuli were grouped into four different levels of arousal and two levels of valence. Two separate classification algorithms were implemented for the arousal and valence recognition. Experimental results demonstrated that system was able to achieve a recognition accuracy of 77.33% on the arousal dimension, and 84% on the valence dimension. In the work [65] the authors use SCR signals associated with emotions, such as calmness, happiness, anger, sadness and fear. As for the emotion classification experiment, the overall recognition rates were 67–72% by Fisher, 67–76% by k-NN, 66–72% by LDC and 73–87% by QDC, respectively. In [66] a device is used to identify basic human emotions indexed by Electrodermal Activity (EDA) in real time. The device measures changes in Skin Conductance Level (SCL), caused due to stimulating signals from brain, which results from sympathetic neural activity. Ag/AgCl electrodes, placed on the ventral side of the distal forearm, were

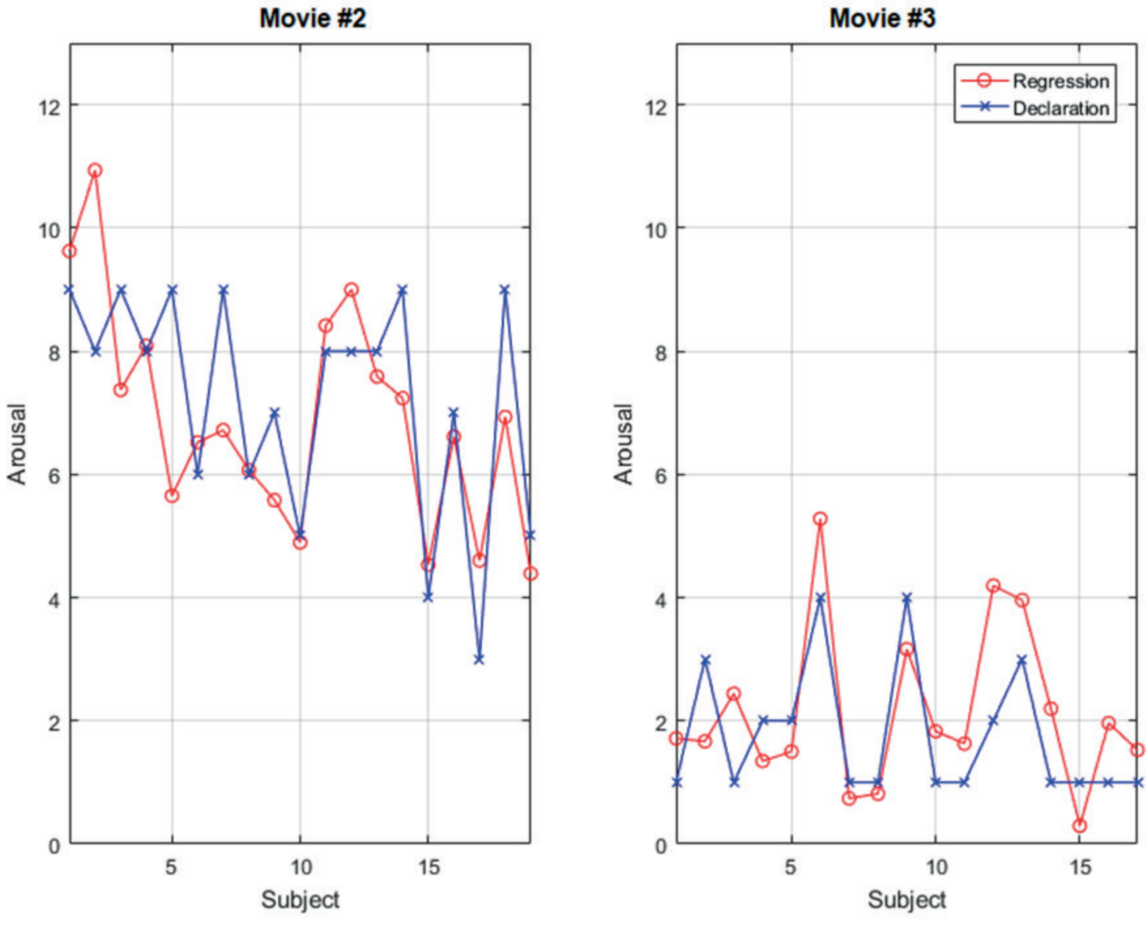

Fig. 10. The estimated level of arousal (Red) and the declared value (Blue) in the questionnaires for all the participants (Left: movie #2, Right: movie #3)

used to evaluate the emotions of the user outside the constrained laboratory environment – without interrupting the normal daily routine. Happiness could be predicted with an efficiency 65% and anger with an efficiency 60% while the remaining emotions had poor success. In [67] the authors showed how the frequency of the external electrical source affected the accuracy of arousal recognition. This suggests a role of skin susceptance in the study of affective stimuli through electrodermal response. The average accuracy was in the range of 62.5% to 63.34%, whereas at 100 Hz, the pattern recognition system showed an accuracy of 71.67%.

In order to fully examine the best features of EDA for the purpose of estimating the level of emotional arousal in the future, we plan to work on a larger number of people and using other databases. We also have plans to compare features obtained using various pre-processing methods.

8. Conclusions

The results have confirmed the possibility of recognizing the emotional excitation of a user using EDA. The average classification accuracy for two classes of the least and the most stimulating movies varies within the range of 61–72%. Some of the features of EDA proved to be more useful for recognizing the level of arousal. The best features that were repeated in the selection results were: *MaxAmpPeak*, *VarAmpPeak*, *StdAmpPeak, MaxAbsAmpPeak*, *VarSC*, *StdSC, ActivitySC, MaxDeltaForward*, *MaxDeltaBack*, *KurtosisAmpPeak*, *SkewnessAmpPeak*. These features are related to the maximum values, energy or statistical properties of the phasic component. The results indicate that such features should be used in the analysis of the EDA for the level of arousal recognition. Of great importance is the quality of the recorded SC signals and the pre-processing methods. In conjunction with the features of other physiological signals (such as ECG, EEG, and EMG), the proposed analysis can produce better results.

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