Stress Identification from Electrodermal Activity by Support Vector Machines

Chapter · May 2019

DOI: 10.1007/978-3-030-19591-5_21

3 authors:

Roberto Sánchez Reolid
University of Castilla-La Mancha

Arturo Martinez Rodrigo
University of Castilla-La Mancha

Antonio Fernández-Caballero
University of Castilla-La Mancha

Stress Identification from Electrodermal Activity by Support Vector Machines

Roberto Sánchez-Reolid[1,2], Arturo Martínez-Rodrigo[1,3], and Antonio Fernández-Caballero[1,2,4]

[1]Universidad de Castilla-La Mancha
Departamento de Sistemas Informáticos, 02071-Albacete, Spain
[2]Universidad de Castilla-La Mancha
Instituto de Investigación en Informática de Albacete, 02071-Albacete, Spain
[3]Universidad de Castilla-La Mancha
Instituto de Tecnologías Audiovisuales, 16002-Cuenca, Spain
[4]CIBERSAM (Biomedical Research Networking Centre in Mental Health), Spain

Abstract. Early detection of calm and stressful conditions is very useful to prevent mental illness due to negative stress. This paper describes the acquisition, storage and processing of electrodermal activity signals to further classify both states through support vector machines (SVMs). The International Affective Pictures System has been used to evoke calmness and stress to validate the classification results. The best results obtained during training and validation for each of the SVMs report around 87.7% accuracy for Gaussian and cubic kernels.

Keywords: Electrodermal activity · Support vector machines · Calmness · Stress.

1 Introduction

Early stress detection prevents health problems related to negative stress. There is a great need to create and adapt technologies to monitor and detect conditions of negative stress in everyday life [21, 3]. Such early detection helps in the process of emotional self-regulation of the individual under stressful conditions [4, 9]. Fortunately, advances have been made in stress detection without disturbing people [16, 17]. The use of non-invasive wearable devices allows a constant monitoring of people arousal state. These wearable are well valued as they are comfortable, lightweight, provide long battery life and allow wireless communication.

Lately, many methods and methodologies have been used to determine levels of arousal through detecting alterations of the central nervous system. One of the most commonly used physiological variables to determine arousal is electrodermal activity (EDA). Moreover, this marker is able to quantify changes in the sympathetic nervous system by changing the conductivity of the skin. In this paper, we have been decided to use a commercial wearable device to record these variations in EDA. Empatica E4 [7] is a wristband dedicated to the measurement of several physiological signals (e.g. electrodermal activity, heart rate, skin temperature).

More concretely, this paper describes how to detect calm and stressful conditions using a wearable, signal processing techniques and support vector machines (SVMs). The use of SVMs, based on supervised learning, brings an innovative approach against a more classic statistical treatment of the signal features [15, 16]. We consider that these classifiers can be implemented in new tools to allow a rapid detection of negative stress conditions.

This paper is structured as follows. Section 2 introduces a description of all materials and software used to identify stress through electrodermal activity acquired from the wearable. In Section 3, there is a detailed explanation of the signal processing, feature extraction and classification methods used to validate the developed emotional model. Then, Section 4 offers several approaches to segment EDA signals. In addition, the results obtained with the different classifier configurations are shown. Finally, Section 5 includes the most relevant conclusions related to this work.

2 Materials for EDA Signals Acquisition and Processing

A fundamental part of this work is EDA signal acquisition and processing. For data acquisition (see Section 1) a commercial device [7] has been selected. The Empatica E4 wristband (see Fig. 1) is a wearable designed to measure and collect physiological signals. The wearable is widely used in clinical and domestic research. It incorporates a variety of sensors that provide great versatility like a photoplethysmograph to measure blood volume pulse, as well as electrodermal activity (EDA), three-axis accelerometer and optical temperature sensors. Each of the sensors has a different sampling frequency. The blood volume pulse works at 64 Hz, the accelerometer at 32 Hz, the skin temperature at 4 Hz and the EDA sensor at 4 Hz. Empatica E4 must be securely attached to the wrist so that the electrodes touch the skin. Otherwise, if the device is not properly connected, the device does not sample well and data are not valid.

On the other hand, we have used the EmoSys software suite as data processing tool. EmoSys software has been developed by some authors of this paper for the integration of a series of devices to acquire both physiological and neurophysiological signals. As shown in Fig. 2, the functionality of EmoSys application is quite simple. EmoSys obtains the physiological signals and stores them into .CSV (comma-separated values) files. These files will be segmented and analyzed using signal processing techniques and artificial intelligence (AI) [19].

3 Methods and Experiment Design

3.1 Participants

A total number of sixteen participants were recruited to carry out this study, concretely 7 women (43.75%) and 9 men (56.25%). All participants were vol-

Fig. 1. Empatica E4 wearable [7].

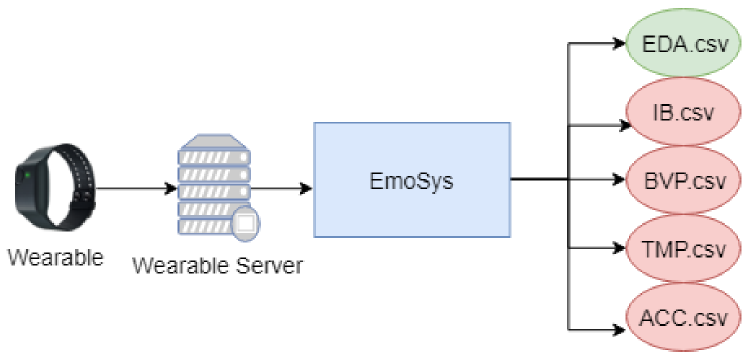

Fig. 2. Acquisition system using Empatica E4 and EmoSys software.

unteers and no one received financial compensation. All of them were in good physical and mental condition. The participants signed a participation agreement to take part in the study. The agreement form provided information about the risks associated with participating. It described the type of images shown and the possibility to stop the experiment at any time. This experiment was designed following the protocols of Helsinki Declaration. It was approved by the Ethical Committee in Clinical Research according to European and Spanish legislation [19].

The experiment was carried out in a controlled environment. Each participant was seated in a comfortable space avoiding external stimuli that could interfere in the correct development of the study. Once the wearable was placed on a volunteer, he/she iwas left alone to perform the experiment.

3.2 E-Prime and IAPS

In order to validate the results put forward in this article, we decided to use two tools widely used in the field of Psychology and Affective Computing. Firstly, E-Prime is a software used in psychological experimentation [20]. This software allows to control experiments and their experimental conditions. It covers the design phase of the experiment and the execution phase too. It allows to create slide shows, show videos and make customized questionnaires to be offered during the experiment.

The International Affective Picture System (IAPS) image library is used to evoke a feeling of calmness or stress in the participant [14]. Indeed, the IAPS image database is commonly used to perform and induce emotions. It consist in a huge set of color images grouped into categories that evoke specific emotional states [2]. The database was originally validated using a graphic scale named Self-Assessment Manikin (SAM) [13]. This questionnaire consist of a to rate how pleasant/unpleasant (valence), calm/excited (arousal) and controlled (dominance) they felt when looking at each of them.

In our experiment, different batches of images that have similar values of valence, arousal and dominance were selected. To evaluate the state of calmness/stress, two conditions were established: LH for low arousal and high valence (stress condition), HL for high arousal and low valence (calm condition). Dominance in all conditions took usually medium values. Table 1 shows the average and standard deviation values for each group consisting of 25 images.

Table 1. Mean value and standard deviation of valence, arousal and dominance for each IAPS images group.

Experimental Condition	Valence	Arousal	Dominance
HL	7.23 (1.54)	3.26 (2.22)	6.44 (2.10)
LH	1.67 (1.21)	6.93 (2.22)	2.79 (2.11)

3.3 Experiment Design

The objective of this experiment is to determine calmness and stress conditions by exposing each participant to a set of images from the IAPS library. The experiment uses the tools described before. As explained before, our idea is to expose every subject to different levels of valence and arousal. Two conditions are established to appear randomly in the experiment. The first condition is to induce stress, the second to induce calmness in the participant.

The experiment starts when the participant is seated and the wearable have been placed on his/her wrist. When the wearable gets connected to the server (see Fig. 1), E-Prime takes over the execution of the experiment. The experiment begins by showing the participant a brief description and how to respond to the SAM questionnaires. After this, the batch of neutral images is shown. These types of images are used to establish a baseline and induce a neutral emotional state in the participant. Once this has been reached, the first SAM questionnaire is answered. Next, E-Prime offers a distracting task which purpose is to eliminate the induced emotional state. This task compels the subject to concentrate

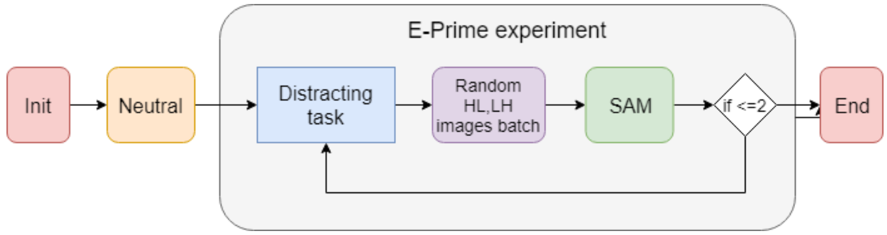

Fig. 3. Flowchart of experiment design as used in E-Prime.

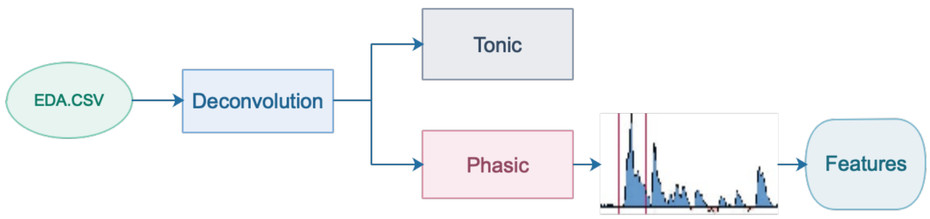

Fig. 4. Flowchart of feature extraction from EDA signals.

and stop thinking about the images shown previously. Then, the system starts to randomly repeat each of the image blocks (HL, LH). When each blocks is finished, the SAM questionnaire is answered.

At the same time the experiment is being performed, physiological data are collected using the EmoSys software. The signals are synchronized with the events related to the occurrence of each batch of images. This synchronization will help to detect calmness and stress conditions.

3.4 Electrodermal Activity Processing and Feature Extraction

EDA is one of the most used measurement to identify the affective state of a person, specially when the arousal level is needed. Previous studies have used EDA to characterize changes in emotional experiences [8, 4, 5]. EDA signals are obtained by measuring the voltage drop that occurs when a small current is applied between two electrodes located on the wearable across two metallic electrodes (see Fig. 1).

Prior to analyzing this physiological response, the data typically undergo several processing steps. Rapid gesture and body movements may introduce signal artifacts in the form of high frequency changes that need to be considered. Therefore, the EDA signals must be filtered (low-pass filter), smoothed (Gaussian smooth) and segmented to attenuate these artifacts.

Electrodermal signals are composed of two components, one is the skin conductance level, commonly referred to tonic signal, and the other component is called skin conductance response (SCR), also known as phasic signal. SCR is considered the useful signal for establishing an individual's response to a stimulus [1]. We will have to perform a continuous deconvolution operation to obtain the two components of an EDA signal (see Fig. 4). This operation prepares the signal for the next stage, the extraction of features.

In this paper, the signal is processed to obtain all the parameters shown in Table 2 to gain better emotion pattern classification performance. This characterizes each of the signal segments and makes it possible for the classifier to differentiate between calmness and stress [22].

Table 2. Features obtained from phasic signals (SCR).

Analysis	**Features**
Temporal	M, SD, MA, MI, DR, D1, D2, FM, FD, SM, SSD
Morphological	AL, IN, AP, RM, IL, EL, SK, KU, MO
Frequency	F1, F2, F3

As shown in Table 2, several time-domain, frequency-domain and morphological metrics are computed over the SCR component. Firstly the name of temporal parameters over SCR are mean value (M), standard deviation (SD), maximum peak value (MA), minimum peak value (MI), and dynamic range (DR), which is the difference between maximum and minimum value. To see the tendencies in skin conductivity we computed the first and second derivative (D1 and D2), their means (FM and FD), and their standard deviations (SM and SSD). In addition, several morphological features were chosen: arc length (AL), integral area (IN), normalized mean power (AP), perimeter and area ratio (IL), energy and perimeter ratio (EL) and ,finally, two statistic parameters, skewness (SK) and kurtosis (KU). Lastly, in relation to the frequency, we calculated the fast Fourier transform (FFT) through bandwidths F1(0.1,0.2), F2(0.2,0.3) and F3(0.3,0.4) [22].

3.5 Stress Identification by Support Vector Machines

Support vector machines (SVMS) are one of the most well-known machine learning methods. Indeed, this method is used in a large number of fields [10, 11]. One remarkable property of SVMs is their ability to learn independently of the dimensionality of the feature space [12]. It has been decided to use SVMs due to the high number of input parameters (23 signal features, as depicted in Table 2) and two classes (calm and stressed). To prevent overfitting, several configuration settings for cross validation are selected. These settings allow to optimize learning performance. In this particular study, SVMs with polynomial and Gaussian kernels are used.

Two sets of data are provided for the training phase. The first dataset of features is gotten after processing each one of the segments obtained with the LH and HL image sets. Each of these segments has a duration of 20 seconds, corresponding to ten images with two seconds duration each. The second dataset corresponds to four second segments for each LH and HL condition, eliminating the first two and last seconds in each section.

4 Results

Once the signals have been processed, the training accuracy of the different SVM topologies is analyzed. As previously told, we have carried out different cross validation tests. Moreover, thirty repetitions are performed for each different SVM and every cross validation set to ensure that the data obtained are homogeneous.

Table 3 shows the training results with segments 20 seconds long. It can be observed that the SVM that works best is the Gaussian type with 70.8% accuracy for a set of cross validation (C.V) of 5. For a C.V. set of 7, the best result is provided by the a linear kernel SVM with an average accuracy of 75.0%. Finally, the accuracy remains at 75.0% for the cubic kernel using a C.V. of 10.

Table 3. Results using segment length of 20 seconds.

SVM type	C.V.	Accuracy	C.V.	Accuracy	C.V.	Accuracy
Linear	5	54.2%	7	**75.0%**	10	70.0%
Quadratic	5	66.7%	7	70.8%	10	58.3%
Cubic	5	50.0%	7	70.8%	10	**75.0%**
Fine Gaussian	5	**70.8%**	7	62.5%	10	70.8%
Medium Gaussian	5	62.5%	7	62.5%	10	62.5%
Coarse Gaussian	5	62.5%	7	62.5%	10	62.5%

On the other hand, Table 4 shows the training results with segments longing 4 seconds. The SVM that works best is the quadratic one with an accuracy of 87.7% for a set of C.V. of 5. Also for a C.V. of 7, two other SVMs work quite well, the linear and the Fine Gaussian, both offering 87.7% accuracy. At last, for a cross validation set of 10 folds, the best result comes from a from a cubic kernel (again 87.7% accuracy). In none of the three cases do we see any improvement in the precision of the training.

Table 4. Results of interval segment of 4 seconds.

SVM type	C.V.	Accuracy	C.V.	Accuracy	C.V.	Accuracy
Linear	5	84.6%	7	**87.7%**	10	86.2%
Quadratic	5	**87.7%**	7	81.5%	10	86.2%
Cubic	5	78.5%	7	80.8%	10	**87.7%**
Fine Gaussian	5	70.8%	7	**87.7%**	10	86.2%
Medium Gaussian	5	82.6%	7	70.8%	10	72.3%
Coarse Gaussian	5	58.5%	7	61.5%	10	61.5%

5 Conclusions

There is numerous literature for stress detection. Most works agree that stress is a very complex subject and measuring it is not an easy task. There are many markers that can be used, many algorithms that can be applied, and many forms of stress that can be observed [15, 18, 6, 16]. Due to the existence of many ways to produce stress, the results provided in all these works should be taken with caution. In this sense, we can say that the results obtained in this paper has given an accuracy of 87.5%. If we compare ourselves with the results obtained in other related studies, it is possible to conclude that ours are quite good. In other similar approaches, stress detection rates range between 70% and 95%. Our approach uses solely skin conductance response features to achieve a high performance comparable to other works.

The most prominent aspect of our contribution is the development of a complete acquisition system [19], a signal processing and a classification model based on SVMs with a high capacity to discriminate between the two calmness and stress conditions considered. The simplicity of the classification model allows this system to work in the long term. Another advance that we have found during the development of this paper is the advantage of having a wearable that is lightweight, portable and with long battery life. The use of such non-invasive device makes it possible to constantly monitor electrodermal activity and have a larger database to work with.

On the other hand, we must consider a number of limitations. Firstly, the realization of the experiment has taken place in a controlled environment on middle-aged subjects. For this reason, the results cannot be generalized beyond the age range of the participants (18 to 44). The second limitation is the quality of the data obtained. In acquisition systems based on physiological signals, it is common that artifacts that damage or worsen the signal appear. To be able to detect these problems in time will help to improve the rest of the process.

As a final conclusion, let us highlight that this study has helped to design an experiment that allows us to detect states of calm and stress. Throughout the study we have verified that there are many factors that can influence this classification, although the results are very acceptable. From the point of view of the previous treatment of the EDA signal, a correct filtering and smoothing of the signal must be carried out to avoid problems. Also, it is necessary to avoid artifacts and events of disconnection of the electrodes with the skin. We must understand that good practices have to be adopted from the beginning. If any of the previous processes fails, it will induce errors in the following stages, increasing the global error and decreasing the accuracy.

Acknowledgments

This work has been partially supported by Spanish Ministerio de Ciencia, Innovación y Universidades, Agencia Estatal de Investigación (AEI) / European Regional Development Fund (FEDER, UE) under DPI2016-80894-R grant, and by CIBERSAM of the Instituto de Salud Carlos III. Roberto Sánchez-Reolid holds BES-2017-081958 scholarship from Spanish Ministerio de Educación y Formación Profesional. Arturo Martnez-Rodrigo Arturo Martnez-Rodrigo holds an European Regional Development Fund (FEDER, UE) under 2018/11744 grant.

References

1. Boucsein, W., Fowles, D.C., Grimnes, S., Ben-Shakhar, G., Roth, W.T., Dawson, M.E., Filion, D.L.: Publication recommendations for electrodermal measurements. Psychophysiology **49**(8), 1017–1034 (2012)
2. Bradley, M., Lang, P.: The International Affective Picture System (IAPS) in the study of emotion and attention, pp. 29–46. Oxford University Press (2007)
3. Carneiro, D., Castillo Montotya, J.C., Novais, P., Fernández-Caballero, A., Neves, J., López, M.T.: Stress monitoring in conflict resolution situations. In: Ambient Intelligence - Software and Applications. pp. 137–144. Springer Berlin Heidelberg (2012)
4. Castillo, J.C., Castro-González, Á., Fernández-Caballero, A., Latorre, J.M., Pastor, J.M., Fernández-Sotos, A., Salichs, M.A.: Software architecture for smart emotion recognition and regulation of the ageing adult. Cognitive Computation **8**(2), 357–367 (2016)
5. Castillo, J.C., Fernández-Caballero, A., Castro-González, Á., Salichs, M.A., López, M.T.: A framework for recognizing and regulating emotions in the elderly. In: Ambient Assisted Living and Daily Activities, pp. 320–327. Springer (2014)
6. Eisenbarth, H., Chang, L.J., Wager, T.D.: Multivariate brain prediction of heart rate and skin conductance responses to social threat. Journal of Neuroscience **36**(47), 11987–11998 (2016)
7. empatica: E4 wristband from empatica (2019), https://www.empatica.com/en-eu/research/e4/
8. Fernández-Caballero, A., Martínez-Rodrigo, A., Pastor, J.M., Castillo, J.C., Lozano-Monasor, E., López, M.T., Zangróniz, R., Latorre, J.M., Fernández-Sotos, A.: Smart environment architecture for emotion recognition and regulation. Journal of Biomedical Informatics **64**, 55–73 (2016)
9. Fernández-Sotos, A., Fernández-Caballero, A., Latorre, J.M.: Elicitation of emotions through music: The influence of note value. In: Artificial Computation in Biology and Medicine, pp. 488–497. Springer (2015)
10. Gola, J., Webel, J., Britz, D., Guitar, A., Staudt, T., Winter, M., Mücklich, F.: Objective microstructure classification by support vector machine (svm) using a combination of morphological parameters and textural features for low carbon steels. Computational Materials Science **160**, 186–196 (2019)
11. Hernandez, J., Riobo, I., Rozga, A., Abowd, G.D., Picard, R.W.: Using electrodermal activity to recognize ease of engagement in children during social interactions. In: 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing. pp. 307–317. ACM (2014)
12. Joachims, T.: Text categorization with support vector machines: Learning with many relevant features. In: European Conference on Machine Learning. pp. 137–142. Springer (1998)
13. Lang, P.J.: Behavioral treatment and bio-behavioral assessment: Computer applications. In: Technology in Mental Health Care Delivery Systems. pp. 119–137. Ablex (1980)
14. Lang, P., Bradley, M., Cuthbert, B.: International Affective Picture System (IAPS): Affective Ratings of Pictures and Instruction Manual. NIMH, Center for the Study of Emotion & Attention (2005)
15. Martínez-Rodrigo, A., Fernández-Caballero, A., Silva, F., Novais, P.: Monitoring electrodermal activity for stress recognition using a wearable. In: Ambient Intelligence and Smart Environments, vol. 21, pp. 416–425. Springer (2016)

16. Martínez-Rodrigo, A., Zangróniz, R., Pastor, J.M., Fernández-Caballero, A.: Arousal level classification in the ageing adult by measuring electrodermal skin conductivity. In: Ambient Intelligence for Health, pp. 213–223. Springer (2015)
17. Martínez-Rodrigo, A., Zangróniz, R., Pastor, J.M., Latorre, J.M., Fernández-Caballero, A.: Emotion detection in ageing adults from physiological sensors. In: Ambient Intelligence - Software and Applications. pp. 253–261. Springer International Publishing, Cham (2015)
18. Salai, M., Vassányi, I., Kósa, I.: Stress detection using low cost heart rate sensors. Journal of healthcare engineering **2016** (2016)
19. Sánchez-Reolid, R., García, A.S., Vicente-Querol, M.A., Fernández-Aguilar, L., López, M.T., Fernández-Caballero, A., González, P.: Artificial neural networks to assess emotional states from brain-computer interface. Electronics **7**(12), 384 (2018)
20. Schneider, W., Eschman, A., Zuccolotto, A.: E-Prime: User's Guide. Psychology Software Incorporated (2002)
21. Sokolova, M.V., Fernández-Caballero, A.: A review on the role of color and light in affective computing. Applied Sciences **5**(3), 275–293 (2015)
22. Zangróniz, R., Martínez-Rodrigo, A., Pastor, J., López, M., Fernández-Caballero, A.: Electrodermal activity sensor for classification of calm/distress condition. Sensors **17**(10), 2324 (2017)