IJCSE International Journal of Computer Sciences and Engineering Open Access
Survey Paper Vol.-7, Issue-1, Jan 2019 E-ISSN: 2347-2693

A Survey on Human Stress Monitoring Technique using Electrodermal Analysis

P. Sudarsan[1*], A. Niranjil Kumar[2]

[1]Department of Electronics & Communication Engineering, Aishwarya College of Engineering & Technology, Erode, Tamilnadu, India
[2]Department of Electronics & Communication Engineering, Dhanalakshmi College of Engineering, Tambaram, Chennai, Tamilnadu, India

**Corresponding Author: sudarsanps@gmail.com*

Available online at: www.ijcseonline.org

Accepted: 02/Jan/2019, Published:31/Jan/2019

***Abstract*—**Stress management systems play a vital role in detecting the stress levels that disrupts an individual socioeconomic lifestyle. According to the World Health Organization (WHO), stress refers the mental health problem that affects the life of an individual. The stress levels can be measured based on the questionnaire by medical and physiological experts. This method fully depends on the answers given by individuals to detect whether they are stressed or not. During the past decades, Electrodermal Activity (EDA) analysis has been performed to measure the changes in the electrical conductivity of the skin. The changes in EDA may be produced by different physical and emotional stimuli that trigger variations in sweat-gland activity. To measure the changes in EDA, different sensors were also designed and many techniques have been developed to analyze the human stress. This paper presents a detailed survey of human stress detection based on EDA analysis to detect their stress levels. Initially, different stress detection methods using EDA analysis are studied in brief. Then, a comparative analysis is conducted to understand the drawbacks in those methods and suggest a new solution to enhance the stress and emotional monitoring system with high accuracy.

***Keywords*—**Stress management, Electrodermal activity, Skin conductance response, Skin conductance level, Electrodermal level

I. INTRODUCTION

Electrodermal Activity (EDA) is a phenomenon where the changes in sweat levels of an individual directly reflect the mental state of that person. It has been also known as Skin Conductance Response (SCR), Electrodermal Response (EDR), Skin Conductance Level (SCL), etc. Normally, sweating is controlled by the sympathetic nervous system and skin conductance is an indication of psychological or physiological arousal. EDA can provide a non-invasive, simply captured, robust and inexpensive method of recording psychophysiological data. If the sympathetic part of an automatic nervous system is highly aroused, then sweat gland activity will also be increased that increases the skin conductance. Based on this, a skin conductance is referred to as a measure of emotional and sympathetic responses. Most of the recent researchers suggested that the EDA is more complex than it seems and research continues into the source and consequence of EDA. For medical diagnoses, skin resistance was one of the primary measurements which involve a pair of electrodes in contact with the skin and passing a small amount of current causing a voltage drop which varies with varying skin resistance when subjected to different stimuli. Generally, it is influenced by many cognitive, emotional and motor processes. The methods of EDA analysis have been focused on two major characteristics of the signal such as phasic and tonic [1]. Fast varying activity is mainly related to the phasic characteristic of the signal whereas the tonic characteristic relates to the slow changes over time i.e., Electrodermal Level (EDL). Various EDA analysis based stress and distress detection method have been proposed during the past decades. Those are focused on analyzing the physiological parameters such as heart rate, skin conductivity, respiration rate, electrocardiogram, electroencephalography data and skin temperature.

The rest of the article is organized as follows: Section II presents the previous researches related to the human stress monitoring based on EDA analysis. Section III illustrates the comparative analysis of those techniques and Section IV concludes an entire discussion.

II. Related Work

A personal health system [2] was proposed for analyzing the discriminative power of EDA in differentiating the stress from cognitive load in an organization atmosphere. In this system, a wearable device was used for monitoring the EDA as a measure of an individual stress reaction. Initially, the collected data was pre-processed and the peaks in the high-pass-filtered EDA signal were detected. Then, descriptive statistics were computed to identify potentially meaningful features. After that, the features were automatically grouped into two conditions such as stress and cognitive load by using different classifiers such as Linear Discriminant Analysis (LDA), Support Vector Machine (SVM) [3] and Nearest Class Center (NCC) with leave-one-person-out cross-validation. Moreover, the best feature combinations were computed for each classifier.

EDA analysis [4] was presented to empathic statements in clinical interviews with fibromyalgia patients. In this analysis, patients with fibromyalgia were invited to a clinical interview in a randomized manner in which interviewer empathic or inattentive character and the emotional or neutral content of the interview were manipulated. Moreover, EDA was measured during the interview. Additionally, the patient's after state and patient satisfaction was also assessed. Long-term monitoring of the EDA [5] was proposed as a promising sensor system. In this system, a correlation between EDA measurements at the fingers and feet were investigated. The main objective of this system was long-term monitoring of physiological and behavioral information related to bipolar disorder patients and providing a better diagnosis of bipolar disorder. Also, the influence of emotional stimulus was evaluated.

Kohonen Neural network stress detection [6] was proposed by using EDA features for identifying the human stress level. In this method, a relaxed and stressed state was differentiated and a series of parameters such as SCR signal power, frequency, gradient, response time and response amplitude was extracted from the EDA signal. In addition, an extremely strict recording protocol was utilized for minimizing the artifacts caused by the worst connection between sensors and skin. Moreover, a Kohonen neural network was used for the classification process. A novel model based on convex optimization methods [7] was proposed for analyzing the SCR of EDA to affective stimuli. The main aim of this model was decomposing the EDA by using the proposed model based on convex optimization.

A quantitative analysis of wrist EDA patterns during sleep [8] was presented by using dry electrodes. In this analysis, EDA patterns were automatically measured in healthy adults based on forearm SCR and actigraphy during sleep. The thresholds were systematically compared for automatically detecting EDA peaks and also the criteria for EDA storms were established. Sparse representation of EDA [9] was proposed with the aid of knowledge-driven dictionaries. In this method, EDA-specific dictionaries were constructed for accurately modeling both slow varying tonic part and the signal fluctuations named Skin Conductance Responses (SCR). Additionally, the greedy sparse representation techniques were used for decomposing the signal into a small number of tonic and phasic atoms from the dictionary. Finally, the SCR occurring in the signal was automatically detected by post-processing the selected phasic atoms.

An efficient automatic workload estimation method [10] was proposed based on the EDA using pattern classifier combinations. In this method, three different decomposition techniques such as Fourier, cepstrum and wavelet transforms were proposed for analyzing the EDA. Also, the efficiency of different statistical and entropic features was discussed and compared. The features were processed by Principal Component Analysis (PCA) [11] and machine-learning techniques for recognizing different levels of an arithmetic process. Moreover, these methods were added to a workload estimation system according to the feature-level and decision-level combinations. A study on EDA during stress [12] was presented to investigate the predictive validity of the Rorschach Performance Assessment System (R-PAS) variables from the stress and distress domain. This investigation was done by testing whether they predicted increased sympathetic reactivity to mild, laboratory-induced stress, occurred one week after Rorschach administration. In this study, a small student sample was contributed and the first meeting (T1) participants were administrated to the Rorschach process according to the R-PAS guidelines. After a week (T2), their EDA was recorded during exposure to a mild laboratory stress-inducing process. According to this, the stress and distress R-PAS variables measured at T1 was positively correlated with increased sympathetic reactivity to stress at T2 that indicates the greater EDA changes from baseline to stress and recovery.

A novel and unobtrusive wearable monitoring device [13] was designed based on the EDA for detecting an individual distress condition from the acquired physiological signals. In this system, a lightweight wearable device was located on the wrist of the subject for allowing continuous physiological measurements. Initially, the signals were collected and processed to extract the features. After that, a statistical analysis was performed for classifying the calm or distress condition. A Compressed sensing based decomposition of EDA signals [14] was proposed for mitigating the effects of the undesired noise components and revealing the underlying physiological signal. In this method, the baseline signal was modeled and allowed for recovery of the user's responses through simple pre-processing followed by the compressed sensing based decomposition. The performance was tested on real-world EDA data which is obtained from a video stimulus experiment.

III. RESULTS AND DISCUSSIONS

A comparative analysis of the merits and demerits of different EDA analysis based stress detection methods whose functional information is discussed in the above section is presented. The following Table 1 gives the merits and demerits of the above-mentioned stress detection based on EDA analysis.

Table 1. Comparison of different cyber-attack detection schemes using different deep learning algorithms

Ref. No.	Methods	Merits	Demerits	Performance Metrics
[2]	Analysis of discriminative power of EDA	The features are independent of the number of peaks occurring during the respective time period.	Further development is required to offer feedback to the user.	Accuracy with best relative features: LDA=75%, SVM=81.2%, NCC=73.4% Accuracy with best non-relative features: LDA=82.8%, SVM=79.8%, NCC=78.1%
[4]	Empathic statements in clinical interviews with fibromyalgia patients	A significant effect of empathy is addressed.	Clinicians must be aware of finding empathic statements.	-Nil-
[5]	Correlation between EDA measurements	Better performance.	The effect of specific emotions on EDA signals was not investigated.	The overall consensus of hand and foot peaks=65%
[6]	Kohonen Neural network using EDA features	Continuous long-term monitoring is possible.	Unbalanced classes and the strong dependence of the initialization.	Recognition rate=93% (number of neighbors=1)
[7]	Analysis of SCR of EDA using convex optimization	Overlapping of SCR is resolved and a globally optimal solution is efficiently obtained.	High computational complexity.	-Nil-
[8]	Quantitative analysis of wrist EDA patterns	High robust.	Further improvement is needed to explain the influences of EDA patterns.	-Nil-
[9]	sparse representation of EDA for SCR detection	Improved performance.	High computational complexity.	MP iteration=5: Root Mean Squared Error (RMSE)=0.05 µs Compression rate=60bits/sec,
[10]	EDA based classification for workload estimation	Ability to capture the complex EDA patterns.	Further improvement is required to discriminate the levels of emotional arousal.	Accuracy: Probabilistic Neural Network (PNN)=82%, Combined Support Vector Machine (CSVM)=90%
[12]	Analysis of E-PAS variables	Better prediction of EDA changes.	Some of the Rorschach scores were not considered.	Correlation: EDA change: stress minus Baseline=0.22 EDA change: recovery minus baseline=0.26
[13]	EDA-based wearable monitoring device	Simple design.	The results of this method were not being generalized directly to the entire population.	Accuracy=89%
[14]	Compressed sensing based decomposition of EDA signals	Better recovery of the user's responses.	Computational complexity is high.	False alarm rate=1: Detection rate=1,

IV. CONCLUSION AND FUTURE SCOPE

In this paper, a detailed comparative study on EDA analysis for detecting individual stress or emotional variations is presented. From this comparative analysis, it is clearly noticed that many researchers have practiced in EDA analysis to monitor the stress levels of a human in different environments with satisfied performance. Among those methods, compressed sensing based decomposition of EDA signals has better performance. Even though, few limitations are addressed in this method. Therefore, the future extension of this study could be focused on further improvement on analysis of EDA signals for detecting stress or emotional changes of an individual that further increases the classification accuracy.

REFERENCES

[1] R. Sioni, L. Chittaro, "Stress detection using physiological sensors", Computer, Vol.**48**, Issue.**10**, pp.**26-33**, **2015**.

[2] C. Setz, B. Arnrich, J. Schumm, R. La Marca, G. Tröster, U. Ehlert, "Discriminating stress from cognitive load using a wearable EDA device", IEEE Transactions on Information Technology in Biomedicine, Vol.**14**, Issue.**2**, pp.**410-417**, **2010**.

[3] Chaitanya Gupte, Shruti Gadewar, "Diagnosis of Parkinson's Disease using Acoustic Analysis of Voice", International Journal of Scientific Research in Network Security and Communication, Vol.**5**, Issue.**3**, pp.**14-18**, **2017**.

[4] A. Finset, T. L. Stensrud, E. Holt, W. Verheul, J. Bensing, "Electrodermal activity in response to empathic statements in clinical interviews with fibromyalgia patients", Patient Education and Counseling, Vol.**82**, Issue.**3**, pp.**355-360**, **2011**.

[5] C. Kappeler-Setz, F. Gravenhorst, J. Schumm, B. Arnrich, G. Tröster, "Towards long term monitoring of electrodermal activity in daily life", Personal and Ubiquitous Computing, Vol.**17**, Issue.**2**, pp.**261-271**, **2013**.

[6] I. V. Bornoiu, O. Grigore, "Kohonen Neural Network Stress Detection Using Only Electrodermal Activity Features", Advances in Electrical and Computer Engineering, Vol.**14**, Issue.**3**, pp.**71-78**, **2014**.

[7] A. Greco, A. Lanata, G. Valenza, E. P. Scilingo, L. Citi, "Electrodermal activity processing: A convex optimization approach", In 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp.**2290-2293**, **2014**.

[8] A. Sano, R. W. Picard, R. Stickgold, "Quantitative analysis of wrist electrodermal activity during sleep", International Journal of Psychophysiology, Vol.**94**, Issue.**3**, pp.**382-389**, **2014**.

[9] T. Chaspari, A. Tsiartas, L. I. Stein, S. A. Cermak, S. S. Narayanan, "Sparse representation of electrodermal activity with knowledge-driven dictionaries", IEEE Transactions on Biomedical Engineering, Vol.**62**, Issue.**3**, pp.**960-971**, **2015**.

[10] P. Ghaderyan, A. Abbasi, "An efficient automatic workload estimation method based on electrodermal activity using pattern classifier combinations", International Journal of Psychophysiology, Vol.**110**, pp.**91-101**, **2016**.

[11] Sumitra Das, Deepak Gupta, "Perfomance Analysics of Human Gait Recognition Based on Principal Component", International Journal of Scientific Research in Computer Science and Engineering, Vol.**4**, Issue.**5**, pp.**12-15**, **2016**.

[12] L. Giromini, R. Morese, A. Salatino, M. Di Girolamo, D. J. Viglione, A. Zennaro, "Rorschach Performance Assessment System (R-PAS) and vulnerability to stress: A preliminary study on electrodermal activity during stress", Psychiatry Research, Vol.**246**, pp.**166-172**, **2016**.

[13] R. Zangróniz, A. Martínez-Rodrigo, J. M. Pastor, M. T. López, A. Fernández-Caballero, "Electrodermal Activity Sensor for Classification of Calm/Distress Condition", Sensors, Vol.**17**, Issue.**10**, p.**2324**, **2017**.

[14] S. Jain, U. Oswal, K. S. Xu, B. Eriksson, J. Haupt, "A compressed sensing based decomposition of electrodermal activity signals", IEEE Transactions on Biomedical Engineering, Vol.**64**, Issue.**9**, pp.**2142-2151**, **2017**.

Authors Profile

Dr. A. Niranjil Kumar received M.E. degree specialized in Applied Electronics in 2006 and Ph.D. in Information and Communication Engineering in 2015, both from Anna University, Chennai, Tamil Nadu, India. He is currently working as a Professor in the department of ECE, Dhanalakshmi College of Engineering, Tambaram, Chennai, Tamil Nadu, India. He has published many papers in video surveillance, background subtraction, Image quality measure and image segmentation. His research is mainly focused on video surveillance.

P. Sudarsan received M.E. degree specialized in Communication Systems from Anna University, Chennai in 2014. He is currently an Assistant Professor in Electronics and Communication Engineering department at Aishwarya College of Engineering & Technology, Erode, India. His research interest includes biomedical signal processing and application in biomedical field.

