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ELECTRODERMAL ACTIVITY (EDA) BASED WEARABLE DEVICE FOR QUNATIFYING NORMAL AND ABNORMAL EMOTIONS IN HUMANS

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ABSTRACT

Emotion recognition through physiological recording is an emerging field of research with many promising results. This work is involved in the construction of a device used to identify basic human emotions indexed by Electrodermal Activity (EDA) in real time; using non-invasive sensors in contact with the skin. The device measures changes in Skin Conductance Level (SCL) caused due to stimulating signals from brain which results from sympathetic neural activity using Ag/AgCl electrodes placed on the ventral side of the distal forearm to evaluate the emotions of the user outside the constrained laboratory environment without interrupting the normal daily routine. The device consists of an embedded system for EDA signal acquisition and a wireless communication module to send processed EDA signals to a remote system. A vibrator attached to the device is used to provide user feedback.

Keywords: electrodermal activity, health care, skin conductance, bluetooth low energy, emotion recognition.

1. INTRODUCTION

In the fast pace world today, humans are subjected to a lot of mental stress. The pressures of survival often forces one to act irrationally. A simple solution to deal with situations that are compelling is to move out of it but is seldom practiced due to the state of mind, often resulting in unpleasant consequences, too late to be rectified. In such a state the human refuses to heed to advices given by another, while if warned by a device, the person is forced to analyse the situation making them aware of their situation and compelling them to take a different decision to counter it.

An example of a situation where irrational behaviour is often noticed is in the case of traffic jams or during a long wait at the signal. When running late for work or when a person has to reach a place urgently, the person often takes decisions which may lead to grave consequences. Another example for irrational decision is when the human is depressed. In this situation, suicidal tendencies are often noticed to relieve mental stress. In other cases a disturbed mind may lead to several health issues like insomnia (lack of sleep), irregular rapid heart-beats, headaches or other health issues.

Several devices like affectiva, fitbit, myo are examples of healthcare devices, which can be worn comfortably by humans for different purposes. Nowadays, with powerful yet small System on Chips (SoCs), it is possible to build compact devices equipped with sensors for several interesting purposes. These devices have the capability to provide large amount of sensor data, opening doors to analysis and processing to extract different features from the same set. These devices also hold the ability to store data locally and upload it into a database when in proximity of WIFI or other internet facilities. Embedded systems are an integral part of Internet of Things (IoTs) enabling ease of data collection, processing and storage. Embedded systems hold the capability of being compact, running various signal processing algorithms, locally, which enable the device to process real time signals and provide necessary feedback to the owner.

The novelty of this work lies in development of a device capable of detecting various emotional states, whose pattern will reflect on the behaviour of an individual and thus their mental condition. This will be helpful in diagnosing various mental illnesses and can benefit medical practitioners in remotely monitoring patients on regular basis. The relevance of EDA in psycho physiological measurements was well established by the year 1972. Since then investigating its many benefits has been on the raise. Considering the work done in recent years we see in [1] the authors, Ming Zher Pho *et al.* have built a novel wrist worn device for unobtrusive continuous measurement of EDA. This is one of the first attempts which successfully built a daily wear device to monitor EDA. The author validates the fact that the region to tap EDA signals need not be restricted to the palms or feet alone, the distal forearm region shows strong correlation with signals from the palm or feet. Further, the authors validate that the signal varies for various activities performed by the human and also investigate the use of these signals in assessing the onset of epileptic seizures. In [2] the authors, A.M Amiri et. al, investigate the relation between extra stimulus and physiological data's response. Along with EDA, ECG and respiration rate are also monitored to find the best emotional reactivity feature that can be considered best to consider as suicide factor. Data is acquired using Biopac MP150 interfaced to a computer.

Participants undergo 15 minutes of baseline resting before administration of the stimulus. The authors prove that physiological data can be very useful in assessing suicidal tendencies. In [3], the authors estimates sleep period time using EDA. EDA signal acquisition is done using BIOPAC systems with the sensors attached to the middle joint of the middle and ring finger of the dominant hand and sleep wake transitions were monitored to detect sleep disorders like sleep apnea. The authors

have made accurate the detection of sleep onset and offset times.

In [4], Greco. A *et. al* have considered investigating how changes in autonomic nervous system activity can be correlated with clinical mood swings to detect bipolar disorder in humans. The authors conclude that variations in EDA components maybe a suitable indicator for discriminating mood states for bipolar disorder. In [5], the authors use EDA as a measure to assess quality of social interactions. 51 children are tested and signals are processed using support vector machines identifying children with better interaction capabilities with adults. [6], investigates the use of EDA to recognize the user's affective state. Children-robot interaction is evaluated to assess several supported behaviour shown by the robot for different affective states in the children. [7], is another work which investigates the use of EDA to diagnose bipolar disorder in humans. The viability of choosing soles of feet as a recording site is investigated. Since the palm is best recording site for EDA, the accuracy of the signals obtained from feet is validated by comparing it with the signals obtained from the palm. The results obtained, suggest that choosing the foot as a recording site is a viable option for daily life recording.

Since the palm is best recording site for EDA, the accuracy of the signals obtained from feet is validated by comparing it with the signals obtained from the palm. The results obtained, suggest that choosing the foot as a recording site is a viable option for daily life recording. [8], aims to EDA as a metric to evaluate in which regions of the supermarket cause stress or negative feelings in customers. The work aims to locate stress spots to locate and solve designing and store management deficiencies. The book [9] by W. Boucsein covers all details about the phenomena, from its principles, recording techniques to its applications in different areas.

The Authors, N.R. Prakash *et.al* [10], tell that stress is a response of the human nervous system during tense situations. When in stress, the efficiency of the vital organs in the body is increased to counter the tense situation. This work is based on monitoring the stress levels in humans for necessary timely management, to help prevent harmful effects of stress on the vital organs. [11], M. Singh et.al is an extension of work [10]. In this work, the authors aim to miniaturize the device to make it more user friendly for continuous monitoring of EDA. They aim to miniaturize the device such that it can be embedded in a wrist band which can be worn at all times whilst at home or work.

In [12], the authors, R. Sahoo *et.al* discuss the use of EDA in assessing stress levels in humans. The work aims to detect stress at a particular time in different positions with moods. They show that the GSR value constantly varies with respect to the surface area contact and GSR variation is maximum when the human is tensed. In [13], K. Subramanya *et al.*, have investigated the use of EDA in predicting an impending cardiovascular arrest, blood pressure (BP), acute hypotensive episode or shock in patients in emergency rooms or intensive care units. The study shows that BP has the strongest predictor of variation in the EDA. In [14], K. Subramanya *et al.* Present a hypothesis and prototype development of electronic device for forecasting hypotension episodes caused by acute failures of circulatory function in critically ill patients. An early detection helps largely in saving these patients from the impending fatal attack. T.V.P *et.al* in the paper [15], make use of wearable device based on EDA and explore its use in identifying basic human emotions. The device measures the skin conductance level using silver/silver-chloride electrodes. Basic thresholds were set for each emotion based on signal samples and activity log provided by 30 participants. Simple peak detection algorithm was used to compute the difference in two subsequent EDA values. The difference is then mapped to an emotion based on the threshold set. This was tested for over a 100 participants and results indicate that cognition, happiness and surprise were detected with an accuracy of 80%, 65% and 60% respectively.

The work so far quoted is the areas in which EDA is by and large used. But, the signal processing techniques employed for feature extraction, can be as simple as computing the slope of the curve to using sophisticated machine learning algorithms. Basically, the mathematical tool employed depends on the application. In [16], Greco et.al has proposed a convex optimization algorithm to analyse EDA signals during affective haptic stimulation. The work proposes a convex optimization based algorithm to characterize the force and velocity of the caressing stimuli. The experiment was performed on 32 participants who were required to wear fabric based haptic system through which the caress like stimuli was conveyed to the subject. The participants were subjected to six kinds of stimuli which comprised of three velocities and two force levels which were administered at random time intervals. Results show that the algorithm performs well for all the considered metrics. This work is particularly helpful for assessment and rehabilitation of patients with severe brain damage known as disorders of consciousness.

Egan. D *et al.* in [17], assess the quality of experience of users in immersive virtual reality and non-virtual reality environments. The work correlate heart rate and EDA to the user's quantity of experience. The results indicate higher quality of experience when the participant is wearing a head mounted virtual reality device as opposed to 2D environment. The study gives positive results in the target assessment and paves ways for deeper mathematical tools like regression to further strengthen the claim. Virtual reality based approach is also used in [18] by Volante. M *et al.*, talks about near visually realistic and non-realistic appearance on emotional response of participants in a medical virtual reality system designed to educate users to recognize signs and symptoms of patient deterioration where one of the measures used was EDA. For the mathematical analysis, analysis of variance on mean EDA was computed. But this method did not

provide desired results while a three way sampling method provided good results.

The active learning, a semi-supervised machine learning algorithm has been employed in [19] for EDA signal classification. The authors, Xia *et al.*, employ this method to significantly reduce manual labelling process to train a machine learning algorithm. The authors provide results which prove that active learning is a promising method to reduce cumbersome manual labelling process to train a machine learning algorithm which considerably reduces the time required for signal classification. An active learner can achieve good performance even with just 16% of data. Although the algorithm is used on EDA signals in this paper, the authors state that this method can be easily adapted for other signals such as ECG or photoplethysmogram.

The Authors, Sioni. R *et al*, [20] present a work which states that although physiological measures like heart rate and EDA are helpful in computing user's stress levels, integrating additional measures could significantly increase the accuracy paving way for new applications. They discuss facial muscle activity and respiratory system activity as the additional measures. They point that the existing measures are impractical as they depend on sweat which significantly varies between each individual. In summary, a device which does not depend on perspiration must be developed which people will not hesitate to use. Much work is required even processing purposes for accurate assessment.

The paper [21] forms the foundation for [16], written by the same authors, Greco. A *et al.*, in this paper proposes a novel algorithm based on convex optimization to process EDA signals. The algorithm was evaluated for three different experiment sessions one of it including its capability to properly describe the activity of autonomic nervous system in response to strong affective stimulation. EDA data was recorded using BIOPAC MP150 an off the shelf available tool, to perform two experiments which comprised of 15 individuals each. One experiment included participants to expire with maximum possible intensity to trigger autonomic nervous system mediated expiration reflex. While the other included to participants to view affective images from a standard database for stimulation purposes. The data obtained was decomposed into two signals, namely, sparse component and smooth component that is interpreted as activity of sudomotor level and the basic excitation level. The results signify the analysis is encouraging, showing good performance for future applications.

Strong stimulus, such as fear involves quickening of heart rate, pupil dilation and increase in perspiration of the human. This is one of the most experimented areas and since it involves increased perspiration, the area attracts several EDA researchers to try various interesting mathematical model for its characterization. One such work is shown in [22] written by Faghih. R. T *et al.,* which proposes an ordinary differential equation model based on sudomotor nerve activity and estimate the fear eliciting stimulus using compressed algorithm. Since skin conductance response (SCR) are the best candidates for depicting sudden physiological changes, the authors made use of SCR data from 8 healthy subjects. The differential equation model describes changes in SC as a function of sudomotor nerve activity. The results show that the algorithm can be used to assess different stress related disorders, changes in brain functions other clinical symptoms. The proposed method they say can also be used to predict a treatment based on the data.

Stress is another factor which attracts a lot of study since this is one of the key factors which affect the physical and mental health of humans. But much of the problem lies in reliably separating stress and relaxation responses. In [23], Ahmed B *et al*., propose ReBreath to identify stress/relax labels based on respiratory patterns. The authors use EDA as one of the physiological measures to validate ReBreath. EDA data is collected using Ag/AgCl electrodes from the middle and index finger of the non-dominant hand. The mention that the SCR in EDA is a good measure of stress as it is not affected by the breathing pattern and is an independent indicator of stress.

Many studies involve the use of EDA for diagnosis of several clinical disorders. But the signals are coupled with noise and several artifacts which are not easy to remove. These factors play a significant role when processing the EDA signals as it hinders in the analysis of the signal. A work that involves in automatically detecting these artifacts is presented in [24]. Team Taylor. S et.al describes the development of a machine learning algorithm for detecting artifacts in ambulatory EDA measurements. Data was collected from 32 participants using Affectiva Q EDA sensors strapped to both the wrists, during physical, cognitive and emotional tasks. For feature extraction purpose, sudden changes in EDA were extracted using Discreet Haar Transform while Wavelet transform was used to reduce noise in the signal. Support Vector machine algorithms are used for successful classification purposes. Thus the team has developed algorithms to successfully distinguish artifacts in EDA.

2. EDA SENSOR

The device in the proposed work employs Bluetooth Low Energy for comes under unlicensed frequency, 2.4 GHz for communication purposes. The wearable device will not hinder daily activities performed by the human. It will also not cause any infection or side effects to the wearer as the sensors employed to collect data are medically approved.

The wearable device based on EDA has two design requirements; one, the electronics required to acquire the data from the wearers wrist and two, the enclosure for the electronics itself. The overall system architecture of this project is shown Figure 1. The sensor module consists of a pair of disposable Ag/AgCl electrodes attached to the ventral side of the distal forearm. A small amount of direct current is given to the “stratum corneum” beneath measuring electrodes in order to excite the sweat glands and acquire the EDA signals. Due to the “baseline wander”, the signals acquired cannot

be processed directly. Hence, there is a requirement of a signal conditioning block. The function of the signal conditioning block is twofold. It not only filters the acquired raw EDA signals, it also serves as an effective current limiter by limiting the current flow through the skin to not more than 10µA/cm2. The output of the signal conditioning circuit is a pair of voltage readings, whose magnitude is proportional to EDA. The measured voltages are fed to the processor to compute skin conductance.

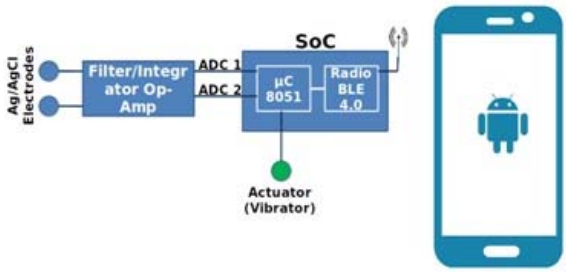

Figure-1. System architecture.

The processor used is CC2540 (from Texas Instruments) with a Bluetooth low energy (BLE) stack. The rate of sampling is 32Hz. It also includes a 3 axis accelerometer, ADXL330 from Analog Devices. A real time clock, DS-1343 from MAXIM is used to timestamp the EDA values for future references. Also, an FRAM, MB85RS256APNF of 256Kbits capacity is used to store the time stamped EDA data. A vibrator is used to alert the user whenever the EDA values exceed a preset threshold. The main criterion for selection of the above components is that they are ultra low power which ensures a robust battery life. The base station serves as an access point, which receives the EDA values. The device is powered by a 3.3V, 600mAh coin cell battery. Being an ultra low power module the battery lasts for a very long time.

3. EDA: DATA COLLECTION AND PROCESSING

For data collection, the device is supposed to be worn for a period of time by different individuals and maintain a diary detailing their activities and how were they feeling whilst wearing the device. Care was taken to ensure that the individuals were comfortable in wearing the device for a sufficiently long period of time. The device was held on the wrist of the wearer using a comfortable velcro strap. Individuals who owned an android phone were requested to provide their phone in order to program the data collection android application onto it. Participants who did not own an android phone were provided with one each (about two individuals were provided with phones). They were requested to switch on the application and keep the phone in their pockets while wearing the device, during the day and all through the night while asleep. The signals were studied with correspondence to the diary maintained by the wearer. Data is sent to the phone using bluetooth, at a frequency of 20Hz.

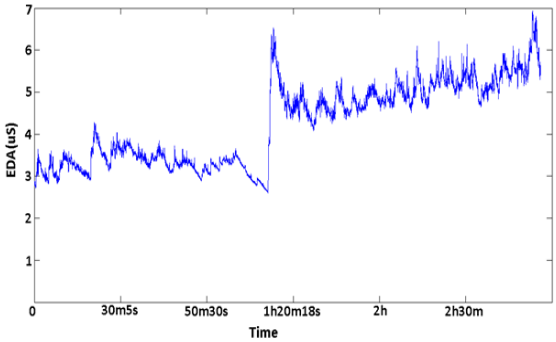

Figure-2. EDA when participant A was active.

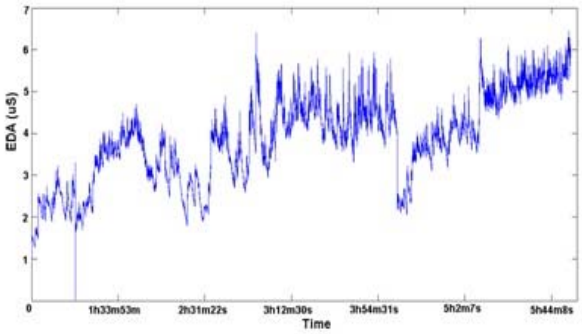

Figure-3. EDA when participant B was active.

The EDA data set collected and stored on the phone is transferred onto a computer. For initial analysis, data-sets across gender and age when awake and when asleep which are depicted in following graphs. The following two graphs show EDA signals acquired when participant was awake and active.

For initial analysis we have made use of simple fixed threshold method to predict each emotional state. First, the raw signal is uploaded to MATLAB and passed through a low pass filter of frequency 1Hz, to reveal general variation of the signal, removing small variations within, to render a smooth signal. The filtered signal was then differentiated using a first order differentiator to render a signal that varies around the origin. Any variation in the signal levels are shown as steep variations above and below the zero line. The y-axis is now divided into thresholds and mapped to a corresponding emotional state based on user feedback. The threshold for each emotional state is shown in the following table.

Table-1. Threshold setting for various emotions.

Emotion	Threshold levels (µSiemens)
Anger	0.013
Fear	-0.005
Happy	0.001
Surprise	0.0023
Nervous	0.003
Cognition	0.005
Neutral	0.01

With these initial these initial thresholds we were able to predict cognition with an efficiency of 80%, happiness was predicted with an efficiency of 65% and anger was predicted with an efficiency of 60% while the remaining emotions had poor success. With these initial promising assessment, the observation made paves way to make use of sophisticated machine learning algorithms to better understand and extract the necessary features successfully.

4. CONCLUSION AND FUTURE WORK

Hectic lifestyle, the race to keep up has led to increased stress and tension in humans. The result of which is decreased level of patience and depression, both of which could lead to grave consequences. Although very many people resort to meditation or yoga to de-stress themselves, the vast majority still continue with their lifestyle without taking proper health-care measures necessary to handle tense situations. One common scenario where impatience openly displayed is during traffic jams, wait at the signal, rash driving etc. in these situations, if a driver takes a wrong decision, the consequences could be serious to fatal. This device holds the capability to assess the state of mind of the human on a real-time basis and provide timely alert to the wearer, prompting the person to think before taking any action. Conscious assessment of the situation helps not only the wearer but the others around. This work aims to detect aggression or anger whilst driving to circumvent a probable mishap. With the initial study and results, we feel encouraged to building a better algorithm to increase the detection efficiency of aggression.

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