

Electro dermal Analyzer to Avoid Accidents Due to Drowsy Drivers

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Abstract—Road safety and road accident mortality rate are a serious concern for the government. With rise in fatal road accidents, who's leading cause is the driver being drowsy behind the wheel, measures to alleviate this problem becomes the prime task. To meet the purpose, methods adopted must be of minimum discomfort for the driver, easy to install, provide good detection accuracy and timely alert to circumvent a probable accident. A good candidate to meet these specifications is EDA. As it detects the level of sweat which directly corresponds to the mental state of the person, using EDA for the purposes of driver safety forms a good option. The novelty of this project lies in making use of EDA as a measure to detect if a person is drowsy or not. Much of the challenge lies in building a device equipped with the necessary sensors and processing the data on real-time. The novelty of this work lies in development of an embedded device interfaced with sensors and actuators to detect and alert a driver when found drowsy using sweat as a parameter.

Index Terms—Road safety, Stimuli and non-invasive

I. INTRODUCTION

EDA refers to the phenomena where the change in sweat levels of a human directly reflects the mental state of the person. Skin resistance was one of the first measurements done for medical diagnoses. It involved a pair of electrodes in contact with the skin and passing a small amount of current causing a voltage drop which varied with varying skin resistance when subjected to different stimuli. The biological aspect of this phenomenon is based on the fact that Skin helps in maintaining water balance and other functions such as “homeostasis” by “vasodilation/constriction” of blood vessels which reflects on the level of sweat produced. There are two kinds of sweat glands; Eccrine and apocrine. The former is found to be more concerned with grasping the behavior than evaporative cooling. The basic principle being the skin becomes a variable conductor under different stimuli, which laid the foundation for extensive research in this field. In short, this psycho-physiological phenomenon involves measurement of electrical conductivity of skin aided by psychologically induced sweating. EDA measurement can be broadly classified into two types; One, Endo somatic method of measurement, which involves finding the amount of current passing through the skin while the potentials are kept constant. Two, Exo somatic method involves measuring the skin potential when the current flow is kept constant; this method measures the skin conductance of

the user. The unit of measure for SC is “Siemens”, since the conductivity is very small; the values are usually given in “microSiemens (μS)”. Skin conductance is further bifurcated into tonic and basic phenomena, the difference between the two, is the duration of time taken to change. The tonic phenomenon, known as the Skin Conductance Level (SCL) depicts the tonic level of skin resistance which corresponds to the nonspecific value of skin conductance taken in the absence of any specific stimulus and takes a longer time to change typically 10's of seconds to 10's of minutes. It shows the general level of arousal. The basic phenomena, known as the Skin Conductance Response (SCR), are short modulations within the SCL which depicts the arousal level of a stimulus and lasts typically for 1-5 seconds; it is shown when the person is subjected to a particular stimulus which is spontaneous and independent of the prior values. Accidents on monotonous drive ways have been on the rise in recent years. One of the leading reasons for this is reported as being drowsiness of the driver. Human brain is a complex system manages several conscious and subconscious activities of the body. The subconscious activities include heart-beat, sweating, digestion, sleep etc. when being drowsy or sleepy concentration levels are low, as are sweat levels and heart-beat. Several devices like affective, fitbit, myo are examples of health care 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. In this paper section II describes the usefulness of EDA for health care applications; section III Captures the crux of the problem. Finally, section IV summarizes the paper based on the survey made on the topic.

II. EDA – USEFULNESS

In times when several sophisticated techniques are available to accurately assess the human mind and behavior in controlled laboratory settings, several surrogate methods are also available to do the same with reasonable accuracy for a quick first hand assessment. The attractiveness of EDA lies in its method of capturing data from the human body. The process is noninvasive and can be done during normal day to day activities. In other words, data collection does not require controlled laboratory settings. The inexpensiveness and ease of portability of the device makes it affordable for the common public to procure. It is also well suited since the measurements are noninvasive which rules out any possibility of infection or injury of other kinds. Galvanic Skin Response as it was earlier known, was first observed when the potential difference across the skin changed the human it was tested on was excited. The phenomenon was then mapped to sympathetic neural activity, the one responsible for involuntary actions in human beings. One of the first applications of EDA was for lie detection. It was observed that the human under observation, although physically calm and composed, the action of telling a lie required a significant amount of brain activity which was directly reflected in the change in electrical potentials across the skin surface. This method is even prevalent today to during interrogation process for criminals. Although the method is famously used for lie detection, its application is not restricted to it alone. Its usefulness goes beyond in assessing several mental disorders and other health-care areas. EDA is mainly useful in assessing stress levels.

III. CRUX OF THE PROBLEM STATEMENT

Drowsiness or brief periods of unintended sleep are often common to people in monotonous situations. During these brief episodes, people often mention being totally unaware of it although making full effort to stay attentive. Such episodes can pose a danger when the person experiencing drowsiness is driving resulting in crossing a signal when it is red or a curve in the road going unnoticed. The results of a recent study which involved interviewing 1000 drivers showed that 45% of the male drivers and 22% of the female drivers admitted to being drowsy while driving. A lose in focus while driving can be fatal. Further investigations were conducted to understand what leads a person to become drowsy in some situations. Participants consisting of both genders were requested to undergo a test wherein, half of them were requested to have a good eight hour sleep during the night while the other half were made to stay awake all through the night before attending to their normal routine the next day. Albeit participants deprived of sleep had more likelihood to being drowsy, the other half were not immune to it. Hence it is concluded that a good rest does not guarantee resistant to drowsiness when the situation is monotonous. Since the human brain forms the control house for various regulatory aspects of the body, an activity map of its functions over time provides a perfect picture of the state of

mind of the person. Thus one of the first choices to detect drowsiness with high accuracy is to use EEG. EEG employs a skullcap fitted with several electrodes spanning the skull to tap signals from various parts of the brain. With decrease in heart rate when a person is drifting to sleep or while asleep, ECG forms good candidate to detect drowsiness. Cameras fitted within a vehicle, tracks eye movement and facial expression of the driver. The images are then processed in real time to decide if the driver is becoming weary. Although accurate, these methods suffer from being cumbersome when worn. Surrogate methods employ sensors which track muscle activity, sweat levels, accelerometers and gyroscope can determine to position of the arm with reasonably good accuracy. Several devices like affectiva, fitbit, myo are examples of health-care 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, an integral part of IoT, hold the capability interfacing with several sensors, running various signal processing algorithms, locally, which enable the device to process real time signals, provide necessary feedback to the owner and yet remain compact.

IV. RELATED WORK OF EDA

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 Phoet.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 estimate 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 accurate the detection of sleep onset and offset times. In [4], Greco. 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. The authors in [5] 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. The authors in [6] have investigated the use of EDA to recognize the user's affective state. Children- robot interaction is evaluated to assess several supported behavior shown by the robot for different affective states in the children. Another work which investigates the use of EDA to diagnose bipolar disorder in humans is given in [7]. 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, aim is 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, have discussed 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 found to be

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 hypertensive 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. K. Subramanya et.al, have modeled a hypothesis and prototype development of electronic device for forecasting hypotension episodes caused by acute failures of circulatory function in critically ill patients [14]. An early detection helps largely in saving these patients from the impending fatal attack. T.V.P et.al in [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. 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. The authors Greco. et.al, have developed a convex optimization algorithm to analyze EDA signals during affective haptic stimulation [16]. 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], assesses 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 labeling process to train a machine learning algorithm. The authors provide results which prove that active learning is a promising method to reduce cumbersome manual labeling 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 SioniR. 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 work in [21] forms the foundation for [16], written by the same authors, Greco. A et.al, the 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 occur in many cases 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 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 proposes 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]. The 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 Discrete 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.

V. 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 interfere with 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 $10\mu\text{A}/\text{cm}^2$. 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. 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.

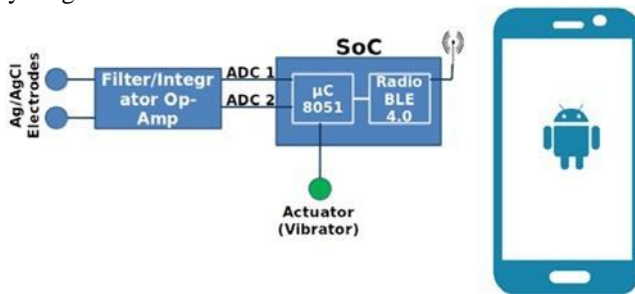


Fig. 1. System architecture of EDA

VI. EDA: DATA COLLECTION AND OBSERVATIONS

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. 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. Figures 4 and 5 depict the EDA signals acquired when participants were asleep which clearly indicates that during sleep, the signal is below $1\mu\text{S}$. Next, signals were collected from participants and lunch, who complained of being drowsy. These signals are shown in Figures 6 and 7. Steep dips to below $1\mu\text{S}$ indicated matched with the time when participant was being drowsy.

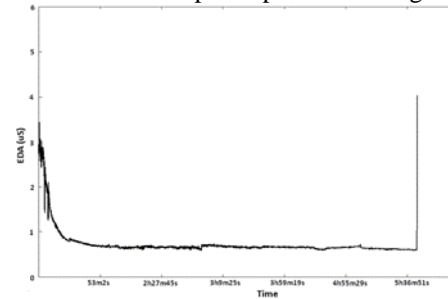


Fig. 2. EDA when Participant A was asleep

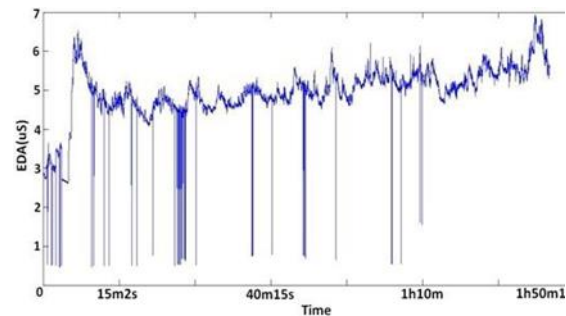


Fig. 3. EDA when participant A was Drowsy

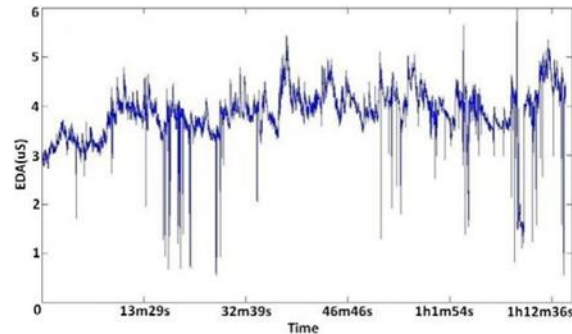


Fig. 4. EDA when participant B was Drowsy

VII. CONCLUSION AND FUTURE WORK

An EDA based wearable device was designed to detect drowsiness in drivers, with the aim of improving road safety. This work aims to detect such episodes and provide a timely alert to circumvent a probable accident. The device will hold the capability to detect drowsiness in real-time. The aim of the work has been successfully achieved and depicted graphically. The project aims to detect drowsiness in drivers with good accuracy and provide timely alert to the wearer. The use of this study is not restricted to assessing drowsiness alone, sweat as a parameter can with used to detect several health

abnormalities particularly the ones pertaining to mental health. The algorithms and signals can be refined and processed respectively to study various other mental disorders and healthcare related issues. Literature is proof enough to depict the plethora of feature extraction possible from the same datasets. The data holds a lot of information, making it possible to use the same data for various applications be it in the area of health-care, cognitive sciences etc. Further, we propose to extend this work for quantification of various emotions in humans which so has been an unexplored to our best knowledge. We plan to quantify positive and negative emotions. Negative emotions as such anger, depression etc. have adverse effects such as rise in blood pressure, suicidal tendencies etc. thus the extension of this work will be focusing on personal health-care devices.

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