EDA as a Discriminate Feature in Computation of Mental Stress

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***Abstract*—In computation of mental stress, various features are determined from a range of physiological signals. During stress, hormones levels inside the body of a stressed person are changed that results in a number of biomedical signals that are communicated among different body organs. A wireless wearable platform has been designed that record these biomedical signals. To induce stress, a series of cognitive experiments were developed that produce stress on the participants. EDA, HRV, respiration and brain signals are used for computing features and the objective was to identify most significant feature or their various combinations. It is verified that EDA features achieves a similar accuracy that can be obtained using various combination of features or using a master set containing all the features. The classification accuracy is more than 80% using EDA with a SVM model containing rbf kernel.**

Keywords-E-health; mental stress; bionedical signals; EDA; SVM; wireless sensors

I. INTRODUCTION

In response to a dangerous situations or a threat, the brain of a human body makes necessary arrangements to cope with the challenge. The sense of that unease form the normal physical conditions is defined as stress [1]. In unexpected situations containing challenges, the nervous system of a person is activated and hormones are released to counter affect that threat. Stress is experienced as when the demand of external or environmental factors exceeds a person's ability to cope with and control these factors [2]. Stress is also characterized by environmental conditions in which people face high demands, but have little control or influence over their external environments [3]. In the studies for stress, it is reported that short periods of stress results in reactions that are damaging for a healthy life such as disturbance in sleep, changes in mood, headache and stomach disorder etc. When stress is prolonged, a wide range of mental and physical health problems emerge including depression, anxiety, cardiovascular diseases, high blood pressure and thoughts of suicidal attempts etc. Other factors that stress can contribute in a daily life are emotional strain and reduction in the quality of life by affected persons. Also there is a significant financial burden on an individual who is coping with stress as it would cost him a reasonable amount to pay for the bills of medical and insurance cover [4].

The Autonomic Nervous System (ANS) which is responsible for response to a stressor, is composed of the Sympathetic Nervous System (SNS) and the Parasympathetic Nervous System (PNS) [5]. Activities in SNS increase during stress conditions and in resting periods, PNS dominates and brings body conditions back to normal. SNS and PNS control the physiological measures such as heart rate variability (HRV), electrodermal activity (EDA) and brain activity (EEG) which are primary signal for computing stress [6]. There are other physiological activities that also activate ANS and necessary precautions should be adapted to separate physical activities' impact from stress related activities [7]. The hormones system becomes active in response to psychological stress. In chronic stress, two types of hormones, HPA and SAM systems are triggered repeatedly and remain active on prolonged basis. Thus they interfere with the release and control of other physiological system which in turn increases the risks of psychological and physical disorders.

In this study, we have identified the most discriminate feature during computation of mental stress. A model to compute stress has been developed that contains wearable wireless sensors to record various physiological parameters. These parameters are changed when a stressor is applied onto a human body. In controlled laboratory conditions, various cognitive tests are performed which act like real life stressors for inducing stress in the participants. In response to stressor, physiological signals that contain HRV, EDA, respiratory affects and brain signals are changed that are recorded. During and in between mental activities, relaxing conditions are applied to relieve the effects of stress. A number of cognitive activities have been designed to produce different levels of stress. A feature selection technique is tested on the obtained features to compute the discriminatory power of features. Classification is performed on individual features and their various combinations. Based on the accuracy, the most discriminate feature is identified along with its various combinations.

II. HARDWARE

Heart rate activity can be recorded by various devices. The gold standard for recording is ECG but it requires two electrodes and wiring which is unsuitable for long term measurements [8]. Pulse oximetry can also be used to measure HRM but it is very sensitive to motion artifacts. The optimal solution is heart rate monitor (HRM) that is used to record heart rate variations in cardiovascular activities or in stressor's response [9]. It contains a strap which is worn around the chest. A wireless transmitter is connected to the strap that transmits heart rate to holster unit. Polar Elecro Inc. manufactures Polar Wearlink HRM which was used in our experiments. In Figure 1, a human body is presented with the complete wearable sensor platform.

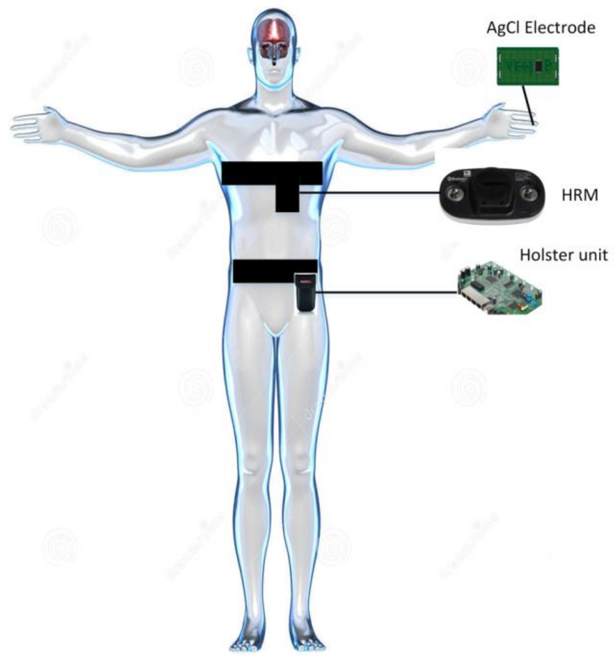

Figure 1: A human wearing a chest strap, an abdomen strap and AgCL electrodes in the fingers.

Respiration contributes significantly in heart rate variations and there is a need to record respiration effects. To monitor breathing effects, a variety of sensing technologies can be used. The variation in abdominal cross section or thoracic is measured by Respiratory Inductive Pletthysmography (RIP) using an abdominal strap that measures changes in the magnetic fields of embedded coils [10]. Placing two electrodes in the rib cage that records impedance changes in the alternating current variations due to respiration are recorded in Impedance Pneumography (IP). For long term monitoring, both these sensors are unsuitable due to postural changes and motion artifacts. In our study, a pressure based respiration sensor manufactured by Thought Technology Ltd. (SA9311M). It is insensitive to motion artifacts and is easily integrated to chest strap with HRM. In Figure 2 a holster unit is presented that contains data process unit with a sensor hub and a lithium ploymer battery that can provide continuous power for about 13 hours.

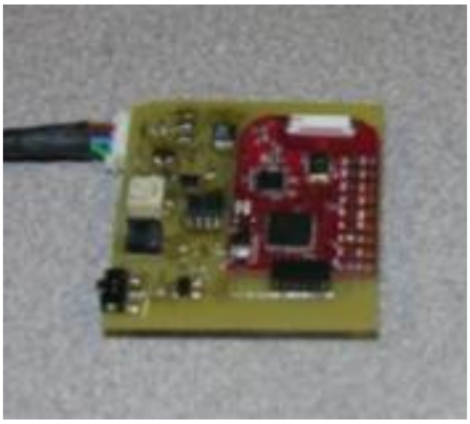

Figure 2: A holster unit.

An electrical voltage of low level is applied to the skin to monitor changes in skin conductance using electrodermal activity (EDA) [11]. In case of stress, body glands release sweat in palms and fingers which in turn increases the skin conductance. EDA can be monitored in palms of the hands but for long term use, they are unsuitable. In our experiments, two AgCl electrodes are attached to middle and index fingers of non-dominant hand to record skin conductance. These electrodes are made by Vivo Metric Systems Corp. (E243). In Figure 2, a PC USB transducer is shown to record sensor data in real time on a PC server.

An abdominal strap contains holster unit with three components integrated to it. The components include a data processing unit, a sensor hub and a battery. A 2 GB mini SD flash card is used for data storage and is mounted on a Vertex Pro motherboard with 400 MHz processing speed (Gunstix Inc.). A sensor hub is also connected to the holster unit which is made up of a 3D accelerometer from STMicroelectronics, a GPS unit form Linx Technologies Inc. along-with a clock unit from Dallas semiconductor Inc. A HRM receiver module is also connected to sensor hub along-with a wireless transceiver used for communication with wireless sensors. A built in charging module is attached in the sensor hub that charges the 3000 mAh Li-Po battery that can be used for continuous data collection up to thirteen hours. It contains HRM in the chest strap to monitor heart rate variation, two electrodes in the fingers for EDA sensor to monitor skin conductance and holster unit in the abdomen for transmitting and storing data [12].

III. COGNITIVE EXPERIMENTS

There are 24 participants containing equal number of male and female subjects. A medical doctor examined the physical health of the participants and each participant provided his/her written consent on the forms. The experimental procedure was briefed to each subject and he/she was not trained for any of the mental activities. . In Figure 3, a sequence is shown for the experimental protocol. It starts with deep breathing to initialize with normal conditions. A mental challenge is followed that induces a pre determined level of stress based on the severity and difficulty of the task. At the end of each activity, deep breathing exercise is performed repeatedly to relieve the body from the effects of stress.

Figure 3: A sequence of activities that starts with normal conditions followed by a mental challenge to induce stress and finally bringing back body to the normal conditions.

To assist the experiments, a protocol was designed to induce mental stress in controlled indoor conditions. There are six deep breathing exercises and five mental challenges for the participants. First of all, the system is calibrated for each individual and an initial deep breathing activity is performed to form a baseline. Each deep breathing session is performed for three minutes. In that session, a subject has to take breathes or inhale for 4 seconds and then breathe out or exhale for 6 seconds. The procedure is repeated and continued for 3 minutes. After the first deep breathing session, a mental challenge of memory search has to be performed by the subject. There is another deep breathing session after each mental challenge to relax the subject and bring back the body to a normal condition. The second mental challenge was color word test that lasted for 5 minutes. A 3rd deep breathing session was performed again to prepare the subject for the next challenge. Next challenges consist of mirror trace, dual task and public speech. The duration of each challenge was 5 minutes. At the end, a final session of deep breathing is performed. Subjects had to rate each mental challenge with various difficulty levels following a Linkert scale, where a minimum difficulty is rated as 1 and extreme stressful challenge is rated as 7. In Figure 4, a screenshot for color word test (CWT) is presented. The user has to respond on sound, text or bar color to progress in the challenge. There are random questions to determine the color based on sound, typing or shown color of a bar. The user gets confused as there is a very little time to concentrate what form of question he/she has to reply as sound, picture and word, all three are depicting different colors.

Figure 4: A screenshot for color word test (CWT).

IV. EDA FEATURE SELECTION

Six parameters are extracted from physiological signals obtained by various wireless sensors. At 500 Mhz, heart rate signals were sampled using a peak detection algorithm. The resulting signal was re-sampled at 4 Hz. Very low frequency (VLF) component was removed from the signal using a band pass filter between 0.04 Hz and 0.4 Hz. Four features were extracted from heart rate variation (HRV) analysis [13]. First extracted feature was AVNN which was an average of time interval between normal heart beats. The second feature was pNN25 which showed the percentage difference greater than 25 msec for adjacent NN intervals. The 3rd feature was root mean square of successive difference (RMSDD) and the 4th was HRV-HF for high frequency power of HRV. For respiration, Resp-LF showed low frequency respiratory power. Finally skin conductance was monitored in SCR that recorded few seconds of short time intervals whereas SCL was ignored that captures the skin conductance impedance for longer time periods.

The EDA features are selected as representative physiological parameters for the proposed model as they are linearly proportional to stress levels in comparison to HRV features which vary inversely. To form a representative signature for EDA, principal component analysis is performed on EDA features and its first principal component is extracted which contains more than 90% variance of these features. There are two components of EDA. Skin conductance level (SCL) is the slowly changing offset and skin conductance response (SCR) is a series of transient peaks.

Two features, mean and standard deviation, are computed from SCL as follows,

$$\mu_{SL} = \frac{1}{N} \sum_{i=1}^{N} R_{SL}(t-i)$$

where μ_{SL} is the average SCL trend for N samples of signature R_{SL}.

The standard deviation is computed as follows,

$$\sigma_{SL} = [\frac{1}{N} \sum_{i=1}^{N} R_{SL}\,(t-i)\,]^{1/2}$$

where σ_{SL} is standard deviation of the conductance signature R_{SL}. Similarly μ_{SR} and σ_{SR} are computed from residual SCR. In our experiments, SCL is used as it maps accurately the perspiration level in a human palm and fingers.

There is a relation between brain activity and stress. The functional magnetic resonance imaging (fMRI) and electroencephalography (EEG) are used frequently to analyze brain activity signals while positron emission tomography (PET) is also used but is less popular. Generally EEG is used most commonly as it has high temporal resolution and low cost. A brain generates electrical signals due to neural activities. Using electrodes at scalp, brain signals are recorded in EEG that represents electrical waveforms of complex nature. Electrodes are charged at 20 to 100 micro volts and are placed on both sides of the scalp that contains right and left brain hemispheres. Frequency, amplitude and shape of the scalp are used to identify and analyze waveforms. During negative emotions, activities in the right hemisphere of the brain dominate than the activities that are produced in the left side of the brain. The right hemisphere is thus the area to be explored for determining stress [14].

Frequency and amplitude is used to categorize EEG signals and determine a particular state of a person. Conscious states are presented by beta and alfa waveforms whereas unconscious states are denoted by theta and delta waves. Stress is mainly indicated by increase and rapid growth of beta wave frequencies and at the same time alpha frequencies are decreased. In right handed persons, the amplitude of alpha waves is slightly higher on the non dominant side. The band pass filtering technique is commonly used for analysis of brain signals [15].

Fourier transform and wavelet packets are used to analyze EEG with respect to frequency, time and spatial domains. Stress is computed using the ratio of power spectral densities of alpha waves frequencies along-with beta wave frequencies. Ratios are defined as following,

$$r_\alpha = \frac{\alpha_{R-}\,\alpha_L}{\alpha_{R+}\,\alpha_L}$$

$$r_\beta = \frac{\beta_{R-}\,\beta_L}{\beta_{R-}\,\beta_L}$$

where α_R and α_L are alpha bands on the right and left hemispheres of the brain and similarly β_R and β_L are beta bands. To determine relaxation levels, summation of alpha along-with theta and summation of alpha, beta and theta measures are used.

V. EXPERIMENTAL RESULTS

In these experiments, wireless sensors were used to read biomedical signals. There are four sensors that monitor HRV, EDA, respirations and brain signals. There were two classes of activities, mental challenges that act like stressors and induce stress. Other kinds of activities are deep breathing exercises that relax the body. The purpose of experimentation is to compute stress levels that were induced by various mental exercises. A SVM classification model was designed that classify the induced parameters into two classes. One was stress class and other was relax class. From HRV, six features were extracted and EDA was employed for three features. Two features were extracted from respiratory signal and three features were computed from brain signals.

Cross validation experiments were designed with four fold cross validation. There were three sets of training data and one set was used for testing. Each time on the next turn, the test set was replaced by a training set and the process keeps on repeating. After tuning the parameters for kernel bandwidth and cost function, individual parameters and their various combinations are employed in an empirical manner.

First of all, HRV features are put in the training set and classification accuracy was computed for the test set. Secondly EDA features were put in the experiments. Similarly respiratory and brain signal features were used to find the classification accuracy. In the second phase, all features were combined and classification accuracy is determined. In the next stage, various combinations of the features such as HRV and EDA, EDA and respiratory, EDA, HRV and respiratory etc. are used. The results are presented in Table 1 and Figure 5.

VI. CONCLUSIONS AND FUTURE WORK

EDA parameters are shown to be most discriminate among all the physiological parameters. The combined feature vector containing all the features from all recorded signals obtained the similar accuracy as was achieved by EDA features alone. Although HRV and respiratory features are important also but EDA features are most significant and discriminate as sweating is directly proportional to various stress levels.

Table 1: Accuracy chart showing the classification rates for various features and their combinations.

	HRV	Respi	EDA	HRV+ R	HRV+ EDA	All
Correct Rate	72	70	82	74	81	82.5
Error Rate	28	30	18	26	19	17.5
Sensitivit y	74	72	78	73	78	79
Specificit y	78	76	81	78	82	84

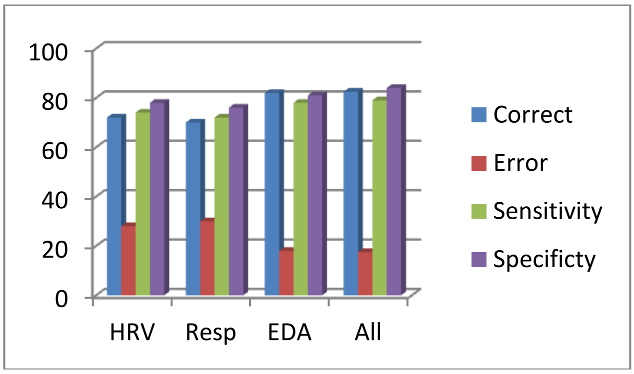

Figure 5: Classification Accuracies chart.

A stress prediction system has been designed that contains wearable wireless sensors that record physiological parameters that vary in response to different stress levels. HRV provides heart rate variations and in stress, heart rate decreases. EDA is the conductance of electrical signals in the fingers of a person and in stress, EDA increases. Similarly respiratory features and brain activity signals also vary stress. To induce stress, a protocol has been designed that contain various mental challenges and different levels of stress are induced when engaged with these activities. Deep breathing is used in between and start of each mental exercise to bring the body back to its normal conditions and relieve the effects of stress. Wireless sensors record the variation in physiological signals and different features are extracted from these signals. For classification, SVM model is used to differentiate stress conditions from the relax situations. Various combinations of features are employed and it is concluded that EDA features alone achieves almost similar accuracy as divided by using all combined features.

In future, the model would be tested on real time stress conditions such as fire fighting scenes and students in the exam centers. In hardware, physiological signals can be recorded with more improved devices. Also, the classification model would be improved by incorporating Bayesian model into the system.

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