Stress Detection of the Students Studying in University using Smartphone Sensors

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***Abstract*—Stress leaves a harmful impact on the health of people and puts their health at serious risk. To assess stress, this study presents an approach to measure the stress levels of graduate and undergraduate students by analyzing the activity behavior of their daily routine. Our approach monitors the activity behavior non-invasively using the smartphone sensors. The activity behavior is classified into three classes with an accuracy of 98.0% using a support vector machine. We build linear relationship between those recognized classes of activity (explanatory variables) and stress level experienced by the students. This approach is based on multiple linear regression that computes a stress score, and categorizes stress in three levels: low, mild, and acute. Such results illustrate that the graduate students experience high stress as compared to the undergraduate students.**

Keywords–Stress; activity and sleep behavior; smartphone sensors.

I. Introduction

A natural defense of the human body, also known as stress, protects individual against any danger. Stress for a short time can be helpful, but long-term stress can negatively affect health. People suffer from stress when they are overloaded and feeling an inability to cope with the demands. Stress is a state in which individuals are expected to perform too much under sheer pressure and in which they can only marginally meet the demands. These demands can be related to psychology, finance, work, and relationships that pose a real challenge or threat to health, and well-being of individuals. If stress is not timely cured and the person is going through constant stress, it can affect human body with headache, depression [1], heart attack [2]-[4], stomachache, high blood pressure, insomnia, and weakened immune system. Clinically, subjective methods such as questionnaires and interviews are conducted to evaluate stress, whereas for objective assessment of stress, many researchers presented their works to detect stress [5]-[11]. However, they tried to measure stress using like invasive sensors EEG [5][9][10], ECG [11], and Galvanic Skin Response (GSR) [6]. EEG or ECG sensors provide state-of-the-art accuracy for stress detection. However, the usage of EEG or ECG to analyze stress is impractical in real-life settings, because people do not feel comfortable to go outside in public places wearing EEG or ECG in their daily-life. People suffering from stress may not choose to openly wear the device because stressed persons are already shy to express themselves and therefore, such wearables may not be socially acceptable to them. Moreover, the efficiency of these devices degrades as users perform any motion-related task. To the best of our knowledge, no one has designed a system for non-invasive detection of stress yet. Therefore, we are motivated to design non-invasive stress detection system.

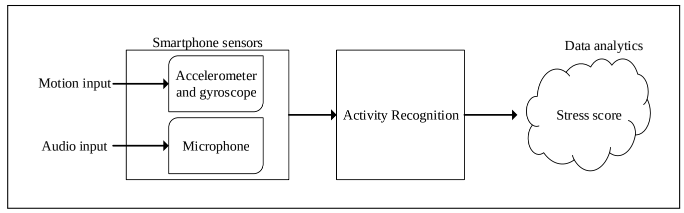

Figure 1. An architecture of stress monitoring system.

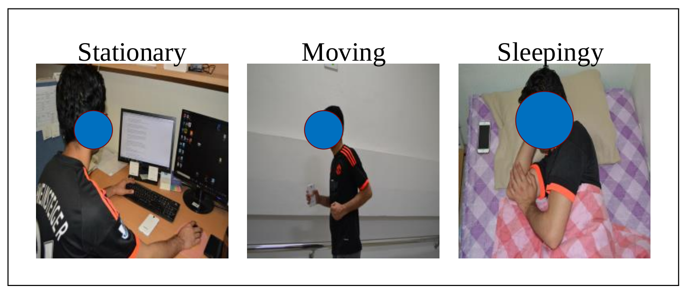

Figure 2. Subject while performing different activities.

In this paper, we present a novel system to measure the stress of the university students by analyzing their activity behavior in daily routine. We choose undergraduate and graduate students to evaluate their stress level, because they are more vulnerable to stress due to a variety of challenges such as poor academic performance [12], finances [13], poor sleep [14], and inability to cope with research demands of supervisor. Besides, high rates of suicide in American and Asian countries are associated with academic related stress [15]. It is imperative to take preventive measures for protecting the students from deleterious outcome associated with stress by monitoring their daily activity behavior.

We have broadly categorized the daily-life routine of the students into three clusters: *stationary*, *moving*, and *sleeping*. We think that poor sleep and sedentary behavior (i.e., stationary) are two main indicators of stress, whereas movement behavior of person signifies less stressed or happy man. Our system consists of motion and audio sensors that records input data with the assistance of an application (App) running on a smartphone. We exploit the motion sensors namely accelerometer and gyroscope-sensors and a microphone sensor of the smartphone as the primary sources of data input to our system. The motion sensors record the activity behavior and the audio sensor records voice signal of the participants

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at the rate of 10 samples/second and 44100 samples/second, respectively, as shown in Figure 1. The activity recognition algorithm is applied to the acquired signals, and recognized activity behavior is transmitted to the cloud server for data analysis to detect stress.

This paper is organized as follows. In Section II, we describe the experimental setup to collect raw data using the smartphone sensors and the proposed approach. In section III, we discuss and evaluate the system performance for stress detection based on the daily activity behavior.

II. Materials and Methods

Our approach employs tri-axial accelerometer, tri-axial gyroscope, and microphone of a smartphone. An accelerometer and gyroscope are dedicated to measuring acceleration and angular velocity of the subjects during *stationary*, *moving*, and *sleeping* states, whereas the microphone records surrounding noise level when subjects are in *stationary* and *sleeping* states. Figure 2 depicts the three of the activities performed by the subject while the smartphone is in the proximity to him. Smartphone app developed by MATLAB is responsible for collecting the experimental data and transmitting the data to the cloud server for further analysis.

A. Experiment Design

We recruited 32 students (16 graduate and 16 undergraduate) of Sungkyunkwan University, average age of 29.7 years with standard deviation of 10.6 years, to analyze our envisioned system. Subjects signed consent form prior to the experiment and whose rights have been protected following declaration of Helsinki. Selected Subjects had no head injury and were not using any medication. We employed same manufacturer and same model smartphone, iPhone 6, for recording the daily activity experimental data, because the majority of participants in the trial had an iPhone 6, and since the idea was to let the participants use the same type of smartphone so as to avoid the normalization problem of the activity data. Each participant recorded their 24 hour activity of daily routine which constituted experimental data of 768 hours. If a person is sleeping, the amplitude generated by a microphone is either near to zero or very small due to snoring, whereas when subject wakes up, he/she has to say "good morning" or "hello", and as to signal the microphone that the subject has woken up, and similarly, subject has to utter "good night" to indicate beginning of sleep. The words spoken at the time of before and after the sleep helps in determining sleep duration of the subject automatically. All participants also participated in a stress-related survey. The data of 25 hours were discarded because some participants could not carry mobile in some unavoidable situations. The students were grouped into two clusters based on educational degree they are currently pursuing in the university: graduate and undergraduate. The daily routine information of both groups forms experimental data for activity recognition. Acquired signals of the sensors are segmented into non-overlapping segments of 20 seconds. The segment length of 20 seconds was selected based on the best performance of activity recognition classifier after exploring a range of 3 to 30 seconds. The activity information was annotated into three classes: stationary, moving, and sleeping.

B. Proposed Approach

Our system for stress detection has three stages. Subjective assessment is performed about stress through a survey in *stage one*. In *stage two*, subject's activity of the whole day is recognized, and stress level is detected based on the recognized activity information in *stage three*. The activity information is comprised of three broad classes: stationary, moving, and sleeping. Our system tries to recognize these activities using an activity recognition classifier. We think that these three classes of activities are essential to determine stress of the university student. We have exploited participants' interaction with a smartphone to indirectly determine their stress level. If participant is stressed, he/she suffers from insomnia and often remains in stationary activity. Therefore, we exploited subjective assessment and daily activity information of participants to calculate their stress levels. The proposed approach tries to exploit relation of sleep, stationary, and moving activities with stress using linear regression. We think that the pressure of supervisor and fear of failure causes the student to sleep less and study for long hours, whereas a person who sleeps less and stays stationary longer than usual becomes victim of stress. Therefore, it is very important to address the problem of stress faced by the university students using a novel non-invasive approach.

C. Activity Recognition

The distinct patterns as shown in (Figures 3(a) to 3(f)) were generated by the motion sensors of smartphone according to the activity subjects performed in their daily schedule. Three segments of 40 seconds in Figure 3 demonstrate a difference in acceleration and angular velocity of each activity. The patterns of moving activity are clearly distinguishable from the rest of the two activities. To some extent, patterns of sleeping and stationary activity are obscure due to being same in nature. For solving this problem, the microphone is used to differentiate sleeping from stationary activity as shown in Figure 4. We have modified the signal of audio input in order to keep the privacy of subjects. Amplitude signal of audio input during sleep stays approximate to zero, whereas the amplitude during stationary (awake) state is higher as shown at extreme ends of audio signal in Figure 4. Since, features play an essential role in the recognition of activities, so features must characterize the patterns effectively without carrying irrelevant and redundant information so that activity recognition classifier perform efficiently. The amplitude based features are extracted from segments of experimental data for training the activity model. Those features are arithmetic mean, standard deviation, interquartile range, kurtosis, geometric mean, median, maximum, range, skewness, energy of a signal, waveform length, entropy, RMS and ratio of RMS to maximum.

Forward Features Selection (FFS) procedure is employed on the computed features to reduce redundancy and avoid overfitting. The top 6 features are selected using FFS and those selected features are fed into Support Vector Machine (SVM) to develop the activity recognition model. The activity recognition model is trained and evaluated using a 32 fold cross-validation technique with leave-one-out. This technique allowed the training of the quadratic SVM on the features from 31 out of 32 subjects and validated the model with the remaining subject. The activity recognition algorithm has classified the acquired signals of the sensors with an accuracy

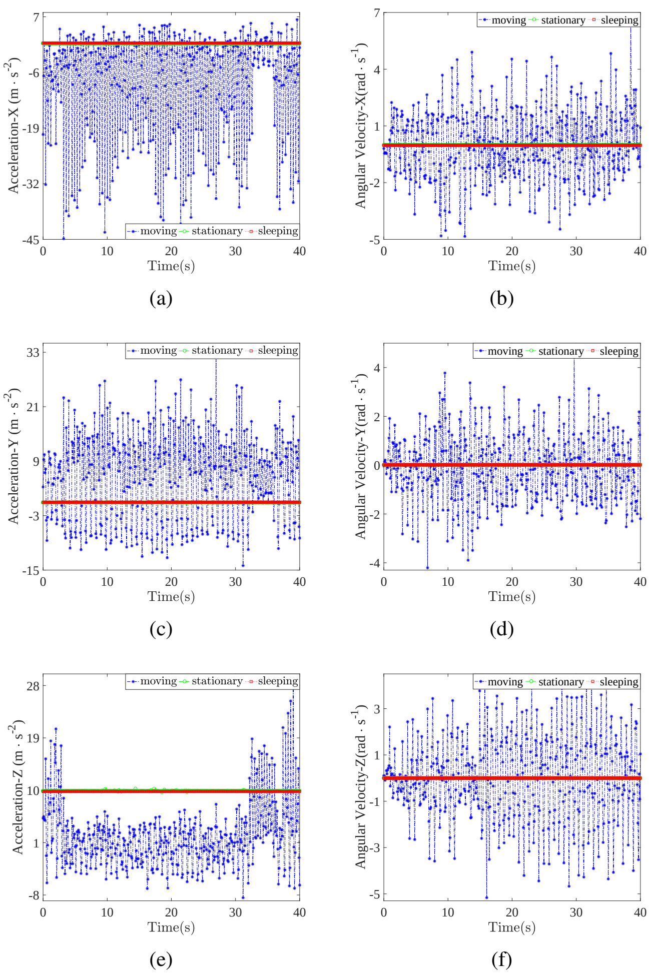

Figure 3. Motion sensors signals; (a), (c), and (e) represents Accelerometer signals in x, y and z axes, whereas (b), (d), and (f) are Gyroscope signals in x, y and z axes.

of 98.0% into three activity classes of *stationary*, *moving*, and *sleeping* as shown in Figure 5. The *moving* class is comprised of walking, running, and any other exercise involving the body motion. SVM is a supervised machine learning algorithm. We implemented SVM for activity recognition using classification learner tool in MATLAB 2016b. One-vs-all strategy and linear kernel function $k(\vec{X_t}, \vec{X_i}) = \vec{X_t}, \vec{X_i}$ is used whose penalty C parameter is 1 by default.

D. Stress Detection

The activity information recognized by SVM is transmitted to the cloud server for data analytics to detect stress (*S*) in the students. We tried to search relationship between stress and three activity classes: *moving*, *stationary*, *sleeping*. We exploited different linear regression models to build a robust model to estimate stress. *Stationary* and *sleeping* activities data are included to develop the stress estimation model because those two variables showed a significant relationship with stress, whereas *moving* activity data was discarded after it showed no any significant improvement in the model. We have computed stress score using (1). We think that sleep duration and stationary activity are essential explanatory variables to

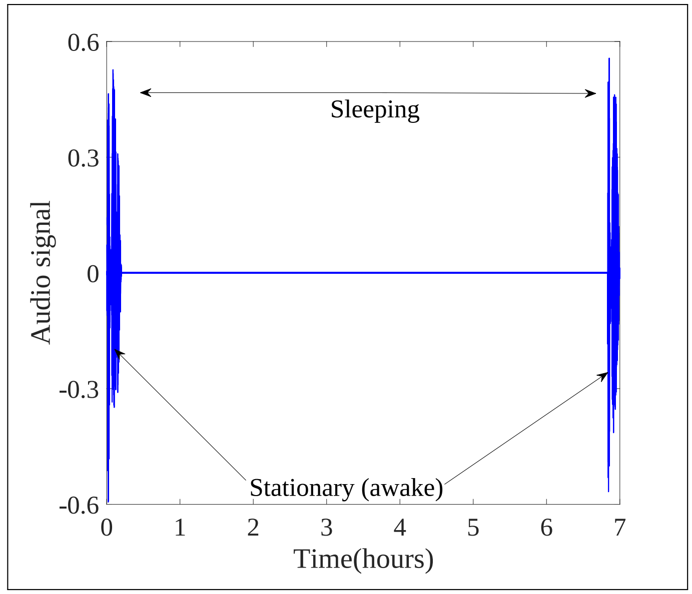

Figure 4. Audio signals for sleeping activity.

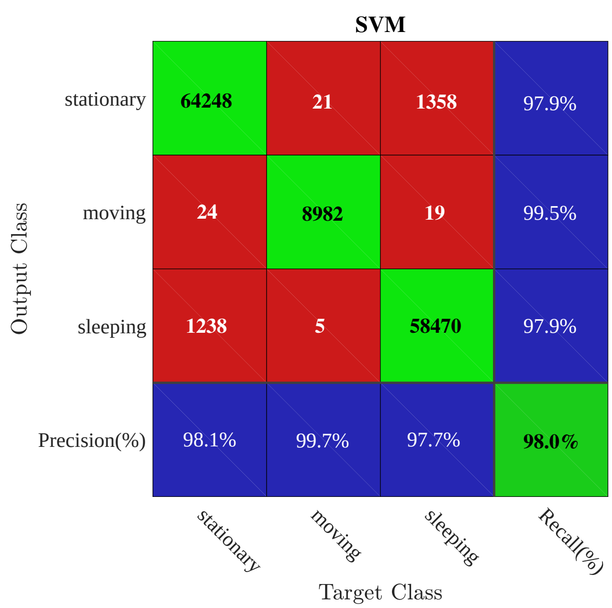

Figure 5. Activity recognition performance of SVM.

determine the stress levels.

$$S = aX + bY + \theta \tag{1}$$

where X and Y represents *stationary* and *sleeping* activity classes, whereas a, b, and θ are parameters.

We employed curve-fitting tool of MATLAB 2016b to evaluate the proposed model, and determined the values of a, b, and θ using least square method. As shown in Table I, the parametric values of the proposed approach are calculated as 0.176, -0.386, and 3.01 for a, b, and θ, respectively. The pvalues of *stationary* and *sleeping* variables are lower than 0.05 which proved the statistical significance of the earlier mentioned variables in estimating the stress score. The adjusted R-Squared value is 0.909 which means 90.9% variance in stress is successfully explained by the proposed model based on two explanatory variables (i.e., *stationary* and *sleeping*). *Stationary* has the effect of a on the stress score, whereas *sleeping* affects the stress score by factor of b. All the parameters have a partial effect on stress. The parametric values of (1) shown in Table I suggest that *sleeping* has a higher effect on stress score than *stationary*, because parameter b is higher in weight than parameter a. If both the variables are 0 in values, then parameter θ affects estimated stress highly. Stress reduces when sleep time increases and vice versa. On the contrary, *stationary* activity is directly proportional to the stress.

TABLE I. LINEAR REGRESSION ANALYSIS OF PROPOSED MODEL

	Estimated parameters	Standard error	t Statistic	P value
Intercept	3.01	0.78263	3.8429	0.00061
Stationary	0.176	0.04124	4.2701	0.00019
Sleeping	-0.386	0.05506	-7.011	1.0393e-07
Number of observations	32			
Root Mean Squared Error	0.287			
R-squared	0.915			
Adjusted R-Squared	0.909			

Three levels of stress are calculated based on lower and upper thresholds. Those three levels of stress are low, mild, and acute. If $S < \delta_1$, the subject is less stressed or normal, he has a mild stress if $\delta_1 \leq S \leq \delta_2$, and he has an acute stress if $S > \delta_2$. The δ_1 and δ_2 represents lower and upper thresholds. Stress level scores for all the students is computed. The result of stress computation shown in Figures (5(a) to 5(b)) has demonstrated that 2 graduate student have acute or high stress and 2 others out of 16 graduate students have mild stress, whereas only 3 out of 16 undergraduate students have mild stress. This statistics of stress experienced by students has validated our claim that graduate students have higher average stress as compared to the undergraduate students due to poor sleep and higher sedentary or stationary behavior.

III. Discussion and Conclusion

The focus of our research was to present an approach to detect stress levels experienced by the students. Our approach uses non-invasive strategy to monitor the three levels of stress in the subjects using a commonly available electronic device (smartphone). We employed the motion sensors and audio sensor of the smartphone to record the overall activity of the individuals. Prior studies have considered stress detection with EEG, ECG and Galvanic Skin Response (GSR) [3][6][9][10][11] which provide a direct method to measure stress and are preferred choice of users in indoor settings, but these devices are socially unacceptable to people going out in public places (i.e., school, office, shopping market, etc.,) while wearing these measurement devices. Our non-invasive method based on the smartphone is user friendly and socially acceptable to users, because the smartphone sensors do not interfere with their daily work and they can use the smartphone to measure their stress levels in public places without letting anybody know.

We have analyzed our approach using two groups of the students. The smartphone recorded the activity of students when they performed routine tasks without interfering in their daily-life tasks. An experiment was performed in order to obtain activity data on the basis of which, stress scores or levels can be detected. The activity recognition classifier grouped the daily-routine behavior of the subjects into three classes: *moving*, *stationary*, and *sleeping*. We experimentally evaluated three of the activity classes to build statistical models for stress computation, but the model is built on only *stationary* and *sleeping* classes. *Moving* activity did not contribute any significant information about stress in the model, therefore, it is discarded. *Stationary* and *sleeping* are two broad classes of activity which are essential to assess someone's stress level. The estimation of stress levels by proposed approach is demonstrated in Figures (6(a) to 6(b)). The curve fit of the stress estimation model is shown in Figure 6(c) which depicts the inverse relationship of *sleeping* with stress and direct effect of *stationary* on the stress. The conclusion drawn from proposed model also agrees with the previous studies that stress causes poor sleep [16][17] and high stationary or sedentary behavior [17] is related to stress.

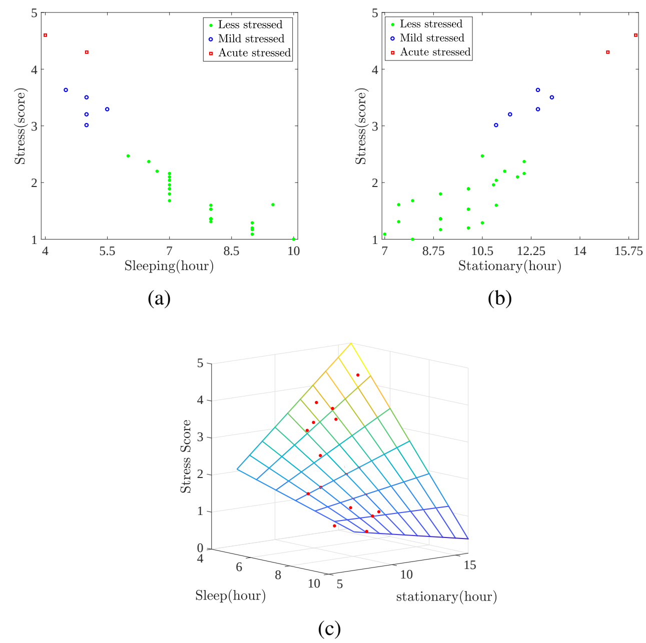

Figure 6. Stress relation with daily life activity behavior (a) Effect of Sleeping activity on Stress Score, (b) Effect of Stationary activity on Stress Score, and (c) 3D curve fitting of the proposed model.

We experimentally found that graduate students suffer higher stress than the undergraduate students studying in the university. Our proposed strategy determined the stress of the students and 2 out of 16 graduate students is suffering from acute or high stress, 2 out of 16 graduate students have mild stress, whereas only 3 out of 16 undergraduate students have mild stress. It is not possible that people carry the smartphone all the time, so it is a limitation of our approach. We will try to integrate motion and biological sensors in arm band or embed to T-shirt for monitoring the activity of individuals and notifying them about their stress levels in real-time as our future work.

We have presented a novel approach based on smartphone sensors to measure the stress level of graduate and undergraduate students studying in the university. Our system has determined three stress levels by analyzing the activity behavior and experimentally found that graduate students are

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more stressed than undergraduate students.

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