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Stress and sleep quality estimation with the use of smart Wearable sensors

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Abstract: The stress and poor sleep quality of a person may be used as two of several components for predicting the onset of mental health problems, in particular depression. Continuous stress monitoring may help users better understand their stress patterns and provide physicians with more reliable data for interventions. Previously, studies on mental stress detection were limited to a laboratory environment where participants generally rested in a sedentary position. However, it is impractical to exclude the effects of physical activity while developing a pervasive stress monitoring application for everyday use. The physiological responses caused by mental stress can be masked by variations due to physical activity.We present an activity-aware mental stress detection scheme. Electrocardiogram (ECG), galvanic skin response (GSR), and accelerometer data were gathered from 20 participants across three activities: sitting, standing, and walking. For each activity, we gathered baseline physiological measurements and measurements while users were subjected to mental stressors. The activity information derived from the accelerometer enabled us to achieve 92.4% accuracy of mental stress classification for 10-fold cross validation and 80.9% accuracy for between-subjects classification.Ergonomic smart sensors that can determine the heart rate variations related to stress and the variability of sleep may provide unique insights to the coping behavior of stressed people. Rather than relying on wearable computers, a single smart miniature sensor that is worn 24/7 should perform the complex embedded recognition tasks while meeting difficult battery life, wireless communications and ergonomic constraints. The development and testing of such a smart sensor is described focusing on implementation within distributed intelligence based architecture. The manner in which the user's heart rate and the user's physical motion is used to measure stress and sleep quality is explained.

Key words: Mental stress, electrocardiogram, galvanic skin response, Ergonomic smart sensors physical activity, heart rate variability, decision tress, Bayes net, support vector machine, stress classifier.

1 INTRODUCTION

Stress is a physiological response to the mental, emotional, or physical challenges that we encounter. Immediate threats provoke the body's fight or flight" response, or acute stress response [5]. The body secretes hormones, such as adrenaline, into the bloodstream to intensify concentration. There are also many physical changes, such as increased heart rate and quickened reflexes. Under healthy conditions, the body returns to its normal state after dealing with acute stressors. Unfortunately, many of the stressors in modern life are on-going. Chronic stress can be detrimental to both physical and mental health. It is a risk factor for hypertension and coronary artery disease [22, 12]. Other physical disorders, including irritable bowel syndrome (IBS), gastroesophageal reflux disease (GERD), and back pain, may be caused or exacerbated by stress [16]. Chronic stress also plays a role in mental illnesses, such as generalized anxiety disorder and depression [11].

Continuous monitoring of an individual's stress levels is essential for understanding and managing personal stress. A number of physiological markers are widely used for stress assessment, including: galvanic skin response, several features of heart beat patterns, blood pressure, and respiration activity [31, 15]. Fortunately, miniaturized wireless devices are available to monitor these physiological markers. By using these devices, individuals can closely track changes in their vital signs in order to maintain better health.

Measuring physiological signals during everyday activity is more difficult than in a rigorous laboratory environment. First, the physiological responses caused by mental stress can be masked by variations due to physical activity [1]. For example, people may have higher heart rate when standing than when sitting. Heart rate may also increase when people are mentally stressed. Hence, using

Heart rate alone as an indicator to detect mental stress may lead to misclassification. Second, signal artifacts caused by motion, electrode placement, or respiratory movement affect the accuracy of measured recordings. Third, it is also difficult to determine the ground truth of a user's stress level when labelling training data in mobile environment. These factors increase the difficulty of developing a pervasive mental stress detection application for everyday use. We introduce an activity-aware, multi-modal system that combines accelerometer, ECG, and GSR information to diffierentiate between physical activity and mental stress. We conducted a user study with 20 participants across three different physical activities: sitting, standing, and walking. With activity information derived from the accelerometer, we achieved 92.4% accuracy for 10-fold cross validation and 80.9% accuracy for between-subject's classification. In the next section, we describe how we can measure the body's responses to mental stress. Next, we discuss prior work on stress detection. Section 4 describes our experimental protocol and our physiological feature extraction and classification methods. Experimental results are presented in Section 7.

2 BACKGROUND

The autonomic nervous system (ANS) regulates the body's major physiological activities, including the heart's electrical activity, gland secretion, blood pressure, and respiration. The ANS has two branches: the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS). The SNS mobilizes the body's resources for action under stressful conditions. In contrast to the SNS, the PNS relaxes the body and stabilizes the body into steady state.

2.1 Heart Rate Variability (HRV) and Stress

Under acute stress, the SNS increases heart rate, respiration activity, sweat gland activity, etc. After the stress has passed, the PNS reverses the stress response [17]. Since the ANS controls the heart, measuring cardiac activity is an ideal, non-invasive means for evaluating the state of the ANS.

An ECG is a recorded tracing of the electrical activity generated by the heart. Figure 1 shows a P wave, a QRS complex, and a T wave in the ECG. The P wave represents atrial depolarization, the QRS represents ventricular depolarization, and the T wave reflects the rapid repolarization of the ventricles [8]. The R-R interval is the time interval between two R peaks and is used to calculate heart rate.

Fig. 1: Electrocardiogram sample Heart rate variability (HRV) refers to the beat-to-beat variation in the R-R interval. HRV analysis can be categorised into time-domain and spectral-domain analysis. Several time-domain parameters include:
-mean HR: mean heart rate (beats per minute);
- mean RR: mean heartbeat interval (ms);
-SDNN: standard deviation of RR-intervals between normal beats;
-RMSSD: root mean square of the difference between successive RR-intervals;
-pNN50: the percentage of heartbeat intervals with a difference in successive heartbeat intervals greater than 50 ms.
Three widely used components can be found in HRV power spectrum:
-LF (0.04-0.15 Hz): a low-frequency component that is mediated by both the SNS and PNS;
-HF (0.15-0.4Hz): a high-frequency component mediated by the PNS; and
-LF/HF: LF to HF ratio that is used as an index of autonomic balance.

2.2 Galvanic Skin Response (GSR) and Stress
GSR is a measure of the electrical resistance of the skin. A transient increase in skin conductance is proportional to sweat secretion [6]. When an individual is under mental stress, sweat gland activity is activated and increases skin conductance. Since the sweat glands are also controlled by SNS, skin conductance acts as an indicator for sympathetic activation due to the stress reaction. The hands and feet, where the density of sweat glands is highest, are usually used to measure GSR. There are two major components for GSR analysis. Skin conductance level (SCL) is a slowly changing part of the GSR signal, and it can be computed as the mean value of skin conductance over a window of data. A fast changing part of the GSR signal is called skin conductance response (SCR), which occurs in relation to a single stimulus. Widely used parameters for GSR include the amplitude and latency of SCR and average SCL value [2]

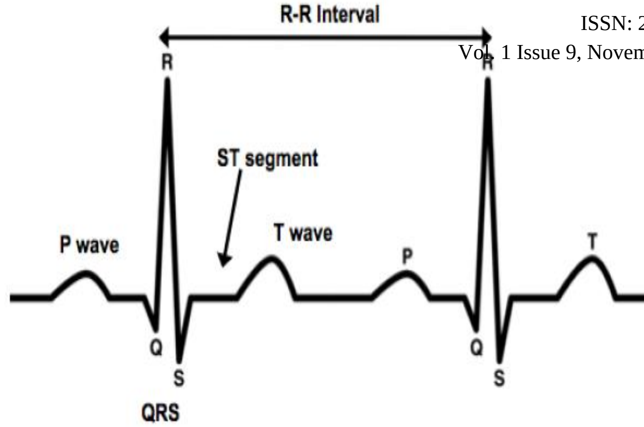


Fig 1. Electrocardiogram sample

3 Methodology:
In this section, we describe the components of the wireless sensor system we used, the procedure of the experimental environment, and the segmentation of experimental dataset.

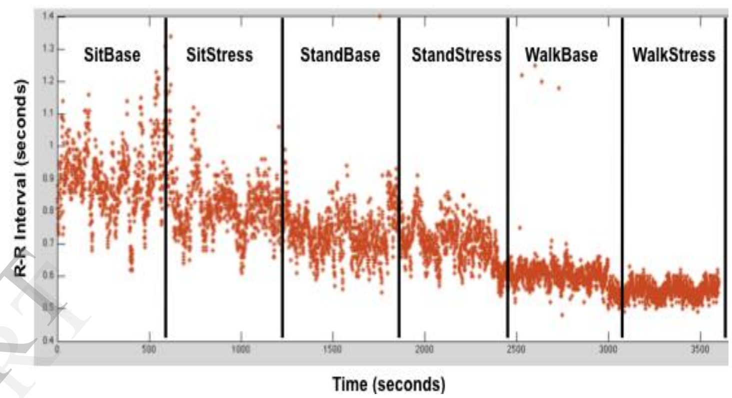
4 Wireless Sensor Network
We used the SHIMMER platform developed by Intel's Digital Health Group. SHIMMER is a small wireless sensor platform with an integrated 3-axis accelerometer designed to support wearable applications. We also used SHIMMER's ECG and GSR daughter boards for data acquisition. The sensor data from the ECG sensor and accelerometer were sampled at 100 Hz, and the data from the GSR sensor were sampled at 32 Hz. Data were transmitted to a PC via Bluetooth connectivity and saved to binary and comma-separated value files. We used three sensor nodes for the wireless sensor network configuration. Photos of the sensors are shown in Figure 2. The ECG sensor node was strapped to an elastic chest belt and three electrodes were placed on the body to form lead II and lead III[1] recording configurations.
The GSR sensor was attached on a wrist band. Then, skin conductance was measured at the base of two fingers by measuring the electrical current that owed as a result of applying a constant voltage. The third sensor node which was placed on the waist belt was used to collect accelerometer data.

5 DATA ANALYSIS
HRV analysis: HRV analysis methods can be categorized into time domain and spectral

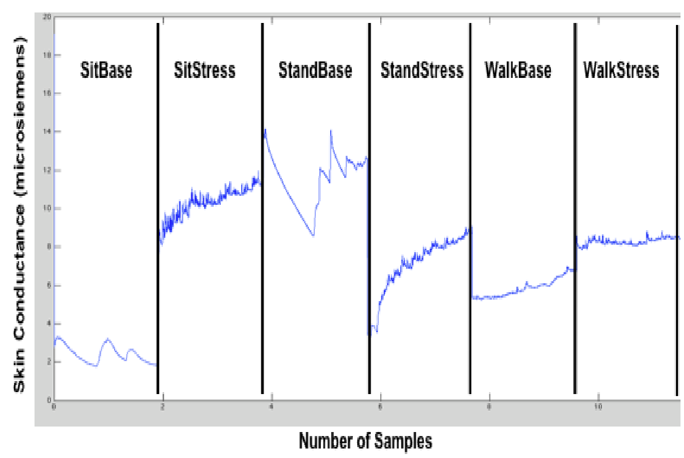
domain analysis. Time domain analysis is calculated directly from RR-intervals over the feature window. Examples of time domain features include mean value of the RR-interval (mean RR), standard deviation of the RR-interval (Std RR), mean value of the HR (mean HR), standard deviation of the HR (Std HR), RMSSD, and pNN50. Moreover, in the spectral domain methods, a power spectrum density (PSD) estimate is calculated for the RR interval series. Frequently used spectral measures are the very low frequency (VLF, 00.04 Hz), low frequency band (LF) and high frequency band (HF), and the ratio LF/HF. These spectral domain features are often interpreted as a measure of sympathovagal balance (autonomic state influence by the sympathetic and parasympathetic nervous system). We first calculated six time-domain features of HRV including mean RR, Std RR, mean HR, Std HR, RMSSD, and pNN50. Then, we applied a Fast Fourier Transform (FFT) to convert the time-domain RR-interval sequence to the power spectrum. The frequency components are used to calculate three spectral-domain features of HRV for each window: LF, HF, and LF/HF ratio.

GSR analysis: Due to the startle response (the physiological response of body to a sudden stimulus), the resistance of the skin can vary. The GSR can measure these subtle differences [29]. All GSR signals were filtered with a 256-point low pass filter with 3Hz cut off frequency to reduce noise. We calculated three GSR features: the total number of the startle responses in the segment, the sum of the response magnitude, and the sum of the response duration. These three features characterize the startle response, and Healey and Picard demonstrated their reliability [10]. Two additional features, mean and standard deviation of skin conductance level, are calculated over the feature window. Figure 5 shows the R-R interval and skin conductance recordings of a subject over six experimental segments.

Accelerometer analysis: Olguin and Pentland's work indicated that an accelerometer placed on hip significantly helped classify activities such as sitting, running, crawling, and lying down [18]. Therefore, we placed one accelerometer on the waist belt close to the hip in order to maximize the difference of signal among sitting, standing, and walking activities. For each of the three axial dimensions, we calculated twelve features: mean value, standard deviation, energy, and correlation of each two axes. Table 1 lists the features derived from the ECG, GSR, and accelerometer data.



(A) RR interval data of a subject



(b) Skin conductance of a subject

Fig.2 ECG and GSR accelerometer data

6 Stress Classification

WEKA machine learning engine is used to train classifiers using various learning methods, including the J48 Decision Tree, Bayes Net, and support vector machine (SVM) for stress inference [9]. We divided the training data into two different sets in order to evaluate how activity information may influence the results of stress inference. One set of training data only includes the ECG- and GSR-related features while the second set also includes the accelerometer information. We also evaluated classification performance for between-subjects datasets and within-subject datasets.

7 Comparison of HRV parameters in six conditions

From our analysis of all HRV parameters, we found that mean HR and RR are the most reliable features to recognize mental stress across three physical activities. The standard deviation of RR and HR did not demonstrate a coherent relation to the baseline and stressed segments. Spectral-domain parameters are sensitive to the physical activity conditions. Hence, this explains why excluding HRV features even increases in accuracy compared to the all-feature combination as shown in Figure 4.

HRV Parameters	Sit Base	Sit Stress	Stand Base	Stand Stress	Walk Base	Walk Stress
*Mean RR (ms)	887.59	814	752.07	722.43	586.03	562.94
Std RR (ms)	70.48	85.39	82.44	68.35	92.47	98.94
*Mean HR (bmp)	69.53	75.59	82.84	85.66	107.09	110.79
Std HR (bmp)	5.94	7.56	8.00	9.50	18.98	16.21
*pNN50 (%)	19.54	15.69	12.09	11.38	4.49	4.23
LF (%)	7.04	8.45	7.49	7.77	9.43	9.45
HF (%)	6.25	6.51	6.33	6.73	13.95	15.64
LH Ratio	1.34	1.51	1.45	1.48	0.67	0.71

Fig 5 Comparison of HRV parameters in 6 conditions

Fig 5 lists five GSR parameters for each segment. For each startle response, we can indicate its duration and magnitude. The total duration was calculated by accumulating the total elapsed time of the responses in the window. The total magnitude was measured by summing up the difference of the onset and the peak of each startle response in window. The number of response occurrences over the one minute window was also recorded. Total duration, total magnitude, total occurrence of the responses, and mean GSR level illustrate an obvious increase from baseline to stressed segment. However, the standard deviation does not provide significant change between conditions.

GSR Parameters	Sit Base	Sit Stress	Stand Base	Stand Stress	Walk Base	Walk Stress
*Total Duration(second)	3.17	14.30	4.16	13.15	13.72	16.32
*Total magnitude(µsiemens)	0.79	2.04	0.75	3.32	1.69	1.97
*Total Occcurence	1.09	6.58	3.13	6.37	5.63	7.47
*Mean GSR(µsiemens)	4.69	4.83	6.19	6.97	6.42	7.22
Std GSR(µsiemens)	0.62	0.53	0.62	0.71	0.63	0.52

Fig. 5 Comparison of GSR parameters in six conditions

8 Conclusion:

Previous mental stress studies were conducted in the laboratory with sedentary subjects. However, the controlled setting in a laboratory is not suitable for mobile mental stress monitoring because physical activity affects the measured physiological signals. The main goal of this study was to determine whether activity information can compensate for the interactive effects of mental stress and physical activity, which affect the accuracy of mental stress detection.

This paper presented a multimodal approach to model the mental stress activation affected by physical activities using accelerometers, ECG, and GSR sensors. Our analysis showed that accelerometer data is necessary to improve mental stress detection in a mobile environment. We also noticed that the Decision Tree classifier has the best performance in our experiments using 10-fold cross validation. Decision Tree is recognized as one of the classification methods with low computational complexity [14]. Therefore, the performance along with the low complexity of the Decision Tree classifier makes it a practical design choice for stress detection on mobile devices.It is also compared how physical activities and mental stress affects HRV and GSR parameters. It is found that GSR features are relatively independent of the three activities. This activity-aware scheme for mental stress detection can facilitate the development of many affective mobile applications using physiological signals (e.g. stress management, affective tutoring, and emotion-aware human computer interfaces). Including activity recognition techniques to interpret users' emotional states helps produce more feasible wearable sensors in everyday life.

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