RESEARCH ARTICLE OPEN ACCESS

System For Mental Stress Detection And Classification

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Abstract:

Due to a rapidly changing lifestyle and increasing workload, there is an urgent need to create new technologies to monitor the physical and mental health of people during their daily life. Continuous stress monitoring will help users better understand their stress patterns and provide physicians with more reliable data for interventions. Stress and fatigue can be monitored by measuring physiological parameters like Electrocardiogram (ECG), and Galvanic Skin Response (GSR) continuously over a period. Autonomic Nervous System (ANS) primarily depends on the emotional responses of the human body to the dynamic surrounding. As a result of this fact, bio-signal recordings reflecting the operating condition of the physiological systems can provide useful information representing the dynamic mental stress levels. In this paper, I gathered baseline physiological measurements of Electrocardiogram (ECG), and Galvanic Skin Response (GSR) signals while users were subjected to multiple mental stressors. Raw physiological signals available at the PHYSIONET website were used to train the classifiers for stress interference. I classified the affective states as “Low Stress”, “Moderate Stress” and “High Stress” using features extracted from ECG and GSR. By using a combination of both ECG and GSR features I was able to obtain a prediction accuracy of more than 90 %.

Keywords — Mental stress detection, electrocardiogram, Feature extraction, Linear Discriminant Analysis, stress classifier

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I. INTRODUCTION

The American Medical Association has noted that stress is the underlying cause of more than 60 percent of all human illness and disease (The Huffington Post, 2016). It is a risk factor for hypertension and coronary artery disease. Other physical disorders, including irritable bowel syndrome (IBS, back pain etc. may be caused, or worsened by stress. It is now widely accepted that stress plays an important role in the lifestyle of today's population. In 'The Global Burden of Disease', which was published in 1996 by the World Health Organization (WHO), it is estimated that depression, stress, and anxiety disorders will become the second most frequent disabilities behind heart diseases. Chronic stress also plays a role in mental illnesses, such as generalized anxiety disorder and depression. Chronic stress is difficult to manage because it cannot be measured in a consistent and timely way. One current method to characterize an individual’s stress level is to conduct an interview or to administer a questionnaire during a visit with a physician or psychologist. This method provides only a momentary snapshot of the individual’s stress level. In addition to the difficulty in measurement, mental health disorders associated with stress are tainted by social stigma, particularly in developing countries like India. A survey conducted in India shows that 69% of people suffering from stress related disorders such as depression were apprehensive that society would consider them to be crazy. These problems may be overcome by using a continuous monitoring and automatic detection system for stress.

Overall, stress is omnipresent in our society. Hence, developing an automatic stress detection system is particularly relevant. Automatic stress detection may improve the safety of drivers, the robustness of speech-based interfaces may aid the prevention of stress-related health problems.

II. OBJECTIVE

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. The body secretes hormones, such as adrenaline, into the bloodstream to intensify concentration. There are also many physical changes, such as increased heart rate, increased sweating and quickened reflexes. These physiological markers of stress are used in this proposed classification system. The main objectives are to:

♦ Evaluate the impact of stress on physiological signals

♦ Use this to accurately classify stress detection

Stress detection is generally achieved using voice and facial data interpretation. However, this data can be consciously controlled. Physiological indicators which are controlled by the Autonomous Nervous System are used instead as they are more accurate. The aim is to detect stressful behavior by analyzing measurements provided by non-invasive wearable sensors - in particular, the Galvanic Skin Response (GSR) sensor, which measures the electrodermal activity of the skin, and the Electrocardiogram(ECG) sensor, which measures the heart rate, are used.

III. METHODOLOGY

The proposed system consists of a microcontroller that constantly reads data from GSR and ECG sensors. The data is split into 60-second frames. Data is passed from the microcontroller to the laptop using serial communication with a baud rate of 9600, where MATLAB is used to extract ten features from these inputs. Extracted features are then normalized to remove interpersonal differences in the sensor values. The normalized features are classified using the already trained LDA model.

The following sections describe each step in more detail.

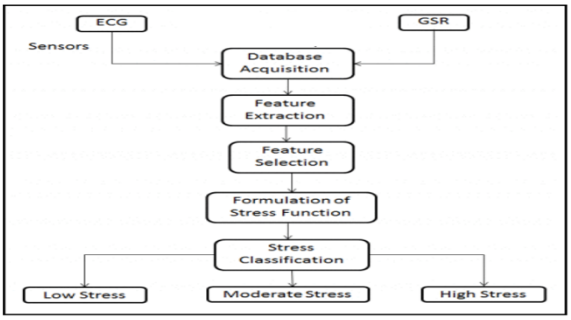

Fig. 1. Proposed system

A. PHYSIOLOGICAL SIGNALS AND FEATURES FOR STRESS DETECTION

Under acute stress, the sympathetic nervous system (SNS) increases heart rate, respiration activity, sweat gland activity, etc.

Since the autonomic nervous system(ANS) controls the heart, measuring cardiac activity is an ideal, non-invasive means for evaluating the state of the ANS. Due to the larger correlation of time domain features with stress, the time domain features listed below were considered:

- mean HR: mean heart rate (beats per minute);
- Std HR: standard deviation of heart rate
- mean RR: mean heartbeat interval (ms);
- Std RR: standard deviation of heartbeat interval
- RMSSD: root mean square of the difference between successive RR-intervals

When an individual is under mental stress, sweat gland activity is activated and increases skin conductance.

Since the sweat glands are also controlled by the 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 Galvanic Skin Resistance(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.

The statistical features given below were calculated:

♦ Mean GSR - mean of the GSR sensor output

♦ Std GSR – Standard deviation of the GSR sensor output

In addition, four features were calculated to characterize orienting responses:

♦ NPeaks - the total number of such responses in the segment.

♦ ΣOM - sum of the startle magnitudes ΣOD - the sum of the response durations

♦ Σ(1/2 OM × OD) - sum of the estimated areas under the responses.

It is known that under stress, the number of peaks and its amplitude increases while rise time decreases.

B. SOFTWARE AND ALGORITHMS

Arduino IDE was used to program the arduino microcontroller. By setting appropriate delay, the AnalogRead() function was used to sample ECG data and GSR signal at 496Hz and 31Hz respectively. This data was passed to Matlab.

The Matlab algorithm consists of three parts: feature extraction for GSR signal, feature extraction for ECG signal and classification. WFDB toolbox, an opensource signal processing toolbox from Physionet, was used to assist with feature extraction.

For GSR, the startle responses had to be identified. The algorithm detected the onsets and peaks of the orienting responses by first detecting slopes exceeding a critical threshold and then finding the local minimum preceding that point (onset) and the local maximum following that point (peak). The features were easily extracted once the peaks were identified.

For ECG, the files had to be annotated with the QRS complexes and RR intervals before feature extraction. This was achieved with the wqrs function of the WFDB toolbox.

C. DATA COLLECTION AND CLASSIFICATION

Raw physiological signals were obtained from the database at www.physionet.org/physiobank/database/drivedb/. The data collected contains multiparameter recordings obtained from volunteers while they drive across cities, highways. Periods of rest are also included. ECG, EMG, Foot GSR, Hand GSR, marker, and respiration was recorded in this database though I considered only the ECG and hand GSR values. Each signal from this database was sampled at an appropriate rate to preserve information. ECG data was sampled at 496 Hz and GSR data at 31Hz. The data was segmented into 60-second frames. Each frame contributed 10 feature vectors, resulting in about 900 frames with 10 vectors/frame. Each frame was labeled as low stress, medium stress or high stress where rest was taken as low stress, highway as medium stress, and city as high-stress regions.

Drive No.	Driving period (min)							Total rec. time (min)
	Initial Rest	City 1	Highway 1	City 2	Highway 2	City 3	Final Rest	
Drive05	15.13	16	7.74	6.06	7.56	14.96	15.78	83.23
Drive06	15.05	14.49	7.32	6.53	7.64	12.29	15.05	78.38
Drive07	15.04	16.23	10.96	9.83	7.64	10.15	15.03	84.87
Drive08	15	12.31	7.23	9.51	7.64	13.43	15.07	80.19
Drive09	15.66	19.21	8.47	5.2	7.06	13.21	NA	68.82
Drive10	15.04	15.3	8.66	5.27	7.04	12.06	14.79	78.15
Drive11	15.02	15.81	7.43	7.15	6.96	11.72	14.99	79.08
Drive12	15.01	13.41	7.56	6.5	8.06	11.68	15.01	77.23
Drive15	15	12.54	7.24	5.99	6.82	12.12	15	74.7
Drive16	15.01	16.12	7.14	5.12	6.81	13.91	NA	64.1

Fig. 2. Time intervals of the driving segments of the database

Fig. 2 was used to appropriately label the data frames. The data frames were then used to train the LDA classifier.

Stress elicitation

For testing the classifier with real time data, several stress elicitation methods were considered. Commonly used methods are, stroop colour word test, mental arithmetic task, public speaking task, cold pressor test, computer work. The most effective stressors are those that combine cognitive load and public speaking. Hence, a combination of mental arithmetic and public speaking tasks were used on 7 participants. The ECG and skin conductance values were measured during these tasks and during the one-minute rest period that preceded the tasks. The collected data was used to test the validity of the classifier.

D. DATA ANALYSIS

❖ FEATURE EXTRACTION AND NORMALIZATION :

Each participant's GSR and ECG data was split into 60-second windows. This duration was selected because all the ECG features used, require minimum 60-seconds long measurement to become significantly different between stressful and non-stressful situations. Furthermore, given that a typical peak in the Skin Conductance (SC) signal lasts for 7-10 seconds, the 60-second window is enough to observe and measure sufficient number of SC peaks, in order to reliably average their characteristics. Features were extracted as explained previously.Both the EDA and the ECG bio-signals exhibit large interpersonal variations. In studies related to the measurement and quantification of stress, the most common way to minimize these variations includes normalization of the 20 features calculated during stress using the corresponding features during baseline for each subject, or the scaling of the signal amplitudes from each participant between zero and one. These methods perform very well in eliminating the interpersonal variability.

❖ CLASSIFIER :

Discriminant analysis is a classification method. It assumes that different classes generate data based on different Gaussian distributions.

♦ To train (create) a classifier, the fitting function estimates the parameters of a Gaussian distribution for each class

♦ To predict the classes of new data, the trained classifier finds the class with the smallest misclassification cost

The model for discriminant analysis is:

Each class (Y) generates data (X) using a multivariate normal distribution. In other words, the model assumes X has a Gaussian mixture distribution

♦ For linear discriminant analysis, the model has the same covariance matrix for each class; only the means vary.

♦ For quadratic discriminant analysis, both means and covariances of each class vary.

Linear discriminant analysis was found to be more suitable in this case.Prediction is done so as to minimize the expected classification cost:

Diagram

$$\hat{y} = \underset{y=1,\ldots,K}{\arg\min} \sum_{k=1}^{K} \hat{P}(k|x)C(y|k)$$

- $\hat{y}$ is the predicted classification
- K is the number of classes.
- $\hat{P}(k|x)$ is the posterior probability of class k for observation x.
- $C(y|k)$ is the cost of classifying an observation as y when its true class is k.

IV. RESULTS AND OBSERVATIONS

The dataset obtained from the Physionet Database was divided into frames of one second each and used to develop a Linear Discriminant Model. Following which, GSR features and ECG data were extracted from seven people : 3 males and 4 females belonging to the age group 20-40 years. The trained LDA model then classified the frames as different categories of stress namely:

1. High Stress
2. Medium Stress
3. No Stress

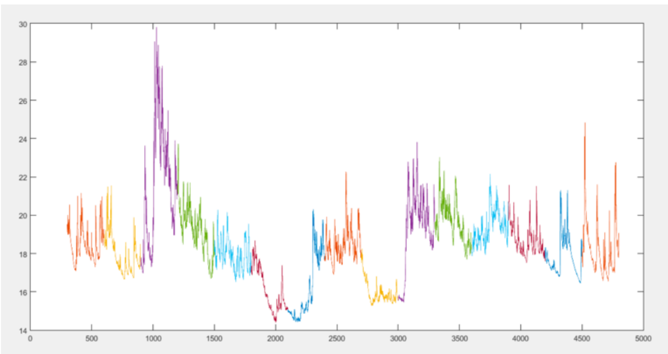

Fig. 3. Real time GSR data

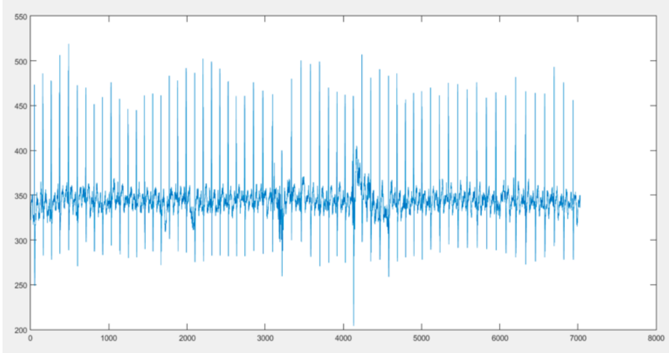

Fig.4 Real time ECG Data

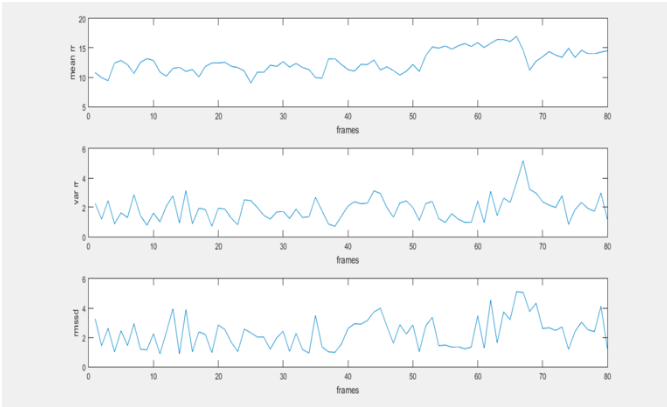

Fig.5 Heart rate features

features

779x11 double

	1	2	3	4	5	6	7	8	9	10	11	12
9	-0.0812	0.0040	0	0	0	0	-1.4390	5.5160	14.4462	1.2894	1.4087	
10	-0.0930	0.0028	0	0	0	0	-0.5003	5.3131	14.3485	1.2732	1.0954	
11	-0.1038	0.0032	0	0	0	0	-3.2221	6.3395	14.8906	1.5012	1.2971	
12	-0.1137	0.0020	0	0	0	0	-1.8085	6.3091	14.5231	1.4792	1.4895	
13	-0.1208	0.0027	0	0	0	0	-0.0169	4.8339	14.1343	1.1316	1.1415	
14	-0.1295	0.0024	0	0	0	0	-0.1469	5.5084	14.3030	1.3023	1.4088	
15	-0.1352	0.0021	0	0	0	0	5.3257	12.4041	12.9722	2.2359	1.2560	
16	1.6651	0.8677	4	7.1960	12.1290	16.7367	23.4353	8.8509	10.2418	1.6990	1.6533	
17	1.5667	1.2662	6	8.3800	22.0645	20.4131	23.9347	6.6102	8.9245	2.5317	2.2017	
18	2.3233	0.2406	14	16.2300	25.0323	15.6506	16.3698	6.3098	11.2771	0.9093	1.0650	
19	1.6953	0.2950	8	9.9600	24.9032	17.4504	15.8123	10.0223	11.6049	1.6381	2.0125	
20	1.7495	0.3143	9	11.7870	32.3871	28.8657	15.4643	46.0030	13.0411	2.2296	2.8013	
21	1.5591	0.2025	11	11.8430	36.7742	25.4455	9.5803	5.4967	12.3816	0.9593	1.0132	
22	1.4071	0.2937	4	5.5160	19.8710	13.7744	9.2785	6.3613	12.3816	1.1467	1.2543	
23	1.3074	0.2929	6	5.5000	18.4516	10.9517	8.2495	7.7364	12.4933	1.3988	1.0591	
24	1.3666	0.2944	8	7.9830	36.3871	25.8368	13.6104	7.1280	11.8125	0.8957	0.9001	
25	1.1767	0.1742	7	2.4390	15.2903	2.7066	10.7135	5.9456	12.0513	1.9007	2.4863	
26	1.6594	0.2751	9	12.9970	35.0968	29.5756	9.5610	5.3985	12.2468	0.8552	0.9105	
27	1.5509	0.1847	9	9.0130	32.7097	22.0655	15.7446	5.9223	11.5122	0.9272	1.0715	
28	1.1427	0.1498	5	4.3110	31.6774	16.5249	8.5094	9.1058	13	1.7360	2.3064	
29	1.3622	0.4681	7	5.3130	24	8.7895	9.7425	6.8043	12.3026	2.0521	2.4111	

Fig.6 Snippet of Feature Matrix with all 11 features

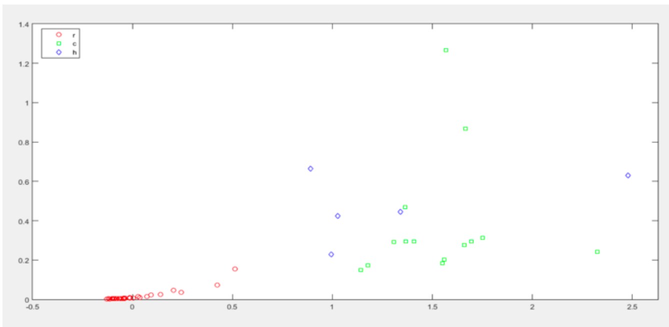

Fig.7 Scatter plot of data points

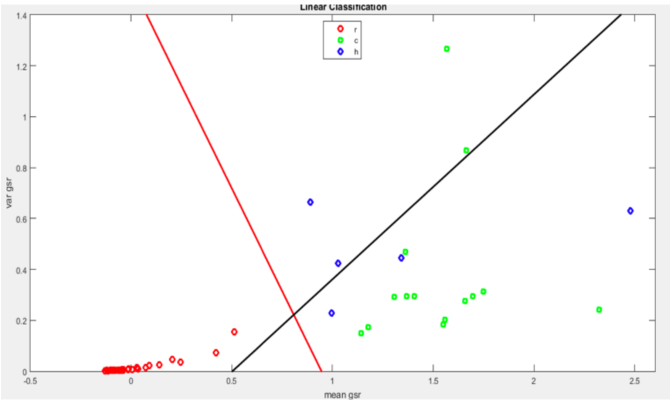

Fig.8 Classification Boundary

	RESUBSTITUTION ERROR	CROSS VALIDATION ERROR
ONLY HR FEATURES	0.1623	0.1677
ONLY GSR FEATURES	0.1419	0.1485
GSR AND ECG FEATURES	0.127	0.1273

Fig.9 Classification error of a single test subject

	PREDICTED NO STRESS	PREDICTED MEDIUM STRESS	PREDICTED HIGH STRESS
ACTUAL NO STRESS	78%	18%	4%
ACTUAL MEDIUM STRESS	5%	75%	20%
ACTUAL HIGH STRESS	2%	17%	81%

Fig.10 Confusion matrix of all 7 test subjects – Only Heart rate Features

	PREDICTED NO STRESS	PREDICTED MEDIUM STRESS	PREDICTED HIGH STRESS
ACTUAL NO STRESS	87%	11%	2%
ACTUAL MEDIUM STRESS	7%	83%	10%
ACTUAL HIGH STRESS	3%	8%	89%

Fig.11 Confusion matrix of all 7 test subjects – Only GSR Features

	PREDICTED NO STRESS	PREDICTED MEDIUM STRESS	PREDICTED HIGH STRESS
ACTUAL NO STRESS	93%	5%	2%
ACTUAL MEDIUM STRESS	4%	92%	4%
ACTUAL HIGH STRESS	1%	4%	95%

Fig.12 Confusion matrix of all 7 test subjects – GSR + HRFeatures

V. CONCLUSION

This project presented a stress detection system using physiological sensors. A simplified stress test was designed and conducted within this research that would elicit mental stress to participants. The system focused on being a real-time response system, collecting real-time data from individuals when performing stress tests and classifying them under the labels : highly stressed, medium stressed and no stress.

Algorithms were developed for feature extraction of GSR and ECG signals and a linear discriminant model was designed to classify the data under the three labels of stress.

From the experiment, we can conclude that there is a strong linear relationship between stress and Hand GSR. The physiological measurements could predict mental stress with high accuracy.

VI. REFERENCES

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