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Machine Learning-based Signal Processing Using Physiological Signals for Stress Detection

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***Abstract*— Stress is a common part of daily life which most people struggle in different occasions. However, having stress for a long time, or a high level of stress will jeopardize our safety, and will disrupt our normal life. Consequently, performance and management ability in critical situations degrade significantly. Therefore, it is necessary to have information in stress cognition and design systems with the ability of stress cognition. In this paper a signal processing approach is introduced based on machine learning algorithms. We used collected biological data such as Respiration, GSR Hand, GSR Foot, Heart Rate and EMG, from different subjects in different situations and places, while they were driving. Then, data segmentation for various time intervals such 100, 200 and 300 seconds is performed for different stress level. We extracted statistical features from the segmented data, and feed this features to the available classifier. We used KNN, K-nearest neighbor, and support vector machine which are the most common classifiers. We classified the stress into three levels: low, medium, and high. Our results show that the stress level can be detected by accuracy of 98.41% for 100 seconds and 200 seconds time intervals and 99% for 300 seconds time intervals.**

Keywords- Machine Learning; Signal Processing; GSR; EMG; HR; Respiration; KNN; SVM.

I. INTRODUCTION

Stress happens when a person is unable to deal with high demand placed upon him or her. The effects of stress are seen physically, mentally and emotionally [1]. Existing research [2, 3] have shown that physical and mental stress can be detected by the physiological information of human being. The physiological information, which can be acquired by biological or physiological sensors, usually includes Electrocardiogram (ECG), Galvanic Skin Response (GSR), Electromyogram (EMG), Respiration (RESP), Finger Temperature (FT), Skin Temperature (ST) and blood volume pulse (BVP). Work-Related stress detection using biological signals can be divided into two categories:

1. Using EEG (Electroencephalographs) signals

2. Using GSR, ECG, EMG, ST, RESPIRATION, etc. or combination of them

Although detection of stress using EEG sensor, results in high accuracy but Use Electroencephalographs electrodes due to the harsh conditions of its use is not always available [4-6]. The second mode is using GSR, ECG, EMG, ST and RESPIRATION sensors or combination of them. Using these sensors is easier than EEG. However, after obtaining signals from these sensors, Signals can be processed by using Wavelet transform [7] or calculating statistical and/or nonlinear features for extract desired factors [2-13].

Jennifer A. Healey and Rosalind W. Picard [2, 3], recorded and analyzed physiological signals like ECG, EMG, GSR for foot and hand, and respiration (RESP) during real-world driving tasks to detect a driver’s stress level in three different area. They extracted 22 features from five signals and used linear discriminant function (LDF) to classify stress level.

K. Soman, et al. [8] based on the driver dataset published on [2, 3], using ECG and Respiration Signals and extracted QRS power spectrum and breathing rate. They showed a positive relation between QRS power and breathing rate for stress of drivers.

Y. Deng, et al. [9] based on the driver dataset published on [2, 3], use different feature sets and then employed five machine learning techniques such as naïve Bayes(NB), support vector machine(SVM), C4.5 decision tree, linear discriminant function (LDF), and k-nearest neighbor (KNN) for classify stress level.

Yong Deng, et al. [10] based on the driver dataset published on [2, 3] select appropriate features and reduce number of them from 22 to 5 applying principal component analysis (PCA). These features result was in accuracy of 78.94%.

P. Karthikeyan, et al. [11] used ECG, EMG, Heart Rate Variability (HRV), GSR, and ST signals that obtain from the 40 subjects applying mental arithmetic tasks for stress-inducing stimuli. If Higher-order spectra (HOS) of HRV was, results was 93.75% of accuracy and without usage of HOS, accuracy of stress detection was reduced nearly 75%.

H. Kurniawan, et al. [12] used Speech and GSR Signals that employing Stroop Color test, Trier Social Stress test and Trier Mental Challenge test for stress-inducing stimuli were collected. Different features of GSR and Speech were used separately and four classifiers were applied. Best accuracy for GSR was 70% and for speech was 92%.

Zhai and Barreto [13] used four physiological signals, GSR, Blood Volume Pulse (BVP), Pupil Diameter (PD), and ST for detect computer users stress and used three machine learning techniques, NB, SVM and Decision Tree, to classify stress level.

In majority of this works, high accuracy is obtained whenever large number of sensors or large number of features are used, this means that large amount of processing and time will be unavoidable to obtain result. In this paper tried to get high accuracy for different number of sensors and different number of features. The process of stress detection in this paper is divided into three stages; first extract 78 features from five physiological signals, second based on how many sensors are used, appropriate features is selected and finally SVM [14] and KNN [15] machine learning techniques are utilized for classification of features.

II. METHOD

A. Data Aquistion

We have used physiological signals from the database of the PHYSIONET website (http://www.physionet.org/) that create by Jennifer Healey and Rosalind Picard.

These databases contains several signals from healthy volunteers, that they were driving on a route through open roads including city street as high stress, highway as medium stress and rest as low stress around Boston.

Database contains 17 drivers that we use seven drivers (drivers 06, 07, 08, 10, 11, 12 and 15), which have complete information.

Five signals of each driver; Galvanic Skin Response for Foot (FGSR), Galvanic Skin Response for Hand (HGSR), Electromyogram (EMG), Heart Rate (HR) that derived from Electrocardiogram (ECG) sensor, and Respiration (RESP). For instance, different signals for ‘drive06’ in Healey and Picard’s experiment are shown in Fig. 1.

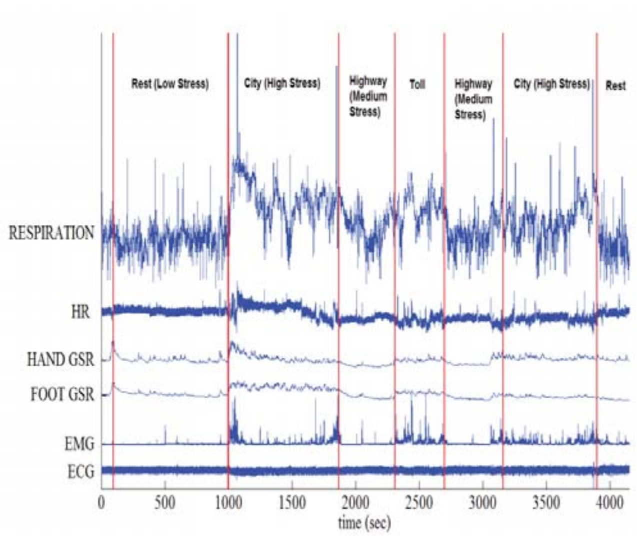

Fig. 1 Different signals for ‘drive06’

For processing these data, whole data is divided into individual segment for different states. Here various time intervals segmentations such 100, 200 and 300 seconds for three levels of low stress (relax), medium stress and high stress is applied to signals mentioned in fig. 1.

Each signal are divided into nine segments for 100 seconds intervals state; which three segments with 50% overlap belong to first rest period as low stress (Fig.2), three segments with 50% overlap belong to first city period as high stress (Fig.3), and three segments with 50% overlap belong to first highway period as medium stress (Fig.4).

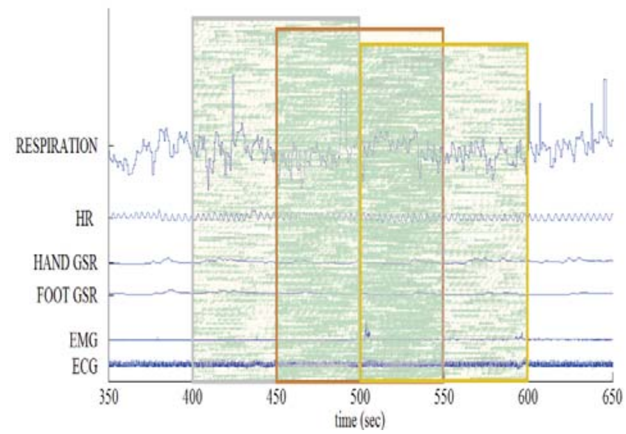

Fig. 2 First rest period which have three segments with 50 % overlap

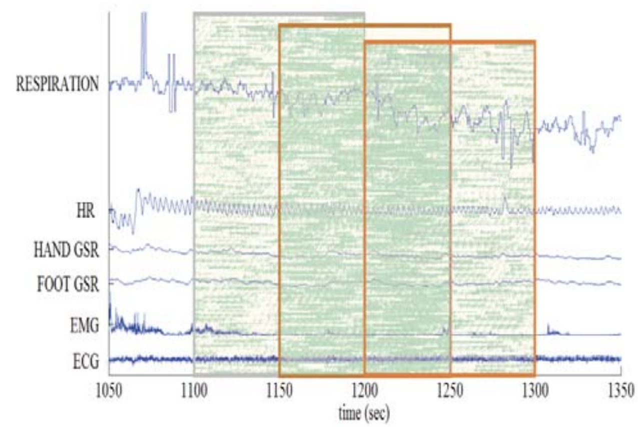

Fig. 3 First city period which have three segments with 50 % overlap

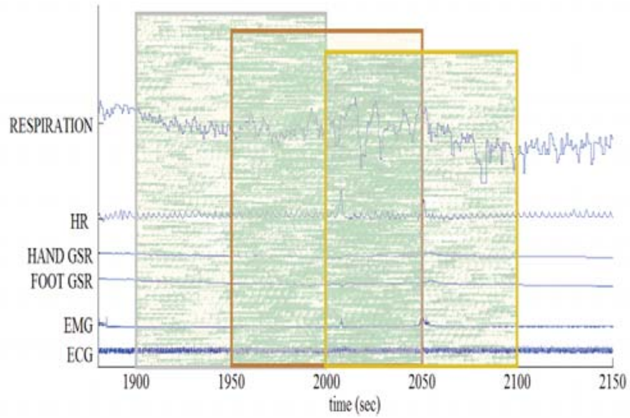

Fig. 4 First highway period which have three segments with 50 % overlap

Same job is done for 200 seconds intervals. For 300 seconds intervals, each signal is divided into three segments, first segment belong to first rest period as low stress (Fig.5), second segment belong to first city period as high stress (Fig.6) and third segment belong to first highway period as medium stress (Fig.7).

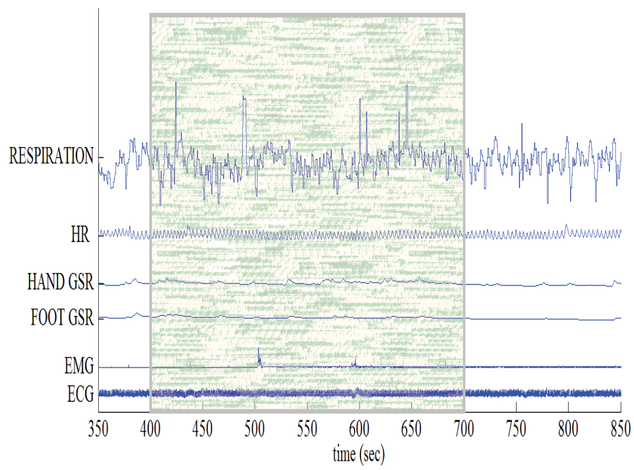

Fig. 5 First rest period for 300 seconds state

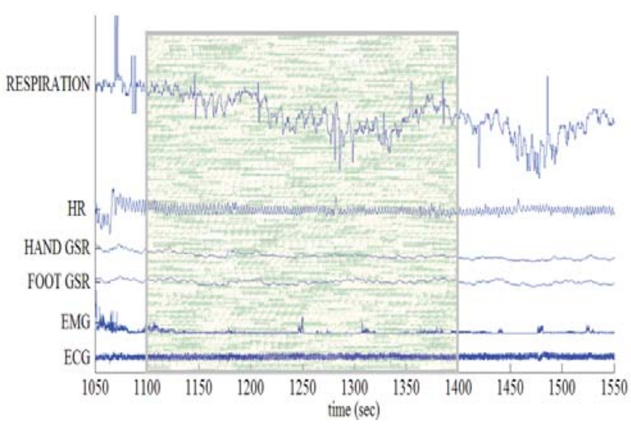

Fig. 6 First city period for 300 seconds state

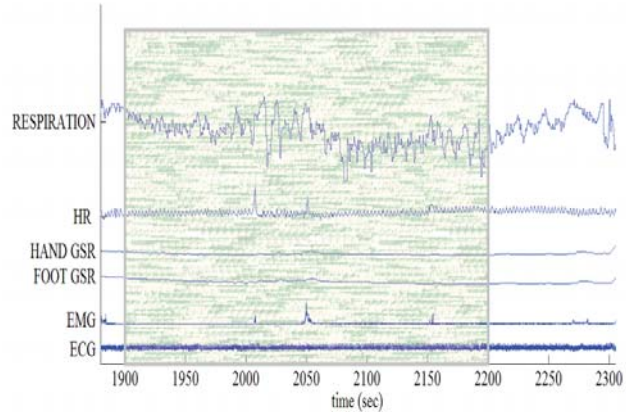

Fig. 7 First highway period for 300 seconds state

B. *Feature Extraction*

78 features are extracted for each segment. All features are chosen, based on the most important and most used for physiological signals according [2-13]. These features are summarized in table 1.

Table 1 Feature symbol and description

	Feature Symbol				
Feature Description	EMG	HR	Foot GSR	Hand GSR	RESP
Mean Normalization	EMG1	HR1	FGSR1	HGSR1	RESP1
Root Mean Square (RMS)	EMG2	HR2	FGSR2	HGSR2	RESP2
The average power 0.01 to 0.1 Hz	EMG3	HR5	FGSR3	HGSR3	RESP3
The average power 0.1 to 0.2 Hz	EMG4	HR6	FGSR4	HGSR4	RESP4
The average power 0.2 to 0.3 Hz	EMG5	HR7	FGSR5	HGSR5	RESP5
The average power 0.3 to 0.4 Hz	EMG6	HR8	FGSR6	HGSR6	RESP6
The average power F1 to F2 Hz	EMG7	HR3	FGSR7	HGSR7	------
The average power F3 to F4 Hz	EMG8	HR4	FGSR8	HGSR8	------
Ratio low band / high band	EMG9	HR9	FGSR9	HGSR9	RESP7
Means of differences between adjacent elements	EMG10	HR10	FGSR10	HGSR10	RESP8
Means of differences between adjacent elements 2nd times	EMG11	HR11	FGSR11	HGSR11	RESP9
Interquartile Range (IQR)	EMG12	HR12	FGSR12	HGSR12	RESP10
Sum of Rise time from the 10% to 90% of reference levels	EMG13	HR13	FGSR13	HGSR13	RESP11
Peak 2 Peak	EMG14	HR14	FGSR14	HGSR14	RESP12
Sum of local peak	EMG15	HR15	FGSR15	HGSR15	RESP13
Number of local peak	EMG16	HR16	FGSR16	HGSR16	RESP14

In table 1, some frequency is unknown that we introduced them in table 2.

Table 2. Unknown Frequency in table 1.

Signal/Freq.(Hz)	F1	F2	F3	F4	Low Band	High Band
EMG	0.4	0.5	0.01	7	0.01 to 0.1	0.01 to 7
HR	0.01	0.15	0.15	0.5	0.01 to 0.15	0.15 to 0.5
Foot GSR	0.02	0.5	0.5	1.5	0.02 to 0.5	0.5 to 1.5
Hand GSR	0.02	0.5	0.5	1.5	0.02 to 0.5	0.5 to 1.5
Respiration	-	-	-	-	0.01 to 0.1	0.3 to 0.4

C. Feature Selection

The feature vectors contains 78 features for any segment of all signals, this cause the problem of long training times and complicated computing, so selecting the best features, improve the computational speed of classification. A feature selection algorithm can be shown as the combination of a search technique for nominate new feature subsets, along with an evaluation measure which scores the different feature subsets. The simplest algorithm is to test each possible subset of features finding the one which minimizes the error rate. In Weka software all features has been ranked by CfsSubsetEval and InfoGainAttributeEval. Another algorithm is based on machine learning techniques, which select best features. In Weka software, best features have been found for classification by choosing ClassifierSubsetEva and SVM classifier. In this paper both algorithms are used for finding best features. In first way, by combination of both algorithms, all features was ranked and best of them was selected and then combined with features that selected in second algorithm, and classification is done for different states. In second way, only the features used that selected in second algorithm and classification is done only for one state. After selecting effective features, SVM and KNN with cross-validation are used for classification. Matlab 2012a is used for signals processing and feature extraction. Then SVM and KNN are applied for classification using WEKA3.6.

III. Results

For three states, 100 second intervals, 200 seconds intervals and 300 seconds intervals, Results separately for SVM and KNN for different number of sensors and different number of features are shown in the table 3,4,5,6,7,8.

Table 3 Analysis features for 100 seconds intervals by using SVM

Features used for 100 seconds state	Number of Features	SVM Classification	Number of Sensor
ALL	78	90.47 %	5
RESP 2,3,4,5,9,10,14 - HR 1 - EMG 8,14,16 -HGSR 8,10,13,15 - FGSR 4,9,10,15,16	20	98.41 %	5
RESP 2,5,9,10 - HR 1 - EMG 16 - HGSR 8 - FGSR 4	8	96.82 %	5
RESP 2,5,9,10 - HR 1 - HGSR 8	6	93.65 %	3
RESP 2,5,9,10 - HGSR 8	5	87.30 %	2
RESP 1,2,5,9,14	5	84.12 %	1
ClassifierSubsetEval feature selection : EMG 3,14,16 - HGSR 7,15 - FGSR 9 - RESP 4,9,10,14	10	82.54%	4

Table 4 Analysis features for 100 seconds intervals by using KNN

Features used for 100 seconds state	Number of Features	KNN Classification	Number of Sensor
ALL	78	85.71 %	5
RESP 2,3,4,9,10,14 - HR 1 - EMG 8,14 -HGSR 8,13,15 - FGSR 4,10,14,15,16	17	93.65 %	5
RESP 2,3,10,14 - HR 1 - EMG 14 - HGSR 8 - FGSR 14	8	95.23 %	5
RESP 2,10,14 - HR 1 - EMG 14 -- HGSR 8	6	93.65 %	4
RESP 2,10,14 - HGSR 8	4	87.30 %	2
RESP 2,5,9	3	92.06 %	1
ClassifierSubsetEval feature selection : EMG 3,14,16 - HGSR 7,15 - FGSR 9 - RESP 4,9,10,14	10	90.48%	4

For 100 seconds interval state, maximum accuracy of 98.41% is achieved by using SVM classifier, all 5 sensors and 20 features. Also, best accuracy of 96.82% is achieved for few numbers of features by using SVM classifier, all 5 sensors and 8 features. For few numbers of sensors and features, best accuracy of 92.06% is achieved by using KNN classifier, one sensor and 3 features.

Table 5 Analysis features for 200 seconds intervals by using SVM

Features used for 200 seconds state	Number of Features	SVM Classification	Number of Sensor
ALL	78	93.65 %	5
RESP 2,4,5,6,9,14 - HR 1 - EMG 1,4 - HGSR 1, 8,10 - FGSR 4,6,15,16	16	98.41 %	5
RESP 2,4,14 - HR 1 - EMG 1 - HGSR 8,10 - FGSR 15	8	92.06 %	5
RESP 2,4,14 - HR 1 - HGSR 8,10	6	90.47 %	3
RESP 2,4,14 - HGSR 8,10	5	88.89 %	2
RESP 2,3,8,9,14	5	85.71 %	1
ClassifierSubsetEval feature selection : EMG 1,4 - HGSR 1,10 - HR 15 - RESP 3,14	7	92.06%	4

Table 6 Analysis features for 200 seconds intervals by using KNN

Features used for 200 seconds state	Number of Features	KNN Classification	Number of Sensor
ALL	78	88.89 %	5
RESP 3,4,5,9,14 - HR 1 - EMG 1,16 -HGSR 1,10 - FGSR 9,10,14,15	14	92.06 %	5
RESP 4,9,14 - HR 1 - EMG 1 - HGSR 1 - FGSR 10, 14	8	93.65 %	5
RESP 4,9,14 - HR 1 - EMG 1 - HGSR 1	6	90.47 %	4
RESP 4,9,14 - EMG 1 - HGSR 1	5	87.30 %	3
RESP 2,3,9	3	92.06 %	1
ClassifierSubsetEval feature selection : EMG 1,4 - HGSR 1,10 - HR 15 - RESP 3,14	7	95.23%	4

For 200 seconds interval state, maximum accuracy of 98.41% is achieved by using SVM classifier, all 5 sensors and 16 features. For few numbers of features, best accuracy of 95.23% is achieved by using KNN classifier, 4 sensors and 7 features. For few numbers of sensors and features, best accuracy of 92.06% is achieved by using KNN classifier, one sensor and 3 features.

Table 7 Analysis features for 300 seconds intervals by using SVM

Features used for 300 seconds state	Number of Features	SVM Classification	Number of Sensor
ALL	78	80.95 %	5
RESP 3,4,5,6,9 - HR 1 - EMG 3 - HGSR 3 - FGSR 3	9	99 %	5
RESP 3,6, 9 -- HGSR 3	4	85.71 %	2
RESP 3,4,9	3	80.95 %	1
ClassifierSubsetEval feature selection : EMG 3 - HGSR 3 - RESP 9	3	95.24%	3

Table 8 Analysis features for 300 seconds intervals by using KNN

Features used for 300 seconds state	Number of Features	KNN Classification	Number of Sensor
ALL	78	76.19 %	5
RESP 3 ,9,14 - HR 1 - EMG 3 -HGSR 3 - FGSR 3	7	90.47 %	5
RESP 3, 9,14 - EMG 3 - HGSR 3	5	99 %	3
RESP 4,9,14 -HGSR 3	4	90.47 %	2
RESP 3,4,6,8,9	5	85.71 %	1
ClassifierSubsetEval feature selection : EMG 3 - HGSR 3 - RESP 9	3	95.24%	3

For 300 seconds interval state, maximum accuracy of 99% is achieved by using KNN classifier, 3 sensors and 5 features.

As can be shown in table 2 to 7, better accuracy with fewer numbers of sensors and features is achieved for longer time intervals and it should be mentioned that Respiration sensor is the most important sensor for stress detection.
Finally, you can see the results of this paper and three other papers in table.9. As it is specified, results of this paper are more accurate and less features have been used.

Table 9 Compare results

Time int. (s)	Acc. (%)	Classifier	Sensor numbers	Features numbers	Ref.
300	97	Fisher	5	22	[3]
300	78.94	SVM	2	5	[9, 10]
300	99	SVM	5	9	paper
200	98.41	SVM	5	16	
100	98.41	SVM	5	20	

IV. Conclusion

It is shown that the stress level can be detected by biological signals, with different number of biological sensors, different number of features and different time intervals. Best features are selected from all 78 features to classify and high accuracy of 98.42% for 100 seconds intervals, and 200 seconds intervals, 99% for 300 seconds intervals are achieved. It is shown that the most important sensor for stress detection is Respiration.

With use more information about person states in different situation, we can design a pattern to detect stress in different situation, also obtain the exact amount of stress are useful to help doctors to prescribe drugs.

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