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# Proposed new signal for real-time stress monitoring: Combination of physiological measures

M. Saidi[1], H. Hassanpoor[1,2*], A. Azizi Lari[1]

[1] Research Center of Development Advanced Technologies, Khaje Nasir al din Tusi, Tehran, Iran
[2] Department of Biomedical Engineering, Amirkabir University of Technology, Tehran, Iran

**ABSTRACT:** Human stress is a physiological tension that appears when a person responds to mental, emotional, or physical chal-lenges. Detecting human stress and developing methods to manage it, has become an important issue nowadays. Auto-matic stress detection through physiological signals may be a useful method to solve this problem. In most of the earlier studies, long-term time window was considered for stress detection. Continuous and a real-time representation of the stress level are usually done through one physiological signal. In this paper, a real-time stress monitoring system is pro-posed which shows the user a new signal for feedback stress level. This signal is the combination of weighted features of galvanic skin response and photoplethysmography signals. The features are defined in 20-sec time windows. Correlation feature selection and linear regression methods are used for feature selection and feature combination, respectively. Furthermore, a set of experiments was conducted to train and test of the proposed model. The proposed model can represent the relative stress level perfectly and has 79% accuracy for classifying the stress and relaxation phases into two categories by a determined threshold.

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## 1- Introduction

Human stress is a physiological tension that appears when a person responds to mental, emotional, or physical challenges [1,2]. Unfortunately, in modern life, work stress, family and society problem, financial and econom-ic issues, and other external sources, put everyone in the stress situations. Recent studies have shown continuous contact with a stress situation increases the probability of cardiovascular diseases, HIV, cancer, depression and oth-er mental illnesses [2,3]. Therefore, identifying the human stress and providing techniques for managing it becomes a critical issue nowadays. Recognizing stress situations by a human is along a delay after the diseases effects and problems represent themselves. Thus, many objective methods for stress detection are widespread. Questionnaire and meetings with psychologists are some of the common methods that are time-consuming and costly and may not be accessible at all times [2-4]. Also, filling questionnaires needs a good memory and remem-bering events well and is dependent on the ability of pa-tient that describe his/her mood. In some cases, the patient does not know about his/her stress or cause of it[4].

On the other hand, automatic stress detection through physiological signals can be a useful tool to solve this problem and make many researchers interested in work-ing in this field. Stress could be detected by monitoring many physiological changes, such as blood volume pres-sure (BVP), heart rate (HR) that could be obtained through Electrocardiogram (ECG) and Photo-Plethysmograph (PPG), pupil diameter (PD), respiration (RESP), skin temperature (ST), galvanic skin response (GSR) as a consequence of sweat-gland activity, muscle activities measured by Electromyogram (EMG), and brain activities recorded through electroencephalogram (EEG) [5] . Previous studies used different combinations of phys-iological signals to measure the stress level. Table 1 shows a brief literature on different physiological signals applied in stress detection.

Corresponding author, Email: hassanpoor@rcdat.ir

**Table 1: literature review on the physiological signals used for stress detection**

| References | Physiological signals |
|---|---|
| [6] | HRV |
| [7] | BVP, ECG, RESP, EEG and EMG |
| [8] | GSR, ECG, ST, RESP |
| [9] | BVP, RESP, ST, HR |
| [10] | BVP, GSR, and ST |
| [11] | ECG, EMG, GSR, and RESP |
| [1,12] | BVP, GSR, PD |
| [13] | GSR, BVP, PD, and ST |
| [3,14] | HR, GSR, EMG, RESP |
| [15-17] | GSR |
| [18] | GSR, HR |

In spite of several findings in automatic stress detection, it is still an extremely challenging task to develop a practical human stress monitoring system for biofeedback applications. In biofeedback applications, a tradeoff between accuracy and the user inconvenience level should be made. Indeed, sensors with the least discomfort must be exerted on biofeedback systems. GSR and PPG sensors could set up on one hand (on the fingers or wrist) even as a ring tape or wristwatch, which are convenient and ease-of-use devices for subjects. However, almost all of biofeedback systems in

the market usually use only one signal to show a continuous and real-time representation of the subject's stress level [19]. For example, "Biofeedback 2000" (made by SCHUHFEREID cooperation) records several signals such as GSR, temperature etc., but it does not combine them and uses only one of these signals to give feedback of the stress level of the subject during training games. "WILD DIVINE" that records GSR and PPG has the similar issues. "Stress Eraser" uses heart rate (by photoplethysmograph) to provide a feedback signal for the subject. The aim of this paper is designing a real-time stress monitoring system by using a new signal produced by a combination of weighted features of GSR and PPG signals.
Stress detection from these physiological signals and feeding it back to the user, usually occurs during the pro-cedure illustrated in Fig. 1. This procedure consists of five stages as follows:

1) Making database: database is needed for the training and testing the algorithm
2) Feature extraction: extracting features from signals.
3) Feature selection: selecting subsets of features that are useful to build a proper predictor.
4) Feature combination: combining selected features based on a model or equation.
5) Display: a perfect and user-friendly exhibition of the stress level for the test database[20].

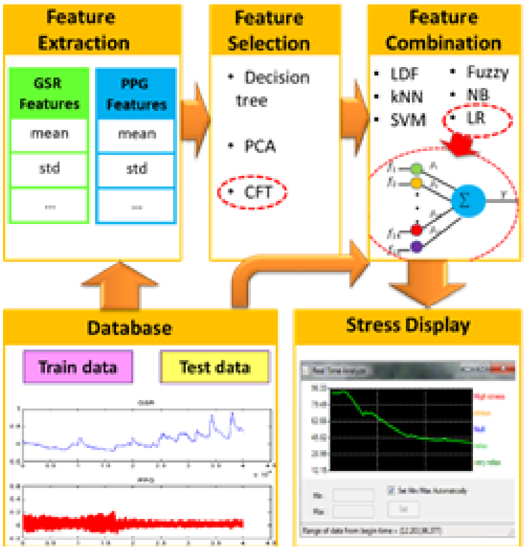


**Fig. 1. The procedure for stress detection through physi-ological signals. This procedure consists of five stages; 1) Making database, 2) Feature extraction, 3) Feature selec-tion, 4) Feature combination, 5) Display. CFT and LR are considered as feature selection and feature combination method in this paper.**

In this paper, the procedure in Fig. 1 with the methods determined by red circular lines in feature selection and combination stages are applied to identify the stress. We design a set of experiments for recording the data during relaxation, neutral and stress situations which are induced by video clips. In the next stage, we extract proper fea-tures that are suitable for real-time monitoring. In the for-mer studies, varying types of features (in time and fre-quency domain) have been extracted from PPG or GSR signals, but most of them are calculated in a long-term time window that is at least about 1 minute. In this paper, a very smaller time window is considered for a real-time monitoring and within the window, a set of features is defined. Correlation feature selection is used to select op-timized subset of the features.
In the previous studies, different algorithms such as lin-ear discriminated function (LDF), support vector machine (SVM), Naïve Bayes (NB), ANOVA analysis, Bayes clas-sifier, k-NN, Fuzzy logic, etc. [5, 18, 20] have been used for integration of features. Since non-linear or chaotic analyses usually require a long-term signal monitoring, we use linear regression model for the real-time monitoring of stress. In addition, this model enables us to represent the subject's stress level continuously (regarding the bio-feedback requirement) while almost in all of the previous studies, representation of stress level was discrete and classified into two categories; stress or relaxation status.
The organization of this paper is as follows. The details of the experimental study are described in section 2. The data analysis method, including feature extraction, feature selection, and information fusion algorithm, are introduced in section 3. The results of the analysis are presented in section 4, and section 5 includes the conclusion.

## 2- Experimental Study

A set of experiments was conducted to train and test the proposed model of human stress. A data collection device that could record PPG and GSR signals was used in these experiments.

### 2- 1- Participants

16 subjects (seven men), 25-32 years old, voluntarily participated in the experiments. All subjects completed the informed consent form prior to the beginning of the experiments. They all had normal or corrected normal vision. Each subject took part in a test with Procedure1, including relaxation and stress phases. To test the model for biofeedback applications, five subjects participated in a test with Procedure 2. Finally, 21 tests were recorded (five tests with procedure 2 and 16 tests with procedure 1).

### 2- 2- Data collection

To record GSR and PPG signals, a new device (Rav-antab) has been designed and developed in our research center (Advanced Technology K.N.Toosi) was used in the experiments (Fig. 2). Ravantab is a comfortable device designed for continuous, real-time data (GSR and PPG signals) acquisition. This unit connects to the computer via a USB cable and converts analog input in the range of 0.3 to 3.7 volts to digital data with 125 Hz sampling rate. This data can be read and analyzed by MATLAB soft-ware.

### 2- 3- Procedure

According to previous studies, there are five major methods to induce or creat stress\relax states [5-, 18, 20];

- Displaying special pictures
- Showing videos with voice
- Showing videos without voice
- Designing a game
- Asking some questions in an interview format

We provide stimuli based on the five categories men-tioned above. Due to a survey of several subjects (includ-ing physiologist), we concluded showing videos with voice is the best way for producing stress/relax phases.
In our experiments, two procedures were pursued. Pro-cedure 1 was designed for training and testing of the mod-el. Thus, it includes relaxation and stress phases. Proce-dure 2 was designed for testing of the model in biofeed-back applications.

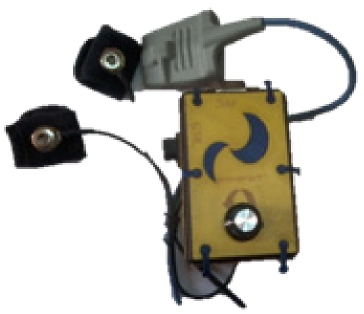

**Fig. 2. The data collection unit and its sensors (PPG and GSR).**

### 2- 3- 1- Procedure 1

Procedure 1 includes four phases (neutral, relaxation, neutral and stress phases) as shown in Fig. 3.


**Fig. 3. The phases of experiment with procedure 1.**

At first, the participants were requested to clean their hands properly before starting the GSR recording. Then they sat in a chair and a monitor (20 inches) was located in front of them. The sensors were attached to their hands and they were asked to put their hands on the armrests of the chair. A brief description of the experiment's phases was given to them. In neutral phase, a picture of nature was shown on the monitor for 1 minute and no voice was played. In the relaxation phase, a relaxing clip (about 6 minutes) was played and the participants were asked to try to relax themselves with it. A stressful clip was played (about 3 minutes) in the stress phase. Afterward, the sub-jects were requested to provide a self-report data on their state anxiety, perceived stress, and relaxation level. If the clips could not relax or stress them properly, the experi-ment was repeated again through the new more stressful or relaxing clips. Stressful clips were on various topics, including the chase and escape, falling off a cliff and fight scenes. All subjects were relaxed with the relaxing sound of the sea.
The examiner evaluated the quality of the signals and inspected the behavior of the examinees during the test.

### 2- 3- 2- Procedure 2

Procedure 2 was performed after designing the model. In this procedure, the output of the model was transferred to an animation picture according to the biofeedback systems. For example, when the subject is more relaxed, a flower flourishes much more. The subjects were requested to see this animation and try to open the flower more and more. In other words, they attempted to relax more and more.

## 3- Data Analysis

### 3- 1- Signal Processing

At first, the PPG and GSR signals are filtered by a band pass and low pass filters, respectively. In feature extrac-tion, in addition to raw signals, standardized signals are helpful to remove characterizations related to the absolute value of the signals. Here, each signal is standardized using the median value of the signal and the signal's inter-quartile range. The median is subtracted from each sample point and its value is scaled by the 75th-25th percentile (inter-quartile) range.
The cardiovascular signal collected from the plethys-mograph is actually a composite measure of two distinct phenomena: the overall volume of blood and the contraction-relaxations of the heart. These two phenomena differ greatly in their frequencies, the blood-volume changes over a few seconds while the pulse occurs about once or twice per second. Accordingly, separation of these phenomena will be useful for analysis. This process is done with an elliptic filter.
For extracting features related to heartbeat, HR signal is derived from the pulse signal (the PPG signal without blood volume). A heartbeat is defined as the time interval between adjacent diastolic tips. This value is assigned to all points in the interbeat producing a square-wave signal. The square-wave signal is smoothed with the same filter used to split the cardiovascular signal.

### 3- 2- Feature Extraction

The optimal size of the time window extracted in the features is an important issue in real-time stress monitor-ing. For a real-time application, the time window for anal-ysis and processing should be as small as possible. How-ever, the amount of information for recognizing stress decreases as the window size decreases. Most of the previous studies used a long-term time window (about or longer than 1 minute) for stress detection. As shown in recent papers[18], reducing the length of the time window to 17 seconds did not decrease the accuracy of detection stress by features mean and standard deviation of HR and GSR signals significantly.
In polygraph study, usually about 20 seconds, elapses between each stimulus to allow sufficient time for the different latencies of the various measures (including PPG and GSR signals) being recorded. According to this prin-ciple, we select 20s time window for feature extraction. Indeed, a virtual stimulus (internal or external stimulus) is assumed at the beginning of the window and reaction to that stressful stimulus (does not last more than the 20s) is computed. In order to sweep the time of a trail, 1s time step between each window is chosen. Thus, the windows have 19s overlap.
A set of features is defined according to the former studies, which used PPG and GSR signals for stress recognition. In [21], these two signals were used to detect deception through the interview questions with the 20s interval between each question. 33 features from 441 features set were extracted by step method. These features are defined based on percentiles, time to percentiles and percentiles crossing. Since these features are aimed to discover the reaction of subjects to relevant questions or in other words, the stress of subjects to these questions can be used to determine stress level in a real-time way. Features 1-25 in Table 3 present these features. In [22] only one feature is extracted from each signal to determine the amount of reaction to different questions (feature 28 and 30). In many studies with the aim of stress detection in different conditions, features 26-34 were used but the time window for feature selection was at least 1 minute. According to the 20 seconds time window criterion, some of the features used in the former studies are not used in this paper. For example, the number of GSR peak in 20 (sec) could not exceed three peaks. Thus, this feature does not have a significant difference in different windows.
In order to select a set of proper features from features reported in Table 3, correlation analysis is used. The proper features are those that have a significant correlation with the expected output of the model. The expected output of the model for the experimental data collected with Procedure 1 is shown in Fig. 4. Since different features have different values, all features are normalized between 0-1 according to the expected output. The features with significant correlation are marked with symbols * in Table 2.

**Table 2. Features set. The selected features are indicated with * symbol.**

| N | Feature | Symbol | Time | Processing | Signal |
|---|---|---|---|---|---|
| 1. | 85th percentile* | DA85th | 1.5 - 9.5 | Derivative | Cardio Tach |
| 2. | 90th percentile* | DA90th | 1.5 - 9.5 | Derivative | Cardio Tach |
| 3. | 95th percentile | DA95th | 1.5 - 9.5 | Derivative | Cardio Tach |
| 4. | Time to 45th percentile | DT45th | 1.5 - 9.5 | Derivative | Cardio Tach |
| 5. | Maximum | DAM | 1.5 - 9.5 | Derivative | Cardio Tach |
| 6. | Time to maximum | DTM | 1.5 - 9.5 | Derivative | Cardio Tach |
| 7. | 55th - 45th percentiles | DA45-55th | 1.5 - 9.5 | Derivative | Cardio Tach |
| 8. | 90th - 85th percentiles | DA90-85th | 1.5 - 9.5 | Derivative | Cardio Tach |
| 9. | Time between 50th and 25th Percentiles | DT50-25th | 1.5 - 9.5 | Derivative | Cardio Tach |
| 10. | 65th percentile* | A65th | 1.5 - 9.5 | | Cardio Tach |
| 11. | 70th percentile* | A70th | 1.5 - 9.5 | | Cardio Tach |
| 12. | 75th percentile* | A75th | 1.5 - 9.5 | | Cardio Tach |
| 13. | 80th - 75th percentiles | T80-75th | 1.5 - 9.5 | | Cardio Tach |
| 14. | 80th percentile | A80th | 1.5 - 9.5 | | Cardio Tach |
| 15. | Time to 50th percentile | T50th | 1.5 - 9.5 | | Cardio Tach |
| 16. | Time between 95th and 5th Percentiles | T95-50th | 1.5 - 9.5 | | Cardio Tach |
| 17. | Minimum | Am | 1.5 - 9.5 | | Cardio Tach |
| 18. | 85th - 75th percentiles | A85-75th | 1.5 - 9.5 | | Cardio Tach |
| 19. | 85th percentile | A85th | 1.5 - 9.5 | | Cardio Tach |
| 20. | 70th percentile | A70th | 1.5 - 9.5 | | Cardio Tach |
| 21. | 65th - 15th percentiles* | GA65-15th | 1.5 – 20 | | GSR |
| 22. | Time between 75th and 50th Percentiles | GT65-15th | 1.5 – 20 | | GSR |
| 23. | Time to 35th percentile | DGT13th | 3 – 10 | Derivative | GSR |
| 24. | Time to 50th percentile | DGT50th | 3 – 10 | Derivative | GSR |
| 25. | Time between 75th and 50th Percentiles | DGT50th | 3 – 10 | Derivative | GSR |
| 26. | Power in low Frequency band (0.1-0.15Hz) * | LFE | 0.5 – 20 | FFT | PPG |
| 27. | Power in low Frequency band (0.15-0.3Hz) * | HFE | 0.5 – 20 | FFT | PPG |
| 28. | amplitude of the largest increase* | GAM | 0.5 – 20 | | PPG |
| 29. | Line Length* | PLL | 0.5 – 20 | | PPG |
| 30. | Mean of Peak to Peak* | mPtop | 0-20 | | PPG |
| 31. | Mean* | Mgsr | 0-20 | | GSR |
| 32. | Standard deviation* | Vgsr | 0-20 | | GSR |
| 33. | Mean* | Mgsrn | 0-20 | Standardization | GSR |
| 34. | Standard deviation* | Vgsrn | 0-20 | Standardization | GSR |

Each test is divided into the windows with the length 20s and 1s time step. Therefore, if a test lasts 600s, it is divided into 600 windows. We used the features of half of all windows of nine tests (about 30% of all data) with procedure 1 as train data in feature selection stage and training the model. These windows were chosen stochastically and removed from test data. Thus other data (about 70% of all data) were used neither in the feature selection nor training the classifier and considered as test data.

### 3- 3- Model

To combine the selected features, a linear regression model is suggested. Label 0 and 1 are used for relaxation and stress phase, respectively to train the model.

To smooth the output signal, a moving average, de-fined as the mean of each window with five former win-dows is applied on the output of the model.

## 4- Results

We investigated the performance of the model in recog-nizing stress state, relatively and absolutely. To evaluate the ability of the model in tracking the stress level rela-tively, the output of the model for each test was plotted. Fig. 5 shows such plots for two tests. As these figures (and other plots) show, the output of the model represents the relative stress level, perfectly.

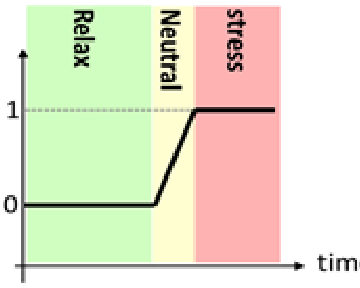


**Fig. 4. The expected output of the model for the tests with procedure 1**

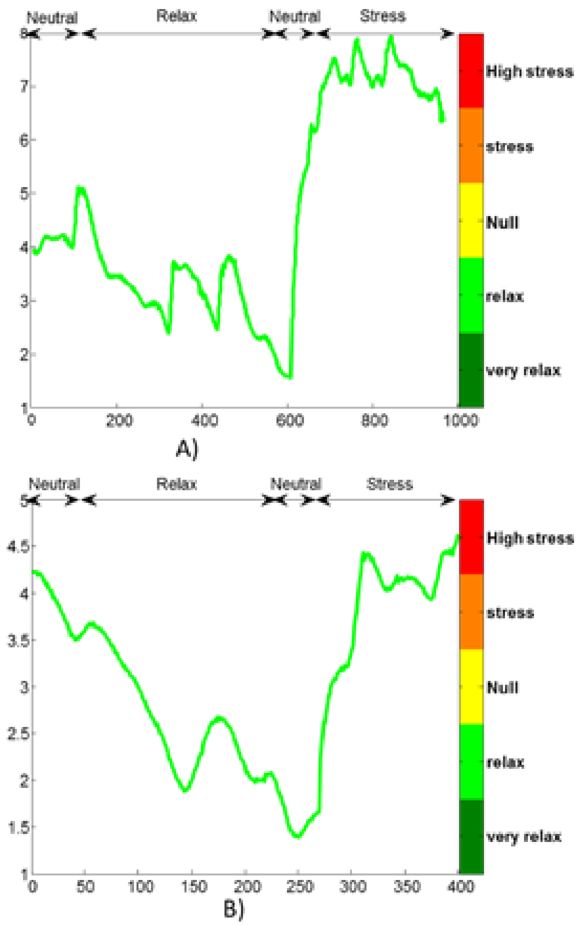


**Fig. 5. The output of the model for two tests with proce-dure 1**

In addition, we normalized the output of the model for each test, between 0 and 1 and calculated the Pearson's correlation coefficient between the observed output and the expected output of the model (Fig. 4). Table 3 shows the Pearson's correlation coefficients for all tests. Correla-tion is significant at the 0.01 level (2-tailed) for all tests.

To evaluate the performance of the model in represent-ing the absolute value of stress level, a threshold based on the training data is chosen to separate the stress and relaxation phases. Then, two methods, quantitative and qualitative analyses are used. In the quantitative method, the value of the output is compared to the threshold value and based stress or relaxation phase is labeled true or false. The data of neutral phase is not important in this analysis. In the qualitative method, a person investigated the plots and scored them between 0-3 based on a good separation of stress, and relax phase by the threshold and a good transition to neutral phase. The results are shown in Table 3.

**Table 3. The results of evaluating the model in represent-ing stress level absolutely (quantitative and qualitative analyses) and relatively (coefficient)**

| Test | Pearson's coefficient | Qualitative method from 3 | Quantitative method from 100% |
|---|---|---|---|
| 1. | 0.901 | 3 | 98% |
| 3. | 0.817 | 2 | 68% |
| 5. | 0.882 | 3 | 95% |
| 7. | 0.854 | 2 | 81% |
| 9. | 0.912 | 3 | 97% |
| 11. | 0.935 | 3 | 96% |
| 13. | 0.806 | 2 | 58% |
| 15. | 0.765 | 3 | 80% |
| 17. | 0.866 | 2 | 64% |
| 19. | 0.945 | 3 | 94% |
| 21. | 0.812 | 3 | 80% |
| 23. | 0.931 | 3 | 91% |
| 25. | 0.901 | 3 | 86% |
| 27. | 0.810 | 1 | 41% |
| 29. | 0.892 | 2 | 85% |
| 31. | 0.882 | 2 | 50% |
| | 0.870 | 2.5 | 79% |

A comparison between our results and those of former studies in the literature is provided in Table 4. These re-sults highlight the improvement achieved in this paper in comparison to other approaches. Although, the stress de-tection rate is about the average of other approaches, the improvements in term of continuous representation of stress (both in time and in level) and the number of physiological signals involved are the special improvements of this paper.

As Table 3 illustrates, the correlation between the ex-pected output and the observed output is highly significant for all tests. However, the accuracy of classifying is low in some of the tests. For example, Pearson's coefficient for test 16 is 0.882 while the accuracy of classifying is 50%. Fig. 6 shows the output of the model for this test. The output signal tracks stress state correctly, but in comparison with the threshold, all samples are under the threshold line and classified as relaxation categories.

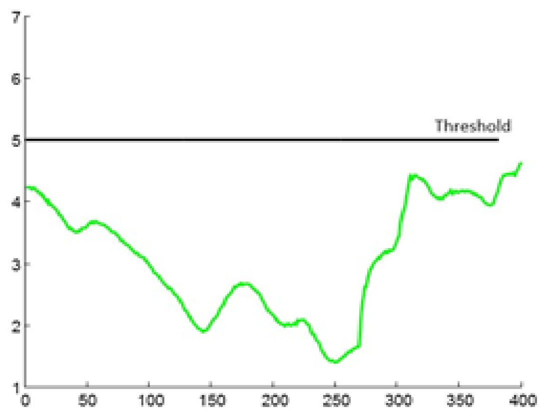


**Fig. 6. Comparison of the output of the model for test 16 and threshold obtained from the training data**

**Table 4. The comparison of the proposed model's characteristics and results with those of the former studies**

| References | Physiological signals | continues/phasic | Accuracy | discrete/ continues output | population |
|---|---|---|---|---|---|
| [7] | BVP, ECG, RESP, EEG and EMG | phasic | 62.2-88.2 | discrete | NA |
| [8] | GSR, ECG, ST, RESP | phasic | 62.2-68.2 | discrete | 22 |
| [11] | ECG, EMG, GSR, and RESP | phasic | 97.4 | discrete | NA |
| [12] | BVP, GSR, PD | phasic | 57.14-80 | discrete | 6 |
| [1] | HRV, ST, GSR, PD and other physical signals (gaze, head move, facial expressions, …) | continues | 86.2 | continues | 5 |
| [13] | GSR, BVP, PD, and ST | phasic | 78.65-90.14 | discrete | 32 |
| [3] | HR, GSR, EMG, RESP | phasic | 65.46-85.46 | discrete | 16 |
| [15] | GSR, ECG, RESP, HR,EMG | phasic | 85.6-90.53 | discrete | 16 |
| [18] | GSR, HR | phasic | 86.3-99.5 | discrete | 80 |
| This Paper | GSR, HR | continues | 87.0 | continues | 16 |

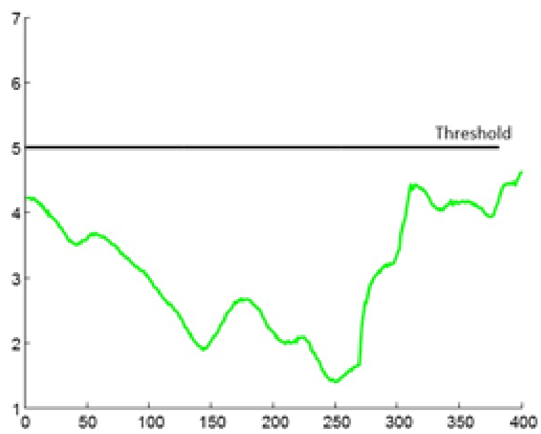


**Fig. 6. Comparison of the output of the model for test 16 and threshold obtained from the training data**

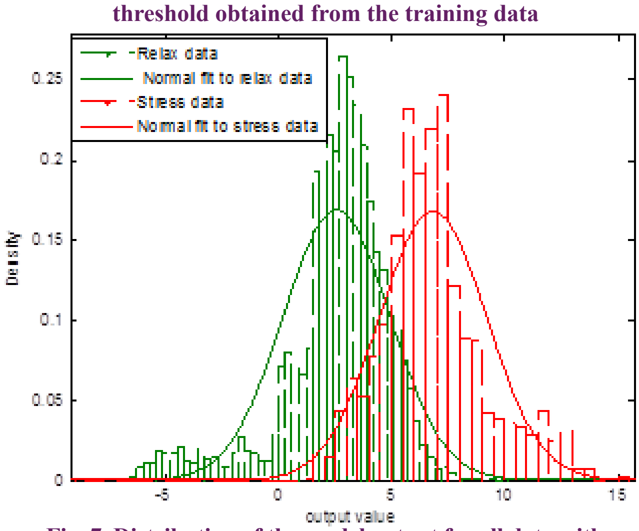


**Fig. 7. Distribution of the model output for all data with procedure 1 in relaxation (dashed green line) and stress (dashed red line) phases. Gaussian curves fitted to density distributions are shown for two phases (red: stress and green: relaxation).**

Fig. 7 depicts the distribution of all data (train and test data) in relaxation and stress phases with procedure 1. Gaussian curves fitted to the density distributions are plot-ted in this figure. T-test analysis shows the difference be-tween two phases is significant.

Table 5 shows the mean, mode, maximum, minimum and standard deviation of data for two phases.

**Table 5. Statistic parameters of Gaussian curves fitted to density distributions for model's outputs in two phases (stress and relaxation)**

| Parameter | Mean | Median | Min | max | Std |
|---|---|---|---|---|---|
| Stress phase | 6.8304 | 6.6594 | -6.4620 | 15.2423 | 2.3742 |
| Relaxation phase | 2.5622 | 2.8984 | -8.8662 | 9.9358 | 2.3615 |

For all subjects who participated in Procedure 2, a de-creasing trend, representing relaxing during the time, was observed in the model output. The subjects illustrated that animation changed with their states real time.

## 5- Conclusion

In this paper, a new model for real-time tracking the stress level was introduced. This model is proper for stress recognition, especially in biofeedback application for an-nouncing subjects about their stress level in real-time. A set of 34 features was defined in 20s time windows by 1s time step. The optimized features were selected by the correlation feature selection method and were combined by the linear regression model. Evaluating the output of the model showed that the model can represent relative stress level accurately. The mean of Pearson's correlation coefficient between the expected output and the normal-ized observed output of the model for all tests with Proce-dure 1 (including relaxation and stress phases) was 87%. In addition, according to the self-report of subjects and observation of the decreasing trend of the output signal during the relaxation exercise (Procedure 2) the output of the model provided a proper feedback of the subject's state

Increasing the output of the model during the neutral phase of Procedure 1 (before starting the stressful stimu-lus) was an interesting phenomenon in our observations. Indeed, the expectation of a stressful event may lead to increasing the stress. The classifier accuracy in categorizing the data of stress and relaxation phases was 79%. It should be noted that measuring the absolute value of human stress with gener-alization capability is difficult, according to large inter-subject and inter-situation variation in physiological re-sponses. Previous studies [8, 23] have shown that the changes in physiological measurements are more indica-tive of the mental states' transition than the absolute measurement values. Thus, a few former studies proposed the use of the neutral state of the subject to overcome this challenge. Our suggestion to improve the model in measuring the absolute value of stress for a specific person is performing a pretest with a protocol, including the highest stress and relaxation experiences by the subject, and retraining the model with this data. In this way, we can personalize the model for each subject.

Finally, the proposed model has the capability to re-place by single bio signal analyses, which are used in cur-rent biofeedback systems, by making the interface be-tween the output of the model and proper animation games for relaxation exercises (an example of this work is performed in Procedure 2 of our experiments).

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