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# Stress Level Evaluation Using BP Neural Network Based on Time-Frequency Analysis of HRV

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***Abstract* - Physiological stress is human body's response to a challenge by multiple systems in the body, in which ANS (Autonomic Nervous System) plays key roles. This paper proposes a stress level evaluation method based on time-frequency domain analysis of HRV (Heart Rate Variability) features combining statistical optimization. The most reliable and efficient indicator to ANS is HRV features obtained from time and frequency domain analysis of R-R intervals recorded during the modified Stroop test. A BP Neural network is utilized to train HRV features selected by t-test and one-way Anova test and classify new samples into four stress level categories i.e. relaxed state, low stress, medium stress and high stress. Weighing factors in classification and number of neurons in hidden layer are considered for optimized network. The proposed method has been validated by experimental results.**

***Index Terms -Stress evaluation, HRV, Stroop test, BP Neural Network.***

## I. INTRODUCTION

With the rapid social and economic development, stress induced by varieties of factors in life is affecting ordinary people, and has been considered a key impact factor in health. To prevent stress-related diseases primarily, evaluation of an individual's current stress level is the first step. And studies have shown that stress is caused by an imbalance between external stimulus and individual's ANS controlling ability [1], which results in changes of several physiological processes in human body like increased muscles tension, blood pressure, concentration of hormones and heart rate etc. Therefore, stress evaluation using such physiological signals is adequate.

In general, stress levels evaluation involves three processes: Data acquisition, features extraction and classification. According to most articles, data acquisition aims at getting reliable response signals under stress-induced experiment to interpret stress levels. Therefore the design f stress-induced experiment and methods to obtain stress response signals are critical to stress evaluation. Compared to physical, psychological and behavioral signals, physiological signals are more reliable methods to determine stress level. And these signals are Blood Volume Pulse (BVP), Galvanic Skin Response (GSR) or Skin Temperature. However, they usually require electrodes to be attached to chest or stomach and long period to determine stress level [2]. Thus in this paper HRV signals are recorded because it requires non-invasive methods that cost less.

Another critical factor, as mentioned in most articles, is stress-induced experiment. Stroop test is generally used as the stressor as it has been shown to be the perfect candidate to alter the sympathetic and para-sympathetic function of ANS in short term and artificial environment [3]. However, it only induces two levels of stress: Non-stressed and stressed level. And no stress scale is utilized to validate the test. In this paper Stroop test is redesigned and validated by POMS scale.

Feature extraction provides different classification models with features to learn patterns to classify levels of stress. According to most articles features are extracted through HRV time-frequency analysis, which quantifies the mean or standard deviation of R-R intervals and calculates the power of high and low frequency components of HRV [4]. In this paper, Statistical approach is used after HRV time-frequency analysis to extract more reliable features.

Machine learning has been successfully used for stress classification. Healey and Picard professors conducted an experiment on evaluating drivers' stress levels in different situations using KNN classifier [5]. Sets et al classifies stress levels based on GSR signals using SVM and LDA hybrid classifier [6]. In this paper Artificial Neural Network is used as the classifier because it is robust and provides an insight to irrelevant features.

The rest of this paper is organized as follows: Section II reviews the literature work about Stroop test, HRV analysis and Neural Network. In section III, results of statistical analysis and classification are presented with description. Section IV draws the conclusion and discuss about future work.

## II. METHODOLOGY

### A. Modified Stroop Test

The Stroop effect interprets the influence of interference on human's reaction time. In Stroop test subjects are supposed to click on the exact space of the screen of IPAD, which shows the true color of words printed on the screen. In general the delay occurs when a word "blue" or "red" is displayed on screen in a color different from its real color, and causes slower reaction time and increasing mistakes. This effect is utilized to study the physiological changes and responses to stress induced by different situations. In literature survey, this tool is utilized as the indicator of various cognitive-perceptual processes according to Renaud and Blindin [7]. In another paper it is a color recognition task and a classical paradigm in neuro-physiological assessments of mental fitness according to Williams et al [8]. HRV features are found to be efficient in describing the Automatic Neural System which is indirectly related to stress according to Salahuddin et al [9]. Changes caused by stress result in contraction of blood vessels and myocardium in automatic responses of Sympathetic Nervous System (SNS) and Parasympathetic Nervous System (PNS), and they lead to changes of HRV. Stroop performance is accompanied by heightened HR levels during the performance of a Stroop task according to Patrice et al [10]. ANS is related to imbalance between external high demands and controlling ability caused by stress, thus HRV extracted under Stroop test has a strong relationship with ANS according to Langewitz et al [11]. Stroop test is demonstrated as an effective stressor to subjects as P. Karthikeyan et al [12] did a survey of development in Stroop color test. In general Stroop test is designed as a card game or a computer game for subjects, which requires them to use mouse to click on screen or directly name the words. To analyze HRV, stress levels are designed as two states i.e. relaxed state and stress state.

Modified Stroop test is designed for producing more stress levels and more accurate indicators of correct rates. Instead of using computer or cards, modified Stroop test is designed in four stress states by IPAD APP Stroop Test. Selecting the words through directly touching the screen reduces the spare time caused by moving the mouse. To design a test suitable for all categories of people, four stress levels are considered. Subjects are supposed to take a subjective assessment POMS in pre-test which includes six segments. Those whose tension-anxiety and depression-dejection scales are beyond standards are excluded from this experiment ensuring that all subjects are in relaxed state before experiment. In Relaxed state HRV features are extracted from subjects sitting still in a room. Next in low stress state subjects are supposed to select the true color name matching the actual color which differs from the words displaying on the screen of IPAD in 2 seconds, and physiological signals are recorded. In medium stress state subjects are supposed to select the true color in 1.5 seconds, the correct rates and physiological signals are also recorded. In high stress state everything is the same as in medium stress state except for the time span changing into 1 second, and subjects should select the words matching the meaning of words displayed in red. 14 subjects get through the 4 processes continuously and each for 5 minutes. Thus 56 sets of HRV features are extracted.

The data sent by device are R-R intervals, which is the period between the onset of the P wave and the beginning of the QRS complex. It is obtained from physiological signals processed by device.

### B. *HRV Analysis*

The automatic nervous system (ANS) consists of two parts: a) sympathetic nerve system (SNS) b) parasympathetic nerve system (PNS). For maintaining body state under stable conditions， the SNS becomes activated against threats while PNS work in opposite direction. Thus SNS increases the heart rate and PNS decreases it [13]. It is known as HRV analysis by analyzing fluctuation in beat to beat periods to separate the role played by both branches. And HRV reflects on the activity of the sympathetic and vagal components of ANS which indicates the variation of R-R intervals. There are three major methods for extracting HRV features: a) Time domain analysis b) Frequency domain analysis c) Nonlinear analysis.

Changes in heart rate during a time period are measured in time domain analysis. And indices from analysis are classified into two categories i.e. beat- to-beat intervals and intervals derived from the differences between adjacent NN intervals. As is shown in table I, the first category covers parameters like SDNN, SDANN and SD, while the second covers RMSSD etc.

SDNN reflects the long-term components accounting for variability in recorded periods. SDANN is an index of variability having an average of 5 min interval over 24 hours. In this experiment it is not used due to 5 minutes' time limit. RMSSD is common parameters based on the differences in the intervals. All these indices are stable independent of day and night variations. RMSSD is more stable thus it is priority for clinical use.

In frequency domain analysis the periodic oscillations of heart rate signal at different frequencies and amplitudes are illustrated, and it reflects the amount of their relative intensity in the heart's sinus rhythm. Indices from frequency analysis are obtained based on power spectral, which is transferred from R-R intervals using Fast Fourier Transformation (FFT) and Fourier Power Spectral Method. When R-R intervals are recorded, Matlab program transfers it using FFT which is shown as follows:

$$x(k)=\sum_{n=0}^{N-1}x(n)W_N^{kn},k=0,1,...,N-1,W_N=e^{-j\frac{2\pi}{N}} \tag{1}$$

And the spectral density is calculated using Fourier Power Spectral Method as follows:

$$\mathrm{p}(k)=\frac{x(k)^2}{N} \tag{2}$$

N is the length of R-R intervals. Fig.1 and Fig.2 illustrate the process of power spectral obtained from R-R intervals. Table II summarizes the indices extracted from frequency domain analysis.

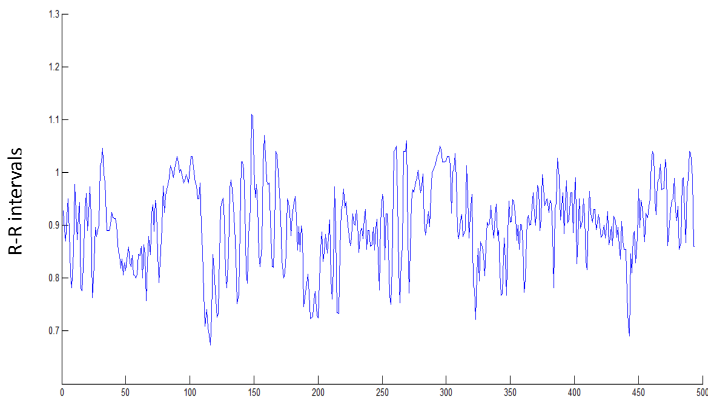
TABLE I
TIME DOMAIN INDICES

| Variables | \Description | Formula |
|---|---|---|
| MEAN | Average of all RR intervals | $MEAN=\frac{1}{N}\sum_{i=1}^{N}RR_i$ |
| SDNN | Standard deviation of all RR intervals | $SDNN=\sqrt{\frac{\sum_{i=1}^{N}\left(RR_i-\overline{RR}\right)^2}{N}}$ |
| SDANN | Standard deviation of the averages of RR intervals in all 5-minute segments of the entire recording | $SDANN=\sqrt{\frac{\sum_{i=1}^{288}(\overline{RR_i}-\overline{RR_{5min}})^2}{288}}$ |
| RMSSD | Square root of the mean of the sum of the squares of differences between RR interval | $RMSSD=\sqrt{\frac{\sum_{i=1}^{N-1}\left(RR_{i+1}-RR_i\right)^2}{N-1}}$ |

TABLE II

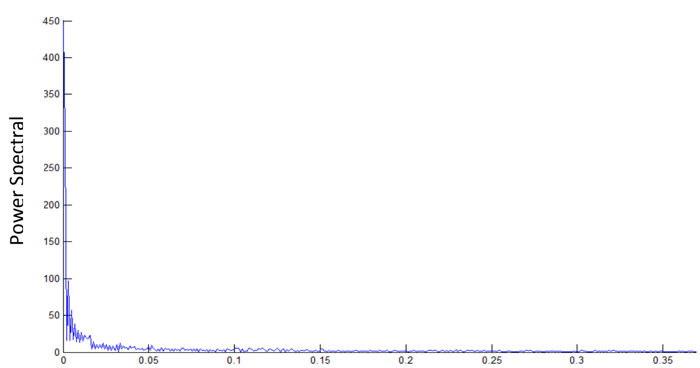
FREQUENCY DOMAIN INDICES

| Variables | Description | Formula |
|---|---|---|
| TF | Variance of all RR intervals(0.003~0.4Hz) | $TF = \sum_{k=a}^{b} p(k),$ a=0.003,b=0.4 |
| VLF | Very low frequency (0.003~0.04Hz) | $VLF = \sum_{k=a}^{b} p(k)$ a=0.003,b=0.04 |
| LF | Low frequency power (0.04~0.15Hz) | $LF = \sum_{k=a}^{b} p(k)$ a=0.04,b=0.15 |
| HF | High frequency power(0.15~0.4Hz) | $HF = \sum_{k=a}^{b} p(k)$ a=0.15,b=0.4 |
| LF/HF Ratio | Ratio of low-high frequency power | $LF / HF$ |




Time

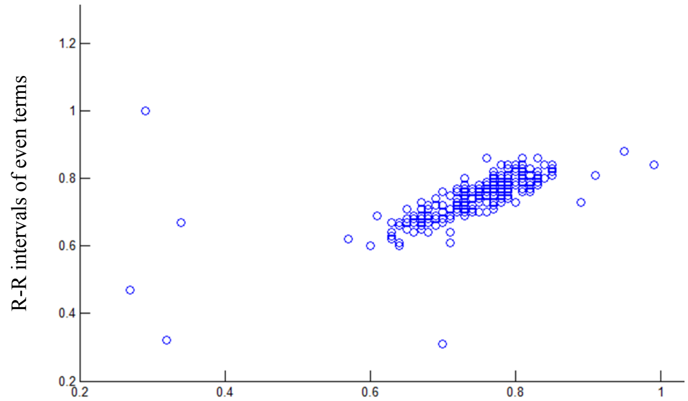
Fig. 1 R-R intervals based on uniformly spaced time series




Frequency

Fig. 2 Power spectral

Nonlinear analysis is used to explore the chaotic disciplines in sinus rhythm, and Poincare scatter diagram is utilized as the nonlinear analyzing method in this paper. A scatter diagram is a coordinate system displaying the distribution of points based on the adjacent R-R intervals. It can reflect overall conditions of HRV and instant changes of sinus rhythm.




R-R intervals of odd terms

Fig. 3 Scatter Diagram

As is shown in Fig. 3, the scatter diagram of a subject suffering medium stress is displayed and quantitative indexes are extracted based on scatter diagram. VAI is used to define the degree of points that deviate from the 45° line while VLI is utilized to calculate the degree of vectors that deviate from the length which is average of all vectors. And formulas are as follows:

Vector Angle index (VAI):

$$VAI = \frac{\sum_{i=1}^{N} |\theta_i - 45^\circ|}{N} \tag{3}$$

Vector length index (VLI):

$$VLI = \sqrt{\frac{\sum_{i=1}^{N} (l_i - \bar{L})^2}{N-1}} \tag{4}$$

VAI feature is used to measure the scatter plot of 45° line between R-R intervals phase dispersion degree while VLI is used to measure the hydrophobic degree of scatter diagram on the length direction.

### C. *Neural Network based on BP Feedforward Algorithms*

Artificial neural network (ANN) is non-linear mapping structures based on the function of human brain, which can identify and learn correlated patterns between input data sets and corresponding target values. Research on noninvasive risk evaluation of diabetes mellitus based on neural network is conducted by L. Vanitha et al [14]. Lenka Lhotska et al use neural network of two learning methods for stress classification of a tested people whose physiological parameters are measured. Sharma N. Gedeon's research proposes and tests a variety of ANNs that can be used to classify stress in reading using a novel set of stress response signals. According to these articles ANN with supervised model based on BP feedforward algorithms is effective to perform the classification tasks. To evaluate stress levels, the feedforward BP algorithms of ANN for classification are used and the supervised model contains the testing data set which covers classified data and predicts the classes of unknown data.

The ANN consists of three layers: input layer, hidden layer and output layer. In Fig. 4, the input data contains optimized HRV features, and output data is "1000", "0100", "0010" or "0001", which respectively represents relaxed state, low stress sate, medium stress state or high stress state.

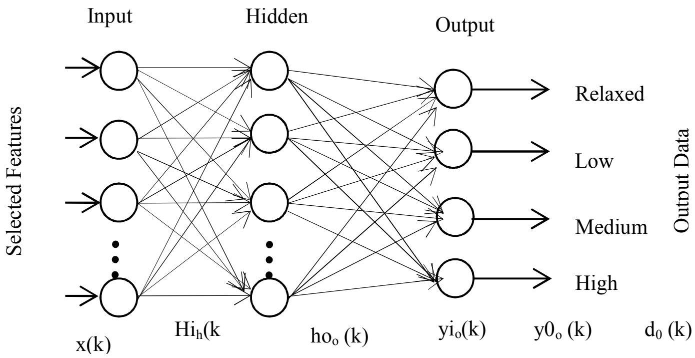



Fig. 4 Neural Network Architecture

TABLE III
VARIABLES IN NEURAL NETWORK

| Variables | Symbol | Formula |
|---|---|---|
| Input Vectors | x | Train Data: $x=(x_1,x_2,...,x_n)$ |
| Desired Output | $d_0$ | Train Data: $d_o=(d_1,d_2,...,d_q)$ |
| Input Vectors for Hidden Layer | hi | $hi_h(k)=\sum_{i=1}^{n} w_{ih}x_i(k)-b_h, h=1,2,...,p$ |
| Output Vectors for Hidden Layer | ho | $ho_h(k)=f(hi_h(k)), h=1,2,...,p$ |
| Activation Function | f(net) | $f(net)=\frac{1}{1+e^{-net}}$ |
| Weights between Input Layer and Hidden Layer | wjk | Optimized by Network |
| Input Vectors for Output Layer | yi | $yi_o(k)=\sum_{i=1}^{p} w_{ho}ho_h(k)-b_o, h=1,2,...,p$ |
| Output Vectors for Output Layer | yo | $yo_o(k)=f(yi_o(k)), o=1,2,...,q$ |
| Weights between Output Layer and Hidden Layer | $w_{ho}$ | Optimized by Network |
| Thresholds in Neurons of Hidden Layer | $b_k$ | Optimized by Network |
| Thresholds in Neurons of Output Layer | $b_o$ | Optimized by Network |

In initializing the network, there are n neurons in input layer, p neurons in hidden layer and q neurons in output layer. The k-th sample is selected randomly from n samples for input layer and desired output data, which is then normalized. The network is initialized when error function, computational accuracy and max training time is set up. Thus all variables are shown in TABLE III.

As process end above the error obtained from the difference between $y_0(k)$ and $d_0(k)$ is used to determine whether it is necessary for another loop or starting mark for the next process of another sample. E is the global error which helps estimate the accuracy and adjust the weights and thresholds in network, and the optimal network with optimized weights and thresholds is obtained when E accord with pre-set accuracy.

In stress levels evaluation weights of features are considered for reflecting the degree of importance of the prediction accuracy. To calculate the degree of the importance several indices are introduced:

a) Relevant significant coefficients

$$r_{ij}=\sum_{k=1}^{p} w_{ki}\left(1-e^{-x}\right)\left(1+e^{-x}\right), x=w_{jk} \qquad (5)$$

b) Correlation Index

$$R_{ij}=|(1-e^{-y})/(1+e^{-y})|, y=r_{ij} \qquad (6)$$

c) Absolute influence coefficient

$$S_{ij}=R_{ij}/\sum_{i=1}^{m} Rij \qquad (7)$$

## III. DATA ANALYSIS AND CLASSIFICATION

In this paper, all data gained from recording device and POMS assessment consist of 56 samples from 14 subjects, 4 in which are used to verify the effectiveness of classification. Thus 40 samples are train data and 16 samples are test data. 10 features from Stroop test are used and then some of them are utilized as input data to classify unknown sample into one of four stress levels. Fig. 5 shows the average POMS scores obtained in assessment of each subject's stress situation before and after the test. Given that correct accuracy drops as stress level goes up in Fig. 6, and scores of subscales like Tension-Anxiety ($P<0.05$), Depression-Dejection ($P<0.01$), Anger-Hostility ($P<0.05$) increases significantly, it turns out that stress is definitely induced and divided into several classes by degree of difficulty in Stroop test.

TABLE IV
THE DESCRIPTION OF DATA SETS

| ***Data Collection Device*** | ***The number of samples*** | ***The number of features*** | ***classes*** |
|---|---|---|---|
| Pulse Oximeter | 56 | 10 | 4 |

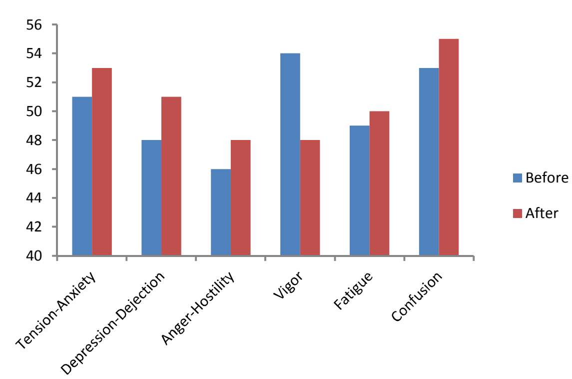



Fig. 5 POMS scores before and after Stroop test

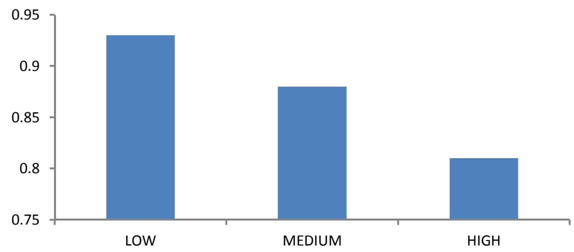



Fig. 6 Correct Accurate of Modified Stroop test

TABLE V
FEATURES IN DIFFERENT STRESS LEVELS

| | Relaxed | Low | Medium | High |
|---|---|---|---|---|
| MEAN(s) | 0.854 ± 0.040 | 0.839 ± 0.032 | 0.822 ± 0.072 | 0.812 ± 0.041 |
| SDNN(s) | 0.953 ± 0.0350 | 0.937 ± 0.037 | 0.916 ± 0.036 | 0.905 ± 0.015 |
| RMSSD(s) | 0.958 ± 0.052 | 0.933 ± 0.028 | 0.927 ± 0.025 | 0.921 ± 0.027 |
| VLF($s^2$) | 0.349 ± 0.291 | 0.634 ± 0.577 | 1.076 ± 1.801 | 1.559 ± 0.769 |
| LF($s^2$) | 0.091 ± 0.015 | 0.123 ± 0.013 | 0.139 ± 0.014 | 0.158 ± 0.010 |
| HF($s^2$) | 0.507 ± 0.094 | 0.456 ± 0.114 | 0.374 ± 0.138 | 0.320 ± 0.138 |
| TF($s^2$) | 0.957 ± 0.742 | 1.433 ± 1.051 | 2.882 ± 5.216 | 3.306 ± 1.841 |
| LF/HF | 0.159 ± 0.129 | 0.217 ± 0.117 | 0.283 ± 0.105 | 0.436 ± 0.116 |
| VAI(s) | 0.029 ± 0.007 | 0.037 ± 0.011 | 0.041 ± 0.025 | 0.044 ± 0.008 |
| VLI(s) | 0.361 ± 0.294 | 0.538 ± 0.425 | 1.616 ± 1.643 | 1.108 ± 1.012 |

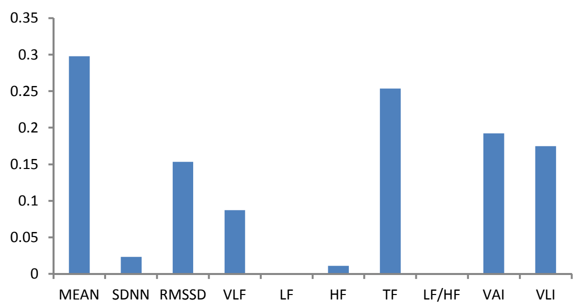



Fig. 7 One-way Anova test results

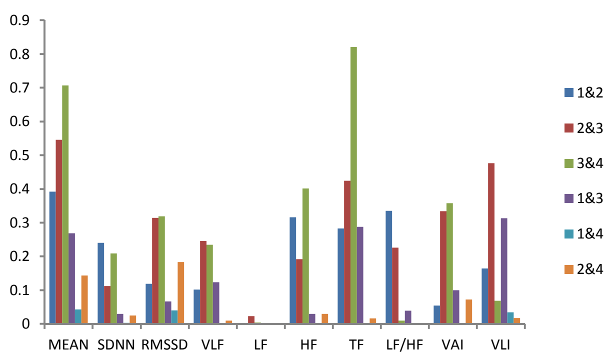



Fig. 8 t- test results

In modified Stroop test R-R intervals are downloaded from PC server, table V summaries 10 features extracted from R-R intervals after using HRV analysis of time, frequency and nonlinear domain. Then One-way Anova test and t-test are applied to analyze the difference between each feature in different states.

As is shown in Fig. 7 and Fig. 8, SDNN, HF, LF, LF/HF differs significantly in overall and between different states. HF decreases while LF increases with the increment of stress levels, which explains the fact that SNS becomes activated against threats while PNS work in opposite direction. Thus these values are sensitive indicators of stress. As for time domain, every domain features except SDNN differs slightly according to Fig. 7 and Fig. 8. Thus SDNN, HF, LF and LF/HF are sensitive indicators of stress levels.

Fig. 9 and Fig. 10 shows the classification rates of 3 selected features and 10 features with respect to different numbers of neurons in hidden layer, and y axis represents classification rates while x axis represents number of neurons. Thus the network with 10 neurons in hidden layer is utilized as the effective classifier. Classification rate based on 3 selected features is significantly higher than that based on 10 features, which illustrate that improved approach is effective. What's more the former network performs better in train speed.

As is shown in Fig. 11, Input data is HF, LF and SDNN based on statistical analysis. LF/HF is the result of HF divided by LF thus it is removed in input data. There are 10 neurons in Hidden layer and overall correct classification rate is 93.75%. High stress level enjoys the highest correct classification rate while low stress level performs the worst. Fig. 12 illustrates that LF, HF contributes mostly to stress evaluation of features extracted.

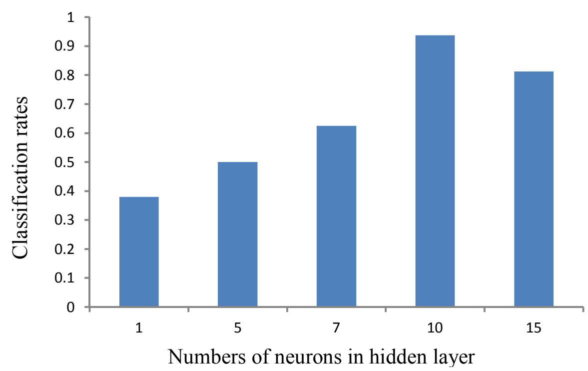



Fig. 9 Classification Rates with respect to number of neurons in hidden layer based on 3 selected features

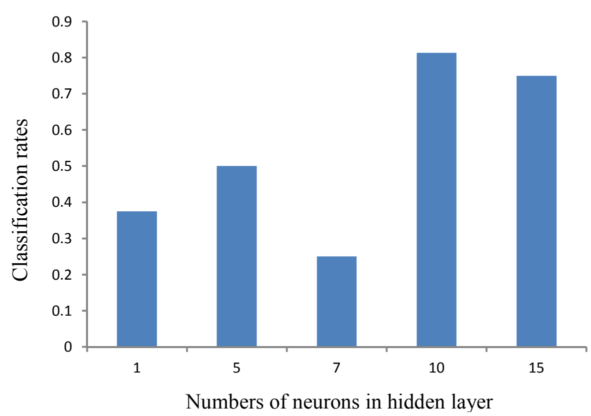



Fig. 10 Classification Rates with respect to number of neurons in hidden layer based on 10 features

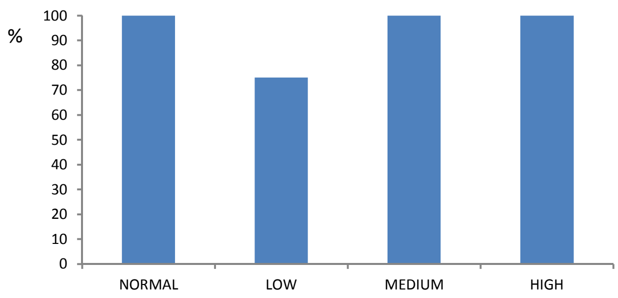



Fig. 11 Classification Rate-Histogram

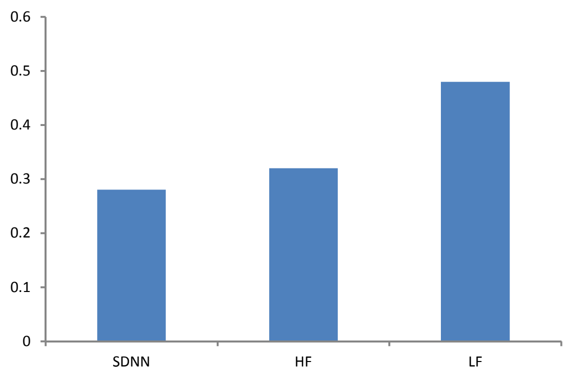



Fig. 12 Weights of Features

It turns out that stress is adjusted by ANS since HF, LF is indicators of activation of ANS. SDNN is the effective indicator of time domain features and nonlinear features like VAI and VLI can evaluate the stress level to some extent.

## IV. CONCLUSION

A stress evaluation method based on BP feedforward algorithms and HRV features is proposed in this paper. Modified Stroop test is used to induce four different stress levels, and after the test the POMS and accurate rates help demonstrate the success of stress inducing and describe the different levels of stress. Pulse Oximeter is applied to record signals during Modified Stroop test and three major HRV analyzing methods are used to extract 10 features from 56 samples, 40 of which are used as the train data and 16 are used for test data. 3 features are selected as the input data after statistical results from Anova and t-test. The best network is chosen to be the evaluation tool of stress levels after considering the numbers of neurons in hidden layer. The importance and influence of HRV features on stress evaluation are considered at the end.

In this experiment stress evaluation system based on neural network can detect different levels of stress with accurate rate at 93.75%. And features like HF, LF are found to be fundamentally important in stress evaluation since these features differ significantly between different stress levels and changes monotonically as the stress level grow from relaxed state to high stress state. Modified Stroop test is used to induce different levels of stress since the anxiety to complete task leads to changes in HRV. Stress evaluation by optimized BP neural network based on 3 selected features proved to be effective after comparison between un-optimized and optimized BP neural network.

The experiments have limitations to detect stress levels of all ages of people since subjects are all graduate students. Other influential factors are not considered such as age, day and night, gender etc. In feature extraction more features are supposed to be considered like blood oxygen and reaction time etc. In future work, feature extraction will be optimized, and more samples are considered to be added in network training. In data acquisition the Stroop test will be further adapted to significantly induce different levels of stress.

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