Stress Detection Based on ECG Using Discrete Wavelet Transform

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Abstract:

Acute stress is the most common form of stress. It comes from demands and pressures of the recent past and anticipated demands and pressures of the near future. This research studied the stress on female students due to mathematical exercises in a noisy environment. Detection of this stress is important because it contributes to diverse pathophysiological changes including sudden death, ischemic diseases (myocardial infarction, angina), and wall motion abnormalities (the motion of a region of the heart muscle is abnormal), as well as to alterations in cardiac regulation as indexed by changes in sympathetic nervous system activity and hemostasis (process which causes bleeding to stop in order to keep blood within a damaged blood vessel unlike hemorrhage). Stress level 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.

HRV (Heart rate variability) can be analyzed using both time domain and frequency domain features. Selection of features which vary with the changes of the stress levels is significant and it is important to show relatively reliable behavior.

Overall, heart rate variability spectra during baseline conditions related to Left ventricular hypertrophy and congestive heart failure are dominated by high frequency activity. Stress is accompanied by an increase in the Power Spectrum Density (PSD) of Low Frequency (LF) and decrease in PSD of High Frequency (HF). Data (ECG signal) was collected by AD (Data acquisition) Instrument from ten female subjects, in the age range of 20 to 24 years were of **asked to perform three levels difficulties of arithmetic tasks.**

A total of ten statistical features were used in this research extracted through wavelet transform, including: Mean, Maximum, Minimum,

Standard deviation, Variance, Mode, Median, power spectral density (PSD), energy, entropy and hybrid of them. The SVM (support vector machines) classifier give highest accuracy of 79.5 based on hybrid feature and ribo 3.7 wavelet through LF range.

Keywords: Stress, ECG, SVM, KNN, DWT

الكشف عن الإجهاد معتمداً على إشارة ECG باستخدام محول المويجات المتقطع DWT

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المستخلص :

يعد الإجهاد الحاد هو اكثر أنواع الإجهاد شيوعاً ويحصل من الضغوطات والاحتياجات ألحاليه والمستقبلية. تم في هذا البحث دراسة الإجهاد على ألطالبات نتيجة حل ألمسائل الرياضية في أجواء صاخبة. الكشف عن الإجهاد مهم لأنه يسهم في تطور التغيرات المرضية في جسم المريض المتنوعة بما في ذلك الموت المفاجئ، نقص ألترويه ألمؤدي الى أما احتشاء عضلة القلب أو الذبحة ألصدريه ، الحركات غير الطبيعية لجدار القلب (لمنطقه في عضلة ألقلب) ، فضلا عن التغييرات في تنظيم حركة القلب التي تسببها التغيرات في نشاط الجهاز العصبي الودي. لإرقاء مستوى الإجهاد من الصعب تحديده لأنه لا يمكن قياسه بطريقة متناسقة وفي الوقت المناسب. أسلوب واحد مستخدم لتوصيف مستوى إجهاد الفرد هو أجراء مقابلة أو تحليل بيانات محدده تؤخذ خلال زيارة الطبيب أو الطبيب النفساني

معدل تغير ضربات القلب HRV يمكن تحليله بدراسة التغيرات الحاصلة بالترددات لفترة زمنيه محدده باستخدام طريقة time domain and frequency domain. تحليل البيانات المتغيرة التي يمكن ملاحظتها في مستويات التوتر المختلفة مهم في تحديد العلاج المناسب.

وعموما، يهيمن على معدل ضربات القلب تقلبات أطياف الترددات العالية لخط الأساس المتعلق بالبطين الأيمن وفشل ألقلب . الإجهاد يصاحبه زيادة في كثافة القدرة (PSD) للترددات المنخفضة (LF) ويقابله انخفاض في كثافة القدرة للترددات العالية (HF) . بيانات إشارة الراسم القلبي (ECG) تم جمعها من قبل جهاز تجميع البيانات. أخذت من عشر أناث من الفئة العمرية من 20 إلى 24 سنة تم تعريضهن لثلاثة مستويات من صعوبات المسائل الرياضية الحسابية.

تم استخدام ما مجموعه عشر نتائج احصائية في هذا البحث أخذت عن طريق تحويل المويجات، بما في ذلك : الحدود المتوسطة ، الحدود العليا ، الحدود الدنيا ، ومعدل الانحراف المعياري ، التباين، الواسطة، والمتوسط، وكثافة القدرة (PSD) ، والطاقة، مقياس الطاقة الهجين. المصنف SVM يعطي أعلى دقة 79.5 على أساس الميزة HYPRID و 3.7 للمويجات نوع RIBO من خلال مجموعة الترددات الواطئة LF .

1.Introduction:

When human body exposed to acute stress stimuli, it responds physiologically by increasing activities of both the hypothalamic-pituitary-adrenal (HPA) axis and the sympathy adrenal system (SAS). Diagnosis of stress depends on a multitude of the factors :

a. **Calculating of Inter Beat Interval (IBI) and feature extraction.**
b. **The features for HRV analysis can be time domain features or frequency domain features and it is difficult to find out the most common and relevant features for each stress level.**
c. **Classifying the features into each stress level is another major task to be addressed in this research based on the most important features and the suitable classifier.**

A lot of approaches to diagnosis stress have been used, including the use of questionnaires, biochemical measures, and physiologic techniques. Most of these methods are subjected to experimental error and must be viewed with caution [1]. When our brain assesses stress, the Sympathetic Nervous System (SNS) prepares our brain to respond. The beat to beat intervals of the heart tend to vary and the Heart Rate variability (HRV) is mostly regulated by the sympathetic and parasympathetic Autonomic Nervous Systems (ANS) [2]-[3]. Hence, the state of the ANS is reflected in the HRV. For this reason HRV was chosen as one of the key criteria to diagnose stress. Heart rate signal is non-stationary and the signal pattern is different for every person. Even the range of the signal depends on the type of subject (man, women, infant, animal) and the physical condition like healthy or sick [4]. So, it is really hard to formulate a general rule to diagnosis the stress. The diagnosis is mainly based on the expert's experience but the number of expert is inadequate in our college.

To obtain HRV, Inter Beat Interval (IBI) must be obtained first from ECG signals. The heart rate in humans may vary due to various factors like age, cardiac disease, neuropathy, respiration, maximum inhalation and cardiac after load due to nervous stress activities. HRV has become a universally recognized method to represent variations in instantaneous heart rate and RR (beat to beat) intervals. Results from the HRV data can reveal physiological conditions of a patient. It is also clinically related with lethal arrhythmias, hypertension, coronary artery disease, congestive heart failure, diabetes, etc.

The easiest way of analyzing the HRV is performing a time domain analysis. Simple time domain features might include mean RR interval, the mean heart rate, the difference between maximum and minimum heart rate, the standard deviation of the NN interval (SDNN), etc.

Frequency domain analysis is the spectral analysis of HRV as the HRV spectrum has high frequency component ranging from 0.18 to 0.4 Hz which is due to respiration. It also has low frequency component ranging from 0.04 to 0.15 Hz which appears due to both the vagus and cardiac sympathetic nerves. The ratio of the low to high frequency spectra which can be used as an index of parasympathetic balance .

Among some main methods to calculate the PSD of RR series, FFT (Fast Fourier transform) is one of the important methods [2][3]. Several studies conducted have proposed link between negative emotions and reduced HRV. Normally both sympathetic and parasympathetic tone keeps on fluctuating. Thus we can relate HRV analysis to the stress level of a person [5]. Zhao et al. [6] had proposed a feature extraction method using wavelet transform and support vector machines. Wavelet transform is used to extract the coefficients of the transform as the features of each ECG segment. At the same time, autoregressive modeling (AR) is also applied to get hold of the temporal structures of ECG waveforms. Eventually, support vector machine (SVM) with Gaussian kernel is used to classify different ECG heart rhythm. The results of computer simulations provided to determine the performance of the proposed approach reached the overall accuracy of 99.68%.

Tayel and Bouridy [7] applied ECG image classification by extracting their feature using wavelet transformation and neural networks. Features are extracted from wavelet decomposition of the ECG images intensity. The acquired ECG features are then further processed using artificial neural networks. The features are: mean, median, maximum, minimum, range, standard deviation, variance, and mean absolute deviation. The ANN was trained by the main features of the 63 ECG images of different diseases. The test results showed that the classification accuracy of the introduced classifier was up to 92%.

2- Methodology

Generally the diagnosis of any type of stress can be through the analysis of biological signals like heart rate, finger temperature, electrocardiogram (ECG), electromyography signal (EMG), skin conductance signal (SC), blood pressure (BP), etc. Most of the methods which used to characterize an individual's stress level are subject to experimental error and must be viewed with caution [1]. Wavelet of digital signal processing tools in MATLAB is able to provide a low cost method in extracting, analyzing the features of ECG signals (Fig.1) and classifying them into different stress level.

Data (ECG signal) was collected by AD Instrument (international company) from fifteen female from the college, in the age range of 20 to 24 years were asked to perform three levels difficulties of arithmetic tasks, therefore the total number of tests are 15*3= 45 tests. These tests were done in our college over three months. Five females' data had been ignored because of their noisy signals, therefore 10 female readings were considered in this study. In this research the tests done over females because they are not easily get really stressed unlike men, therefore the stress ECG signals from females very accurate [1]. Stress was measured in laboratory environment using stress inducement stimuli (mental arithmetic test). The stress levels were determined by the different level complexity of the arithmetic tasks that need to be carried out from not difficult to extremely difficult.

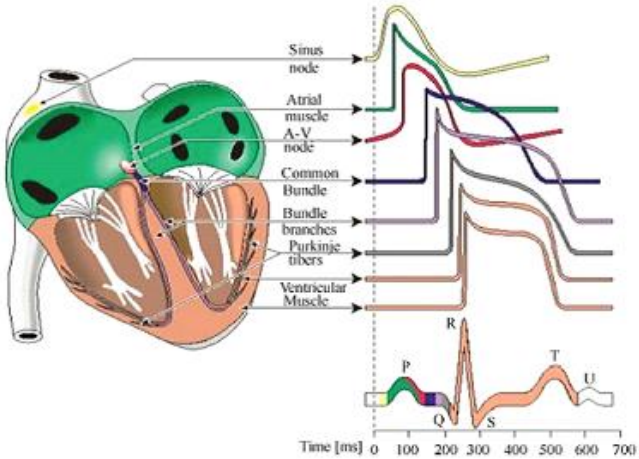

Fig.1 : A typical representation of the ECG waves [8]

Mental arithmetic task is commonly used method to induce the stress in the area of psychophysiology. It is used to increase the mental demand of the subjects by performing a series or combination of arithmetic operation.

In this test, the subjects were asked to carry out one hour of arithmetic task in noise environment. The arithmetic task is consisting of series of calculation (subtraction, addition, multiplication and division), the miscalculations were informed continuously to the subjects and they need to repeat the calculation from the first question until they were asked to stop.

Arithmetic task was performed with three different kind of environment to distract the subject namely; no noise task (control task); variable real life noise; a steady real life noise. The variable real life noises are siren, car engine warm up, thunder getting closer, child crying etc., to distract and induce the stress. The steady real-life noise was to reflect the real-life sounds without any variability (no mixing of different source of noises in laboratory). The noises consist of the collection of background noises from bars and cafes [9]. In this research the noises are collected from noisy places (streets, markets, shops and restaurants) as a simulation.

3- Preprocessing

ECG signal is an electrical signal with an amplitude between 0.5mV to 4mV and its important information lies in the range of 0.05Hz-100Hz. The frequencies beyond that range can be eliminated by using band pass filter.

ECG signal is mixed with noises, therefore appropriate filters must be designed in order to get rid of these noises without degrading the signal of interest. Manpreet *et al.* [10] proposed a preprocessing method which is about the design of cascading of IIR Band pass Zero phase (BP-ZP) Elliptic filter, median filter and Elliptic notch filter as shown in (Fig.2) [10].

ECG signal is continually distorted by three types of predominant noise: low frequency artifacts (0.04 to 0.15 Hz), high frequency artifacts (0.18 to 0.4 Hz) and 50 Hz power line interference.

All designs are performed using filter design toolbox in the MATLAB with sampling frequency 1000 Hz. The 4th order low pass filter is designed with 100Hz cutoff frequency.

Power line interference can be easily identified since it has frequency 50 Hz with level greater then ECG signal. A well-known method qualified of reducing the power line interference is the use of IIR notch filter which designed to remove a very specific, narrow band of frequencies [10]. The center frequency of this 4th order notch filter is 50 Hz with bandwidth 1 Hz. (Fig.3) shows clearly the difference between the EEG signal before and after filtering.

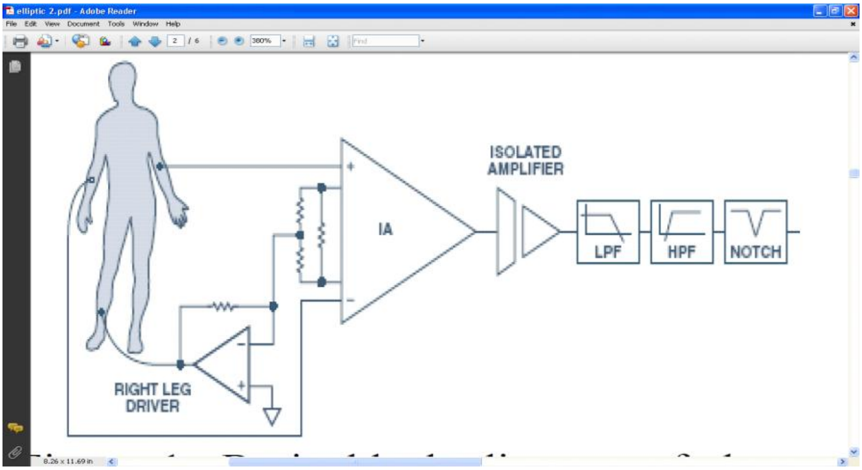

Fig. 2 : Basic block diagram of the ECG Signal filtering system.

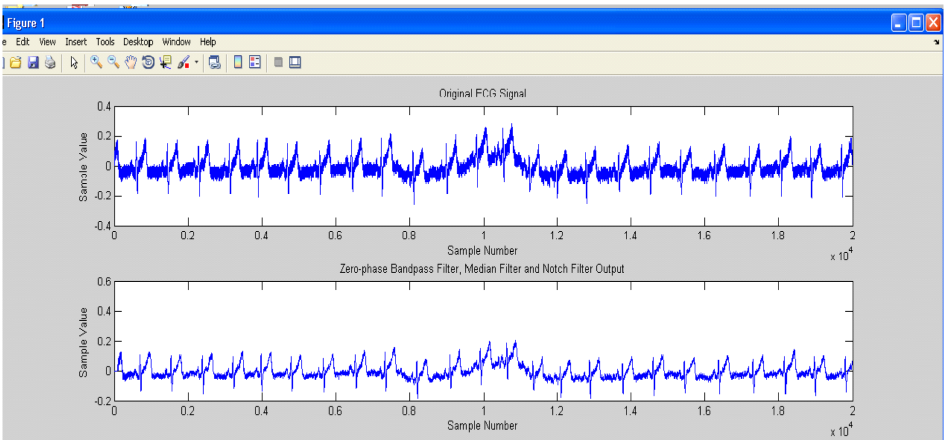

Fig.3 : The raw EEG signal before and after filtering

4-Feture Extraction

The features that can be extracted from ECG signal can be either in time or frequency domain. ECG signal is converted into IBI signal. IBI signal is a time domain signal where difference of time between two consecutive beats is plotted over time. The time domain features is calculated from IBI signal without any modification that represents the statistical change and variation of the signal over time. For frequency domain feature extraction, the time domain signal is converted into frequency domain signal by (FFT).

The power based on the frequency level is calculated as frequency domain feature like Low Frequency (LF) power, Very Low Frequency (VLF) power, and High Frequency (HF) power etc. But the main drawback of FFT is that it is unsuitable for the signal that is non-stationary and does not contain any information related to time. Discrete Wavelet Transform (DWT) is a solution for that. It keeps both time and frequency information and gives relatively better output than FFT.

DWT is also implemented here because IBI is a non-stationary signal. This approach is based on decomposing the segment of interest into frequency bands where a weighted score is given to the band depending on its dynamic range and its diagnostic significance [11].

As described above, the process of decomposing a signal x into approximation and detailed parts can be realized as a filter bank followed by down-sampling (by a factor of 2) as in (Fig.4).

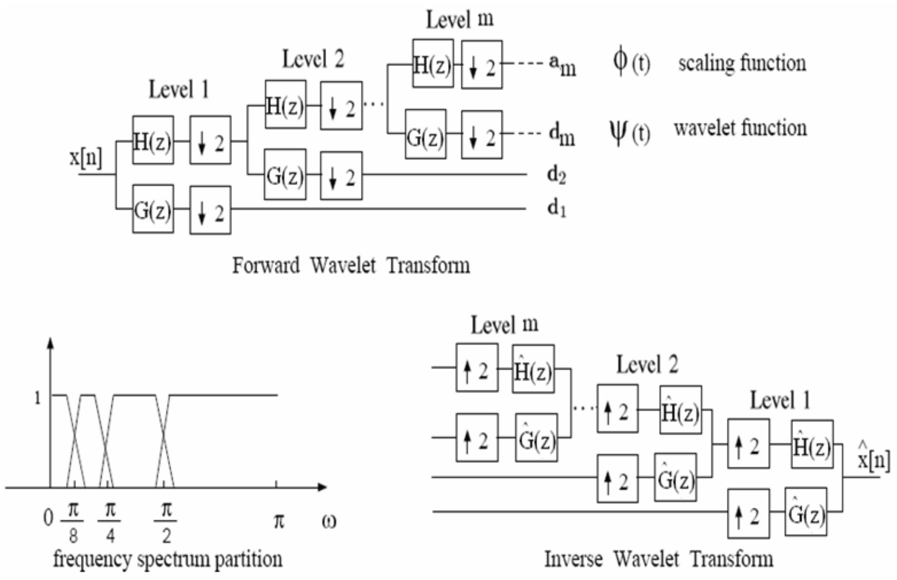

Fig. 4: The DWT and IWT technique up to m level

The impulse responses h[n] (low-pass filter) and g[n] (high-pass filter) are derived from the scaling function and the mother wavelet, respectively. This gives a new interpretation of wavelet decomposition as splitting the signal x into frequency bands. In hierarchical decomposition, the output from the low-pass filter h constitutes the input to a new pair of filters. This results in a multilevel decomposition. The maximum number of such decomposition levels depends on the signal length.

The reconstruction of signal x from the approximation and detail information. This process can be realized as up sampling (by a factor of 2) followed by filtering the resulting signals and adding the result of the filters.

In Chen et al. [12], the wavelet transform as a method for compressing both ECG and heart rate variability data sets has been developed. In Thakor et al. [13], two methods of data reduction on a dyadic scale for normal and abnormal cardiac rhythms, detailing the errors associated with increasing data reduction ratios have been compared. Using discrete orthonormal wavelet transforms and Daubechies D10 wavelets, Chen et al. [14], compressed ECG data sets resulting in high compression ratios while retaining clinically acceptable signal quality. In Miaou & Lin [15], D10 wavelets is

chosen to be used, with the incorporating of adaptive quantization strategy which allows a predetermined desired signal quality to be achieved.

A total of ten statistical features were used in this research, including: Mean, Maximum, Minimum, Standard deviation, Variance, Mode, Median, power spectral density (PSD), energy, entropy, hybrid of the last nine features.

5- The Classifiers

5.1- K-Nearest Neighbor

K Nearest Neighbor (KNN) is one among the simplest nonlinear classifiers used in several signal processing applications. Classification of new test feature vector is determined by the class of its k-Nearest Neighbors. This classifier memorizes all vectors in the training sets and then compares it with the test vector. Therefore, this classifier works based on memory learning. The ranks for the k-Nearest Neighbors based on the similarity scores are calculated using similarity measure, such as Euclidean distance measure. The distance between two neighbors using Euclidean distance can be found using Equation (1) [16].

$$Dist(X,Y) = \sqrt{\sum_{i=1}^{D}(Xi - Yi)^2} \qquad (1)$$

where *D* is the number of coordinates, *X* is a training vector and *Y* is a testing vector. Some researchers used the majority voting for classifying the unlabeled data. This means that a class (category) gets one vote for each instance of that class in a set of k-Neighborhood samples. Then, the new data sample is classified to the class with the highest number of votes. This majority voting is more commonly used because it is less sensitive to outliers. However, in kNN, the researcher needs to specify the value of "*k*" closest neighbor for level classification that gives a maximum rate. The function class in Matlab had been used in this research as follows:

***Class* = *knnclassify* (*Sample*, *Training*, *Group, k*) to classify the rows of the data matrix *Sample* (each feature) into groups (1, 2, 3 and 4 level of stress), based on the grouping of the rows of *Training*. *Sample* and *Training* have matrices with the same number of columns. *Group* is a vector whose distinct values define the grouping of the rows in *Training*. Each row of *Training* belongs to the group whose value is the corresponding entry of *Group*. *knnclassify* assigns**

each row of *Sample* to the group for the closest row of *Training*. *Group* is a numeric vector. *Training* and *Group* have the same number of rows. *Class* indicates for each row of *Samples*, the suitable group. *k* is the number of nearest neighbors used in the classification and for this research, k value ranges from 1 to 10.

5.2 Support Vector Machine (SVM) classifier

The purpose of Support Vector classification is to devise a computationally efficient way of learning good separating hyper planes in a high dimensional feature space as shown in (Fig.5). The SVM works in the high dimensional feature space formed by the nonlinear mapping, (x) of the n-dimensional input vector into a K-dimensional feature space as shown in (Fig.6). The formula of the hyper plane separating two different classes is given by the relation in equation (2)[6].

$$y(x) = W^T \varphi(X) = \sum_{j=0}^{K} \omega_j \varphi_j(x) + \omega_0 = 0 \qquad (2.0)$$

where w = $[\omega_0, \omega_1, ..., \omega_k]^T$ is the weight vector of the network. By introducing the so-called Lagrange multipliers, φ_j is the learning task of SVM is reduced to quadratic programming. On account of these facts, there exist many highly effective learning algorithms, which result in the global minimum of the cost function and the best possible choice of the parameters of the neural network. And all operations in learning and testing is done using so-called kernel functions. The kernel is defined as in equation (3)[6] .These equations were applied in this research through matlab two functions ; "svmtrain" and "svmclassify".

$$K(x, x_i) = \varphi^T(x_i)\varphi(x) \qquad (3)$$

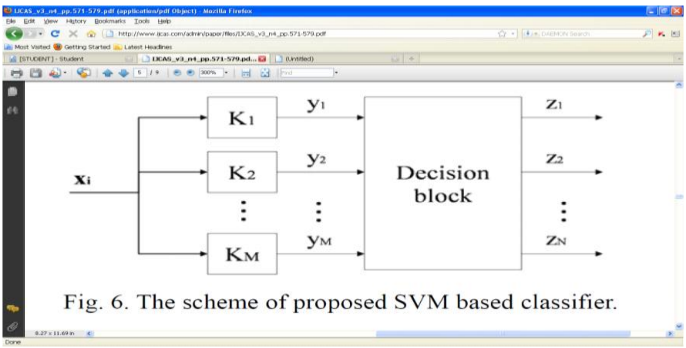

Fig. 5: The scheme of proposed SVM based classifier.

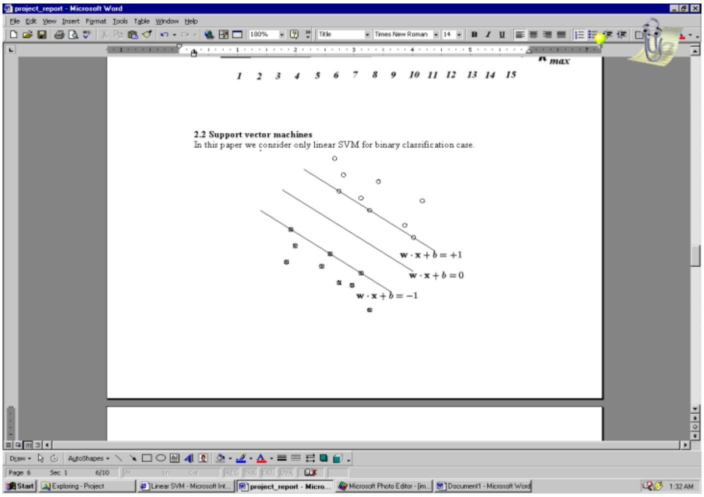

Fig. 6: Finding out the linear separating hyper plane which maximize the margin, (the optimal separating hyper plane OSH)

The accuracy of both classifiers was calculated based on the weigh on the correct class to the total number of samples. the sampling frequency is 1000 Hz which mean 1000 samples per second .Normal person has 76 heart beat in 1 minute, therefore for one beat:
(60 / 76) * 1000 =789 samples needed.
The 789 samples were distributed into 10 folds. Each fold has 79 samples and randomly takes 20 samples from each class for testing. The accuracy for each class is calculated as in equation 4.

$$\text{Accuracy} = \frac{\text{Number of stress correct classification}}{20} \qquad \textbf{(4)}$$

Then the accuracy for four classes was averaged and this done for each *k* value.

6-Results and discussion

The results of preprocessing and features extraction are displayed in this section. Two classifiers are used for classification; they are SVM and KNN. For each classifier, eight (8) wavelet functions are being used and the averaged result of classification is judged respectively. The chosen wavelet functions including Daubechies5 (*db5*) of level

five (5), Daubechies10 (*db10*), Symlet4 (*sym4*) of level five (5), Coiflets5 (*coif5*), ReverseBior3.7 (*rbio3.7*), ReverseBior3.9 (*rbio3.9*), Biorthogonal3.3 (*bior3.3*) and Discrete Meyer. The frequency component which are considered in this research consists of low frequency component (LF), high frequency component (HF) and the normalizing equation, (HF/ (LF+HF) and LF/ (LF+HF). For each frequency component, ten statistical features were extracted which consist of mean, maximum, minimum, power spectral density, variance, mode, median, standard deviation, energy, entropy and hybrid of the these features.

In cases of stress, there is a tendency for increased heart-rate variability (HRV) in the lower frequency ranges (0.04-0.15 Hz) of the ECG. To evaluate the highest classification, the best frequency range is chosen with the best wavelet function through more combination trials of different frequency and wavelets.

The best wavelet family can be chosen by comparing the output of each wavelet which produces a more accurate model for the ECG signal.

By using the wavelet functions, the signals are decomposed at the required level. For this research, all of the decomposition is done at level four. The wavelet functions chosen in this research are based on the literature review [2][4-6]. (Fig.7) shows the decomposition of ECG signal up to level 4 based on db10.

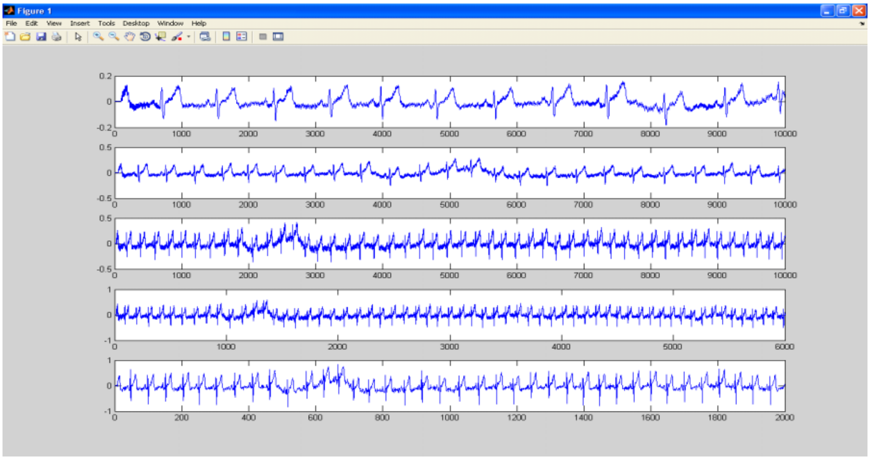

Fig. 7 The decomposition of ECG signal up to level 4 based on db10.

We calculate the accuracy results of four partitions namely; low frequency component (LF), high frequency component (HF) and two of their normalizing equations. The LF produce maximum average accuracy of 78% as shown in Table (1).

Table 1: The average accuracy for each frequency component and its normalizing equation

Frequency component and the normalizing equation	Average accuracies of classification, (%)
LF	78
HF	70
HF/(LF+HF)	72
LF/(LF+HF)	65

Therefore, We will mention the results of accuracy of each feature of LF region only. We noticed that the low frequency component (LF) gives the highest accuracy for stress classification of 54.6% for hybrid statistical features based on wavelet: bior3.3 using KNN classifier (Table 2). While with SVM classifier, we achieved maximum accuracy of 79.5% using hybrid features based on wavelet: rbio3.7 (Table 3).

Table 2: The accuracies achieved in each feature for low frequency component (LF) classified by KNN.

	Mean	Min	Max	PSD	Std	Var	Mode	Med	Ene	Ent	Hyb
bior 3.3	43.2	41	45.8	40.9	53.2	41.6	49.7	42.3	44	41	54.6
db5	41.3	39	44	41.1	51.4	43.8	49.9	40.6	45	45	50.7
db10	42.5	34.5	45.1	40	52.6	42.6	48	40	41	39	43.2
coif5	44	32.5	45	40	50.5	40	48.1	40.1	42	44	49.1
dmey	42.4	32	43.3	42.5	49.9	40.8	40	39.5	41	49	48
rbio 3.7	43.5	39	39.9	41.9	49.9	40.1	43.2	39.9	41	44	49.5
rbio 3.9	44	33.4	39	44	47	40.4	41	37.8	43	46	48.3
sym4	43.2	31	37.9	40	47.6	39.6	40.9	36	41	43	48.9

Table 3:The accuracies achieved in each feature for low frequency component (LF) classified by SVM

	Mean	Min	Max	PSD	Std	Var	Mode	Med	Ene	Ent	Hyb
bior 3.3	53.2	50	45.8	45.9	67	44	49.7	42.3	54	51	79
db5	55	49	44	47.9	66.7	45.8	49.9	40.6	56	55	77
db10	56.7	48.6	45.1	48	66.5	46.7	48	40	57.9	50	73.2
coif5	55	44	45	48	63	45	48.1	40.1	58.1	54	79.1
dmey	54.3	45	43.3	50	65.7	50	40	45	59.9	59	78
rbio 3.7	54	50	43	49.9	69.9	40.1	43.2	43	61	54	79.5
rbio 3.9	53	50	40	49.9	67	40.4	41	40.1	59	56	78.3
sym4	54	47	40.1	50.6	65.5	40	40.9	39	57.9	53	78.9

Suleiman et al. [17] obtained 60% sensitivity for exercise stress testing while Robert et al. [18] achieved 67% sensitivity for cardiac stress testing. Bateman et al. [19] achieved accuracy of 70% based on the processing of the images of ECG signal. While Assuero et al. [20] got 69% accuracy depends on producing ECG image protocol.

Conclusions:

Stress level is difficult to manage because it cannot be measured in a consistent and timely way. HRV can be analyzed using both time domain and frequency domain features. Selection of features which vary with the changes of the stress levels is significant and it is important to show relatively reliable behavior.

Frequency domain analysis is the spectral analysis of HRV spectrum as it has high frequency component ranging from 0.18 to 0.4 Hz which is due to respiration. It also has low frequency component ranging from 0.04 to 0.15 Hz which appears due to both the vagus and cardiac sympathetic nerves. Both components very important to drive the index of parasympathetic balance as a ratio of the low to high frequency spectra.

Stress is accompanied by an increase in the Power Spectrum Density (PSD) of Low Frequency (LF) and decrease in PSD of High Frequency (HF).

A total of ten statistical features were used in this research, including: Mean, Maximum, Minimum, Standard deviation, Variance, Mode, Median, power spectral density (PSD), energy, entropy and hybrid of them.

The SVM classifier give highest accuracy of 79.5 based on hybrid feature and ribo 3.7 wavelet through LF range.

As a future work, we planning to do another study on the males and compare it with this study.

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