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LEVERAGE OF CARDINAL BIOMEDICAL SIGNALS FOR ANXIETY QUANTIFICATION

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ABSTRACT

Anxiety has become a moiety of day today life for many, an inseparable complement of every endeavor. The prevalence of anxiety in patients with cardiovascular disease is threefold higher when compared to general population. This serves as a fountain head of several complications and health hazards. Thus it is a need of the hour to assess and quantify the existence of such emotion in the target group and take prompt action towards its normalization. Although anxiety causes various changes in the body, those reflected by the Central Nervous System and the Cardiovascular System are predominant. This work proposes an atypical approach towards anxiety quantification, wherein an elaborate analysis of two paramount biomedical signals namely the Electroencephalogram and the Electrocardiogram are made independently.

Keywords: Anxiety, Electrocardiogram, Electroencephalogram, Feed Forward Neural Network.

I. INTRODUCTION

Well being refers to ardent nurturing of one's own self, establishing the right kind of climate within and cherishing the joy of an unchaotic peaceful mind. Well being incorporates physical, social, emotional, psychological and economic spheares of it in a single nutshell. Of all the afore mentioned, Emotional well being is the one that is often ignored. Our body and mind are mutual mirror images of each other. Ignorance of the later shows its reflection in the former, ie., the physiological health gets affected.

Emotional health gets affected greatly due to stress and anxiety. These are the two emotions that are often confused; stress is the one that disappears once the stressor is removed whilst anxiety is a strong unpleasant feeling of nervousness that might have been a response to a feared situation that has occurred in the past, which is also feared to happen in the near future. Also stress can give both positive as well as negative impacts. They are categorised as Eustress and Distress respectively. However anxiety has only negative impact on physiological well being. It is also important to note that anniversary dates or times of traumatic events are causatives of anxiety and so the trauma survivors are 100% sure and liable to experience peaks of anxety and depression.

The trauma under concern in this work is the event of *Heart Attack.* Heart attack survivors are extremely liable to experience events of anxiety which might lead to further complications such as tachycardia, increased heart rate and lowered blood pressure. These may ultimately lead to heart failure. It is therefore extremely essential to quantify anxiety in heart attack survivors in order to ensure all forms of their well being.

II. ANXIETY QUANTIFICATION

Anxiety to be quantified necessitates tapping of vital biomedical information. Stress detection is conventionally done by estimating galvanic skin response, processing of facial cues, throat contraction estimation, measuring salivary cortisol levels, perspiration assessment etc. however these become irrelevant when it comes to anxiety detection. This paper deals with anxiety quantification by tapping three vital biomedical signals namely, Electroencephalogram (EEG), Heart Rate (HR), Electrocardiogram (ECG). In addition profound classification algorithms such as Linear Discriminant Analysis, Quadratic Discriminant Analysis, K Nearest neighbours, Complex Decision Tree [ ] and Feed Forward Neural network are employed to segregate normal inputs from those corresponding to anxiety. Here the datasets are taken from MIT-BIH Arrhythmia database through Physionet ATM and yet other databases.

III. ANALYSIS OF EEG

EEG signals taken from various databases are employed as inputs for anxiety quantification. For each dataset, the whole band EEG signal is taken and is split into its sub bands namely Delta (0-3.5 Hz), Theta (4-7Hz), Alpha (8-13 Hz), Beta (14-30 Hz), Gamma (30-80 Hz). After this the region of occurrence of maxima in amplitude is estimated. For this evaluation the region of peak occurrence and emotions corresponding to them are obtained from several literature referred, from which, it was inferred that the Gamma band becomes insignificant when it comes to anxiety. The input whole band EEG, its sub bands in time domain, its sub bands showing amplitude peaks in frequency domain are shown in figures below.

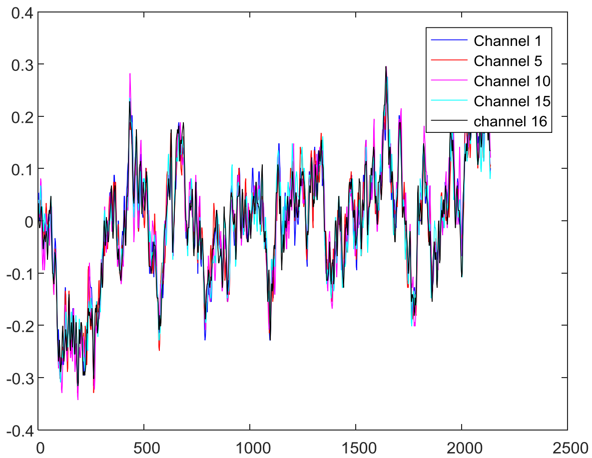

Fig. 1: Whole band EEG

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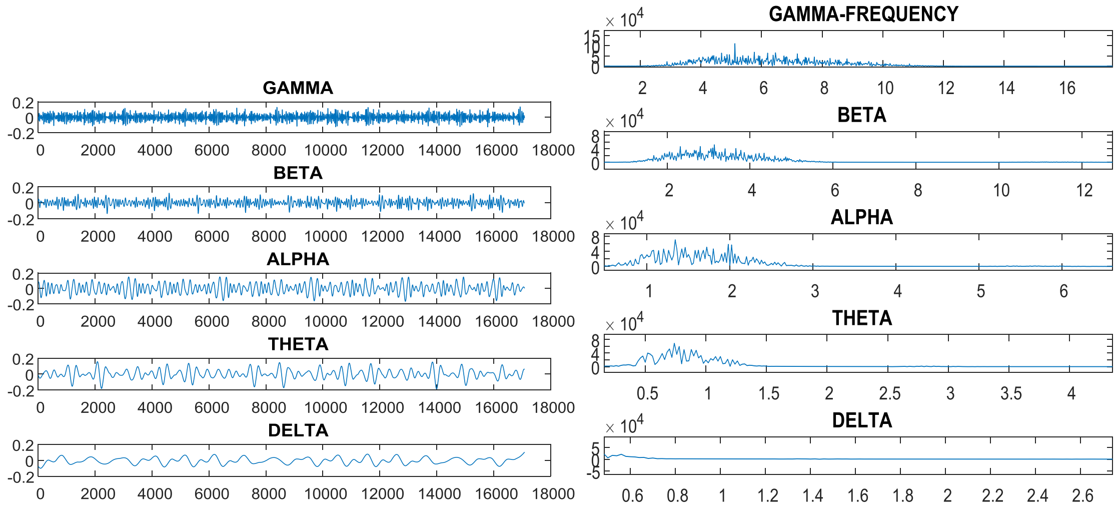

Fig. 2: (a) Time domain sub bands (anxiety); (b) Graph showing Amplitude peaks (anxiety)

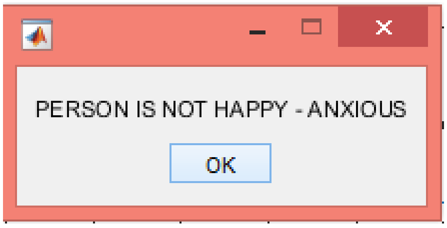

Fig. 3: Message box displaying current emotional state of individual analysed (anxious)

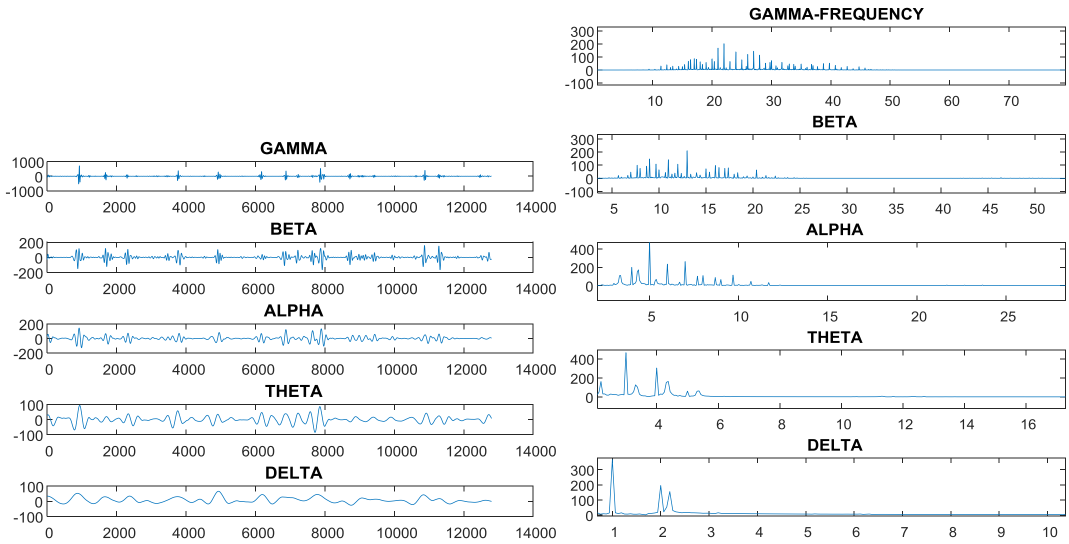

Fig. 4: (a) Time domain sub bands (non anxious); (b) Graph showing peaks (non anxious)

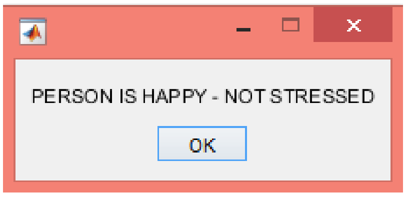

Fig.6: Message box displaying current emotional state of individual analysed (non anxious)

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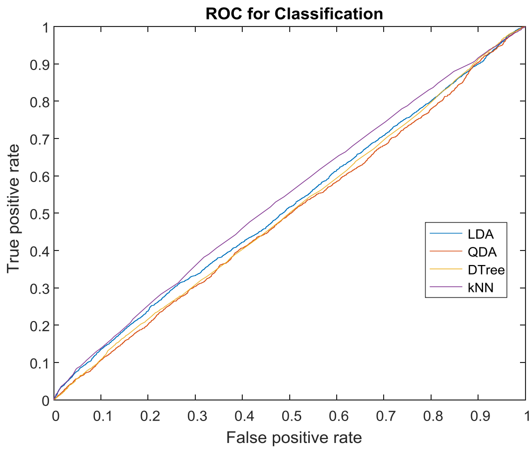

Fig.7: Overall ROC curves

The result of anxiety detection is given by the message box. The above figures corresponds to dataset belonging to a person with anxiety. The following figures shows signals representing normal individual. The above figure shows ROC curves of four classifiers Linear Discriminant Analysis, Quadratic Discriminant Analysis, Complex Decision Tree and K Nearest Neighbours.

IV. PERUSAL OF HEART RATE

The next part of the work describes quantification of anxiety through analysis of heart rate. As no real time data acquisition through relevant hardware circuits is done in this work, we need to extract heart rate from ECG signals taken from MIT BIH databases. The Pan Tompkin's Algorithm is employed for extraction of Heart Rate from ECG.

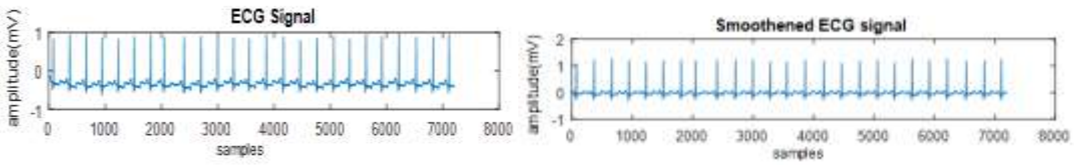

Fig.8: (a) Raw ECG signal; (b) Smoothened ECG signal

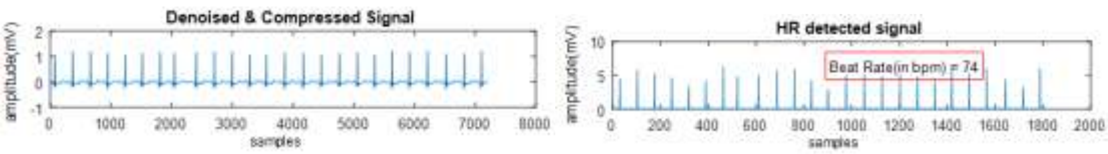

Fig.9: (a) Noise free ECG signal; (b) Heart Rate computed

The various approaches available in the literature to arrive at HR from ECG are spectral analysis, short term autocorrelation method and wavelet based approach. Here in this work the later is employed where Daubechies Wavelet is the Discrete Wavelet Transform (DWT) technique employed with dB4 as mother wavelet.

Previous researches referred state that when we are anxious our heart begins to pace and the heart beat raises by 20 beats per minute more than when calm. Therefore the widely accepted threshold prescribed by physicians and cardiologists are considered for this work as well ie., 60 to 100 bpm is interpreted as normal and beyond this as pertaining to anxiety.

V. EXAMINATION OF ECG

ECTROCARDIOGRAM (ECG or EKG) is a diagnostic tool that measure and records the Electrical activity of the heart in exquisite detail. The first phase includes the acquisition of real time ECG data. In the next phase pre-processing is done. Thirdly, the procured ECG signal is subjected to feature extraction. The extracted features detect abnormal peaks present in the waveform Thus the normal and abnormal ECG signal could be differentiated based on the features extracted. The work is implemented in the most familiar multipurpose tool, MATLAB. This software efficiently uses algorithms and techniques for detection of any abnormalities present in the ECG signal. Proper utilization of MATLAB functions (both built-in and user defined) can lead us to work with ECG signals for processing and analysis in real time applications.

A normal ECG consists of a P wave, a QRS complex, and a T wave. The P wave is caused by electric currents produced by the depolarization of the atria before their contraction, while the QRS complex is caused by electric currents produced by the depolarization of the ventricles prior to their contraction, during the extending of the depolarization in the ventricular myocardium. The QRS complex usually consists of three different waves, the Q, R, and S waves. Note that both the P wave, and the waves that form the QRS complex, are depolarization waves. The T wave is caused by the electric currents produced during recovery of the ventricles from the state of depolarization. This process is takes place in the ventricular myocardium 0.25s to 0.35s after the depolarization. The T wave is characterized as the wave of repolarization. Of which most of our pre processing procedures will aim at distinguishing the QRS complexes alone.

5.1Signal Acquisition

Input ECG signals were taken from MIT-BIH Physionet Arrhythmia database. Totally 41 ECG records that were used to train the neural network, of which 22 correspond to normal records and 19 correspond to abnormal records. This categorization was done with the help of expert cardiologists. The records are digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. Those records are fed to the denoising block to start the processing of the acquired ECG signals.

5.2Signal Pre Processing

Digital signal processing and data analysis are very often used methods in a biomedical engineering research. In this work, the descriptions of a detection algorithm for ECG characteristic points is enclosed. The detection algorithm presented in this work is based on Pan and Tompkins' algorithm for signal de-noising and detection of QRS complexes. At first efficiently designed filters focus on removing supply network 50 Hz frequency and baseline drift due to breathing. A special digital bandpass filter reduces false detection caused by the various types of interference present in ECG signals. The next process after filtering is differentiation followed by squaring, and then integration. The integrated signal is detected by thresholding for QRS complex. P wave and T wave detection are performed by using detected QRS complexes. MATLAB program is developed for the

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characteristic points' detection. The algorithm for peak detection case is modified and it is applied to show ECG characteristic points. Finally, P wave and T wave detection are performed by using detected QRS complexes.

5.3Pan Tompkin's Algorithm

It recognizes QRS complexes based on analysis of the slope, amplitude, and width. In order to attenuate noise, the signal is passed through a bandpass filter composed of cascaded high-pass and low-pass integer filters. Subsequent processes are differentiation, squaring, and time averaging of the signal. The various levels of pre processing done using the Pan Tompkin's Algorithm is mentioned below;

- DC drift cancellation & normalization
- Low pass filtering
- High pass filtering
- Differentiator
- Squaring
- Averaging
- Integration

5.4Dc Drift Cancellation And Normalization:

The DC drift cancellation algorithm reduces noise in the ECG signal by matching the spectrum of the average QRS complex. This attenuates noise due to muscle noise, power line interference, baseline wander, T wave interference. Baseline wandering noise can mask some important features of the ECG signal; hence it is desirable to remove this noise for proper analysis of the ECG signal. The simplest method of baseline wander (drift) removal is the use of a high-pass filter that blocks the drift and passes all main components of ECG though the filter.

The main components of ECG include the P-wave, QRS-complex, and T wave. Specifically, the PR-Segment, ST-Segment, PR-Interval, and QT-Interval are considered as the main segments of the ECG. Each of these intervals/segments has its corresponding frequency components, and according to the American Health Association (AHA), the lowest frequency component in the ECG signal is at about 0.05Hz. However, a complete baseline removal requires that the cut-off frequency of the high-pass filter be set higher than the lowest frequency in the ECG; otherwise some of the baseline drift will pass through the filter. The frequency of the baseline wander high-pass filter is usually set slightly below 0.5Hz.Therefore, knowing that the actual ECG signal has components between 0.05Hz and 0.5Hz, the afore mentioned simple approach for baseline.

The below figure shows the ECG signal with baseline drift, and the following figure shows baseline wander normalized signal.

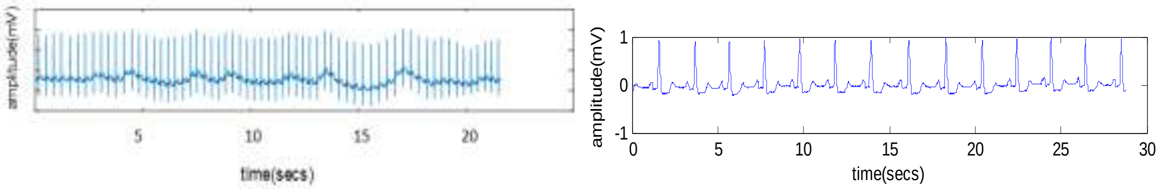

Fig.10: (a) ECG signal with Baseline drift; (b) Baseline wander removed ECG signal

VI. BAND PASS FILTER IMPLEMENTATION

A bandpass filter is designed from a special class of digital filters that require only integer coefficients. Since it was not possible to directly design the desired bandpass filter with this special approach, the design actually consists of cascaded low-pass and high-pass filter sections. This filter isolates the predominant QRS energy centered at 10 Hz, attenuates the low frequencies characteristic of P and T waves and baseline drift, and also attenuates the higher frequencies associated with electromyographic noise and power line interference.

The transfer function of the second-order low-pass filter is given below. The cutoff frequency is about 9 Hz, the delay is five samples or 25 ms.

H(Z) = [(1-Z^-6)^2]/[(1-Z^-1)^2]

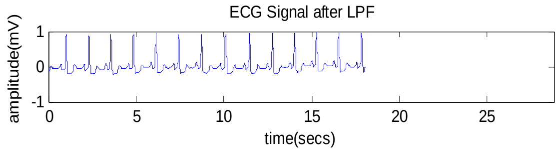

Fig.11: Low pass filtered signal

The high-pass filter is implemented by subtracting a first order low-pass filter from an all-pass filter with delay. The transfer function of the resultant high pass filter is given below. This filter has a delay of 15.5 samples ie; 77.5 ms.

H(Z) = (Z^-16)-[(1-Z^-32)/(1-Z^-1)]

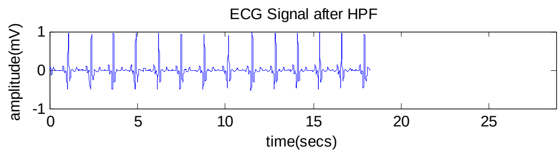

Fig.12: High pass filtered signal

First, in order to attenuate noise, the signal passes through a bandpass filter composed of cascaded high-pass and low-pass filters. Fig.15 shows the ECG signal after processing with the low-pass filter. The most noticeable result is the attenuation of the higher frequency QRS complex. Any 50-Hz noise or muscle noise present would have also been significantly attenuated. Fig. 6.4 is the resultant signal after the ECG signal passes through the high pass filter. Note the attenuation of the T wave due to the high-pass filter. According to the results, the low frequency portions of Fig.10 by using highpass filter.

6.1Derivative Filtering

The next processing step is differentiation, a standard technique for finding the high slopes that normally distinguish the QRS complexes from other ECG waves. This derivative approximates the ideal derivative in the dc through 30-Hz frequency range. The derivative has a filter delay of 10 ms. Fig 6.5 shown below is the resultant signal after passing through the cascade of filters including the differentiator. Note that P and T waves are further attenuated while the peak-to-peak signal corresponding to the QRS complex is further enhanced.

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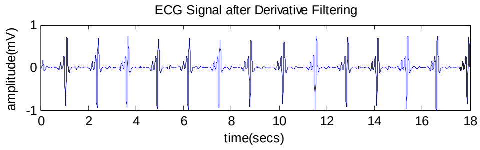


Fig.13: Differentiated ECG signal

6.2 Squaring:

To this point in the algorithm, all the processes are accomplished by linear digital filters. Next is a nonlinear transformation that consists of point-by-point squaring of the signal samples. This transformation serves to make all the data positive prior to subsequent integration, and also accentuates the higher frequencies in the signal obtained from the differentiation process. Thus this operation makes all data points in the processed signal positive, and it amplifies the output of the derivative process nonlinearly. It emphasizes the higher frequencies in the signal, which are mainly due to the QRS complex.

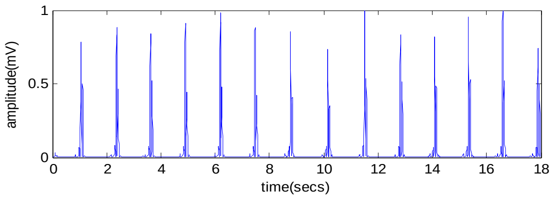


Fig.14: Squared ECG signal

6.3 Averaging:

Signal averaging is done inorder to remove interference and reveal small variations in the QRS complex also called the *late potentials*. Late potentials are thought to be caused by early after depolarisations of cells in the right ventricle. Their amplitude is often too small to show up on a normal ECG. However, when multiple QRS recordings are averaged, random noise is filtered out and late potentials can show up. Such a recording is called a Signal Averaged ECG (SAECG).

Late potentials imply that the substrate for re entry is present, and then be precipitated by such triggers as premature ventricular beats, myocardial ischemia (lack of oxygen), electrolyte imbalance (like low potassium), or autonomic nervous system instability.

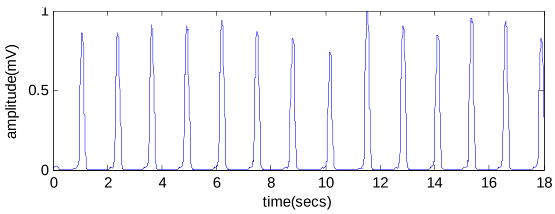


Fig.15: Averaged ECG removing late potentials

VII. INTEGRATION

The squared waveform passes through a moving window integrator. This integrator sums the area under the squared waveform over a suitable interval, advances one sample interval, and integrates the new predefined interval window. Fig. 6.8 shows the output of the moving window integral for the sample ECG signal. The slope of the R wave alone is not a guaranteed way to detect a QRS event. Many abnormal QRS complexes that have large amplitudes and long durations (not very steep slopes) might not be detected using information about slope of the R wave only. Thus, we need to extract more information from the signal to detect a QRS event. Moving window integration extracts features in addition to the slope of the R wave.

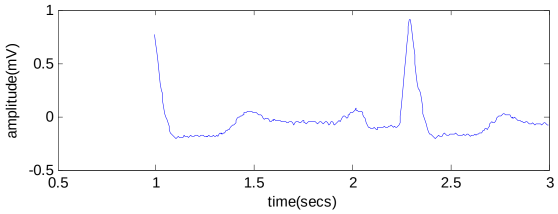


Fig.16: Integrated ECG signal

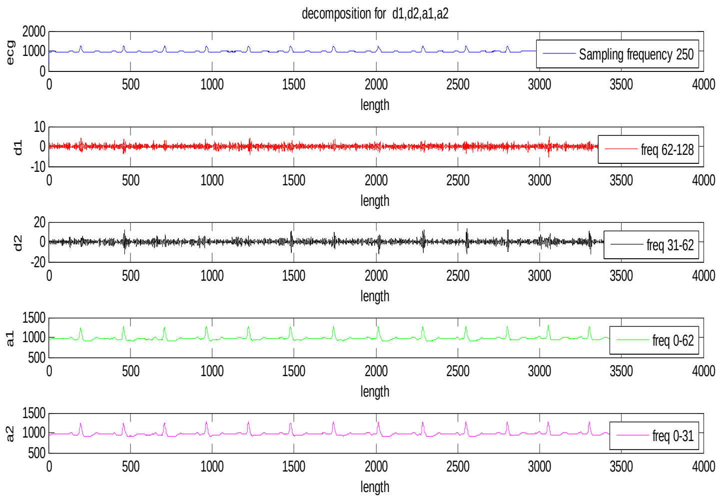
7.1Feature Extraction

A wide range of heart condition is determined by thorough examination of the features of the ECG report. Automatic extraction of time plane features is important for identification of vital cardiac diseases. The wavelet transform describes a multi-resolution decomposition process in terms of expansion of a signal onto a set of wavelet basis functions. Discrete Wavelet Transformation has its own excellent space frequency localization property. Application of DWT in 1D signal corresponds to 1D filter in each dimension.

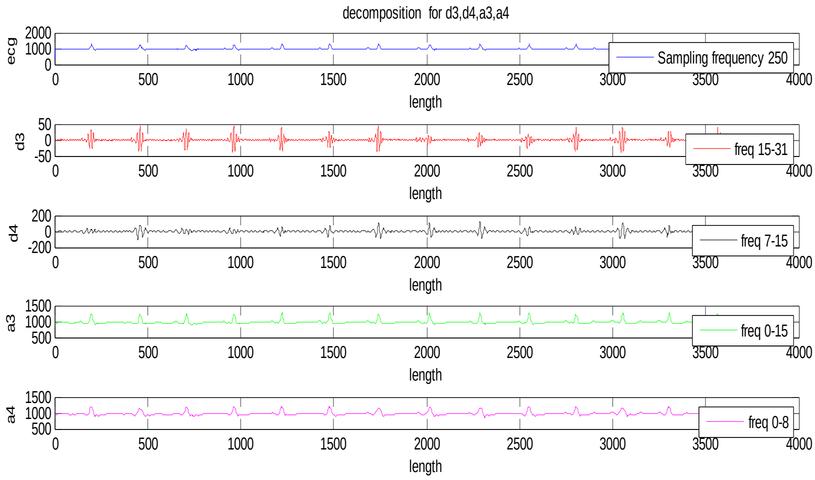
A wavelet is a small wave-like oscillation with an amplitude that begins at zero, increases and then decreases back to zero. The wavelet transform is based on a set of analysis wavelet allowing the decomposition of ECG signal in a set coefficient. Each analysis wavelet has its own time duration, time location and frequency band. The wavelet coefficient resulting from the wavelet transform corresponds to a measurement of the ECG components in the time requirements and frequency band.

VIII. DAUBECHIES WAVELET TRANSFORM:

The below figures shows the features extracted from the input ECG signal using Daubechies wavelet transform. The input Daubechies Wavelet as mother wavelet is divided into 8 non-overlapping multi-resolution sub-bands by the filters, namely db1, db2, db3up to db8, where db is acronym for Daubechies.



(a)



(b)

Fig.17: (a), (b) Decomposition of ECG into approximate and detailed coefficients using db6 mother wavelet

Symlet Wavelet Transform:

The process of distinguishing the pertinent signal characteristics from extraneous content and representing them in a compact and/or meaningful form, amenable to interpretation by human/machine.

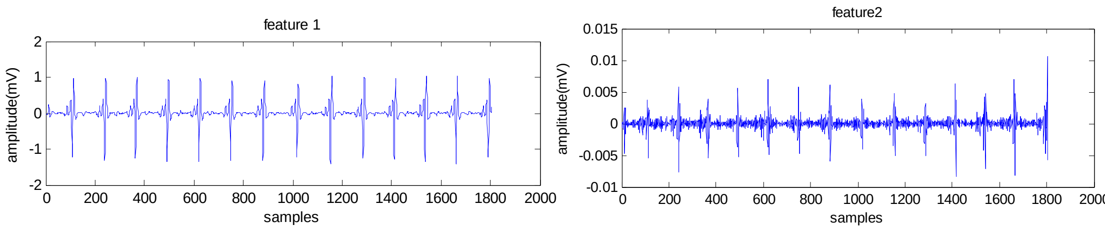


Fig.18: (a) Low frequency feature of sym4 wavelet; (b) High frequency feature of sym4 wavelet

SymN (sym4) wavelets are known as Daubechies' least asymmetric wavelets. They are more symmetric than the external phase wavelets. Thus they are an improvised version of daubechies wavelets on account of their increased symmetry.

Classification Using Artificial Neural Network:

An artificial neuron network (ANN) is a computational model based on the structure and functions of biological neural networks. ANNs are considered nonlinear statistical data modeling tools where the complex relationships between inputs and outputs are modeled or patterns are found. ANN is also known as a neural network. ANNs have three layers that are interconnected. The first layer consists of input neurons. Those neurons send data on to the second layer, which in turn sends the output neurons to the third layer.

Feed Forward Neural Network:

A Feedforward Neural network is a biologically inspired classification algorithm. It comprises of a number of simple neurons, organized in layers. It consists of an input layer, hidden layers and output layer. Any layer that is not an output layer is called a hidden layer. Every unit in a layer is connected with all the units in the previous layer. These connections are said to have different weights, which explains the knowledge of the network. Each unit in the network is called a node. The different phases involved in the functioning of neural network classifier are;

1. Learning phase
2. Classification phase

Feed-forward neural networks are used to learn the relationship between independent variables, which serve as inputs to the network, and dependent variables that are designated as outputs of the network. Learning takes place when a set of 'training set' samples for which the spectra and the class labels are known is presented to the network and network weights are adjusted to minimize the differences between the network outputs and the known 'true' outputs. Once the weights have been adjusted using the samples in the training set, the network can be used to predict the class membership of unknown samples from their spectra.

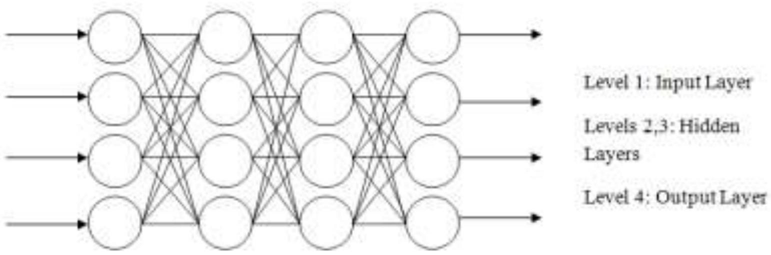


Fig.19: Model of Feed forward neural network

Training Window:

The training window and the schematic of neural network is shown below. Specialized versions of the feedforward network include fitting (fitnet) and pattern recognition (patternnet) networks of which the fitting network is chosen in this work.

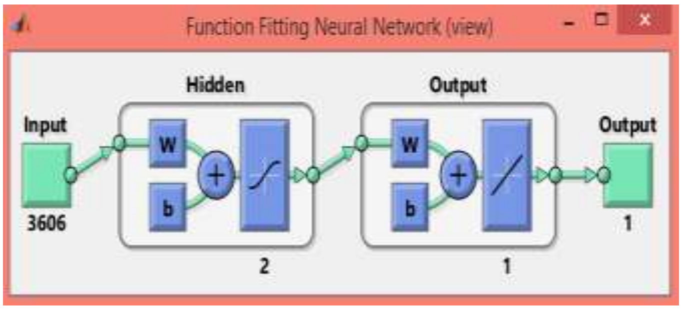


Fig.20: Schematic of NN

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Fig.21: NN Training tool window

i. ***Analysis Of Classifier Performance***

From the training window, the following four plots can be accessed:

1. performance
2. training state
3. error histogram
4. Regression

IX. PERFORMANCE PLOT

The performance plot shows the value of the performance function versus the iteration number. It plots training, validation, and test performances.

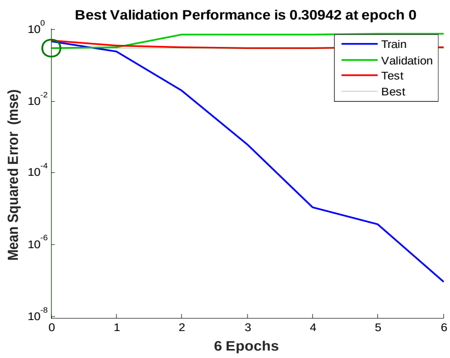

Fig.27: Performance plot

In the above graph the blue line denotes the training phase. A well trained neural network should have very low Mean Square Error (MSE) at the end of the training phase as shown in the graph above. The performance plot and the training state plot shows the MSE dynamics for all datasets in logarithmic scale. The validation plot has reached its minimum during the zeroth epoch and after which the training has proceeded for six more iterations. Although the validation and test curves are similar always, the test curve did not increase beyond validation curve, this denotes that no over fitting has occurred.

TRAINING STATE PLOT:

The training state plot shows the progress of other training variables, such as the gradient magnitude, the number of validation checks, etc.

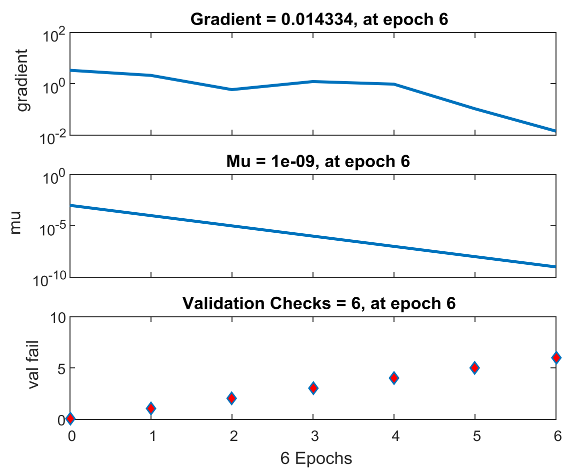

Fig.22: Training state plot

It comprises of three sub plots namely;

1. Validation Gradient coefficient value vs number of epochs: this gives the manner in which the training progresses. Minimum the value of gradient coefficient, better will be the training and testing of network
2. Learning rate (mu) vs epochs: it gives the rate at which the network error decreases as training progresses
3. Validation fail vs epochs: gives the iterations when the validation MSE reaches increased value

ERROR HISTOGRAM:

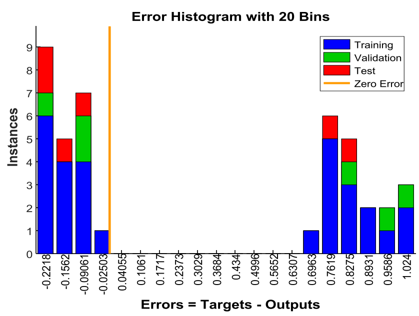

Fig.23: Error histogram

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The error histogram plots the instances vs the errors for stipulated number of bins, where bin is the number of class intervals.

REGRESSION PLOT:

This plot gives the relation between output of network and target. For the training to be perfect, the network outputs and targets must be equal.

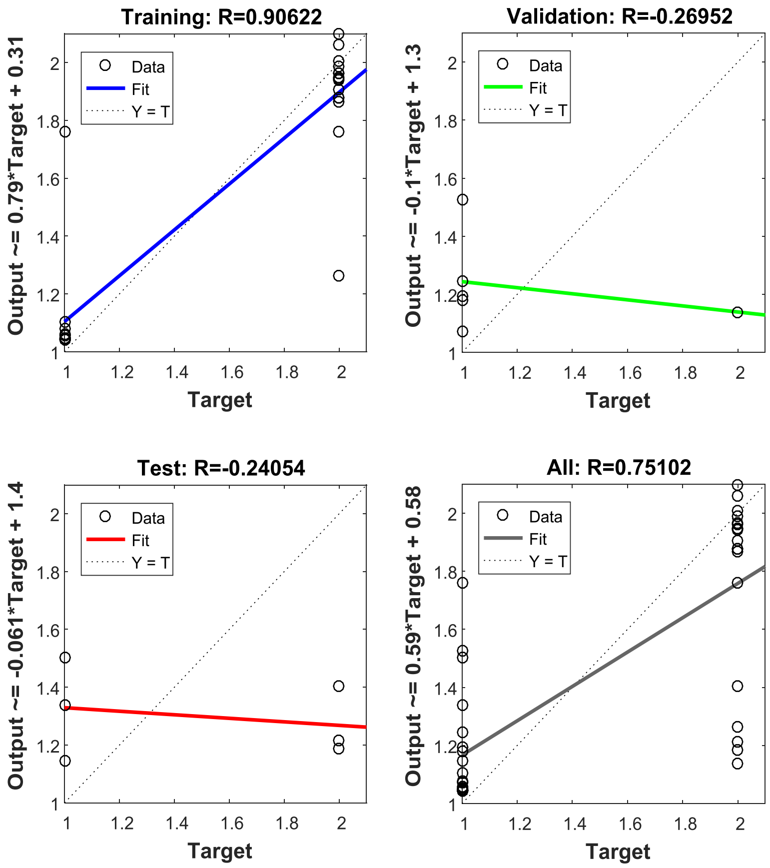

Fig.30: Regression Plot

X. CONCLUSION

Depression & Anxiety are as serious a risk to health as that of smoking in people with heart diseases. The ways in which the body reacts to anxiety is liable to imbibe an extra strain to the heart *(tachycardia, increased BP & low pulse rate)*, which may lead to sudden heart failure. Heart attack survivors are monitored with 24 hrs holter for ECG and BP. It is a wearable device that is used for post cardiac cath monitoring and analysis of adaptability of the patient's health towards the pills prescribed and medication given. Upon analysis of these records with regard to anxiety quantification, if the results prove that traces of abnormality in the waves are encountered many times during the holter period, it evidently indicates that the person is entering into or experiencing Post Traumatic Stress Syndrome which will further worsen the condition and lead to further complication. Therefore these signals are made use of to assess anxiety. In order to add to precision we have taken EEG also into account.

REFERENCES

[1]. G. Giannakakis, M.Pediaditis, D.Manousos, E.Kazantzaki, F.Chiarugi, P.G. Simos, K.Marias and M.Tsiknakis, "Stress and anxiety detection using facial cues from videos", Elsevier Journal of Biomedical Signal Processing and Control, vol. 31, pp.89–101, July 2017

[2]. Athira M S, Sindhu N, Jerritta S, "Human Stress Detection using ECG and HRV Signals", International Journal of Engineering, Technology, Management and Applied Sciences, vol. 5, no. 5, pp. 470-475, May 2017

[3]. Yali Zheng, Tracy C. H. Wong, Billy H. K. Leung, and Carmen C. Y. Poon, "Unobtrusive and Multimodal Wearable Sensing to Quantify Anxiety", IEEE Sensors Journal, vol. 16, no. 10, pp.3689-3696, May 15, 2016

[4]. Mohamed G. Egila, Magdy A. El-Moursy, Adel E. El-Hennawy, Hamed A. El-Simarya, Amal Zakia, "FPGA-based electrocardiography (ECG) signal analysis systemusing least-square linear phase finite impulse response (FIR) filter", Elsevier Journal of Electrical Systems and Information Technology, vol. 3, pp.513–526, April 2016.

[5]. Chetan Umale, Amit Vaidya, Shubham Shirude, Akshay Raut, "Feature Extraction Techniques and Classification Algorithms for EEG Signals to detect Human Stress – A Review", International Journal of Computer Applications Technology and Research, vol. 5– Issue 1,pp. 08 - 14, January 2016

[6]. Ane Alberdi, Asier Aztiria, Adrian Basarab, "Towards an Automatic Early Stress Recognition System for Office Environments based on Multimodal Measurements – A Review", Elsevier Journal of Biomedical Informatics, vol.59, pp. 49-75, November 2015

[7]. Rashmi G, Mr. Chethan Balaji, Rashmi C R, "Human Emotion Classification from EEG using SVM and K-NN Classifier For BCI", International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE) vol.4, Issue 7,pp.1927-1930, July 2015

[8]. Sonal Pokharkar, Amit Kulkarni, "ECG Real Time Feature Extraction using MATLAB", International Journal of Technology and Science, vol. 5, no.1, pp. 1-4, May 2015

[9]. Mohd Norzali Haji Mohd, Masayuki Kashima, Kiminori Sato and Mutsumi Watanabe, "Mental Stress recognition based on Non-invasive and Non-contact Measurement from Stereo Thermal and Visible Sensors", International Journal of Affective Engineering,vol.14, no.1, pp.9-17, January 2015