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A Study On Ventricular Fibrillation And Ventricular Tachyarrythmia Classification Methods Using Continuous Wavelet Transform

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A STUDY ON VENTRICULAR FIBRILLATION AND VENTRICULAR TACHYARRHYTHMIA CLASSIFICATION METHODS USING CONTINUOUS WAVELET TRANSFORM

By

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AUTHOR'S DECLARATION

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ABSTRACT

A STUDY ON VENTRICULAR FIBRILLATION AND VENTRICULAT TACHYARRHYTHMIA CLASSIFICATION METHODS USING CONTINUOUS WAVELET TRANSFORM

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Ventricular Tachycardia (VT) and Ventricular Fibrillation (VF) are fatal cardiac diseases associated with cardiac arrest. It is difficult to manually classify VT and VF signals. However, precise classification of VT and VF signals can assist cardiologists to identify and ultimately prevent onset of VF or VT. In this thesis, some of the underlying features which characterize VF and VT are extracted and are used to efficiently classifying these signals. The features are acquired from energy coefficients matrices using Continuous Wavelet Transform (CWT) through application of Principal Component Analysis (PCA). The features are the vector containing newly generated energy projection coefficients and the vector containing the number of the top 99% principal components (Eigen-Values) for each case. Feature vectors are then passed through Fast Forward Neural Network (FFNN) and Leave One Out Method (LOOM) classifiers for discrimination. The results are then compared for the highest classification results for VF and VT signals.

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Words cannot express my gratitude and appreciation towards all my friends at Ryerson University during my graduate years for walking me through this journey.

Most importantly, I would like to express my deepest and warmest gratitude to my father, Moharram, and to my mother, Farzaneh Shodja for their never ending love, encouragements, and endurance. If I ever achieved anything in my life is because you are in my life.

Last but not least, thanks to my handsome brothers, Amin and Soheil, for always being there for me, and for making my journey fun and unforgettable. I love you from the bottom of my heart.

Dedicated:

To my angel friend: my mother and to my hero: my father.

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Chapter 1

Introduction

1.1 Ventricular Tachyarrhythmia and its Characteristics

(VT/VF) Ventricular Tachyarrhythmia is ventricle related diseases caused by higher frequency heart rates. There are three main categories of VT; Ventricular Tachycardia (VT), Ventricular Flutter (VFl) and Ventricular Fibrillation (VF). The origin of all the categories is in ventricles.

- In normal heart beat, after blood is transferred from atrium to ventricles, there is a delay of 10th of a second for the Atrio-Ventricular (AV) to polarize and contract the ventricle muscles in order to push blood out of heart. However, when heart is undergoing VT, AV-Node changes its position from Atrium-Ventricle boundary to some random location on the lower section of the ventricle. The new node sends signals faster than normal which causes the ventricles to contract very fast. VT is usually evaluated to be three or more beats at a rate of 100 [beats/min] [2]. The QRS interval is narrowed but is mostly rhythmic. Episodes lasting at least 30 (s) are called sustained and otherwise non-sustained. Sustained VT can be terminated using anti-tachycardia pacing techniques.

- VFl refers to beats of 250-350 [beat/min] frequencies which result in low blood delivery to body parts and ultimately unconsciousness. The VFl signal looks like sinusoidal signal.

- Ventricular Tachyarrhythmia (VF) is a form of cardiac malfunctioning which is number one cause of cardiac arrest. The heart frequency is very high and close to 350-450 [beats/min]. VF is mostly followed by VT and if untreated within minutes of its occurrence leads to sudden cardiac arrest in approximately 75% to 85% of cases [3]. In Toronto, it approximately takes an average of 5-10 minutes for the Emergency Staff

(EMS) to arrive by the patient's side. If during this time, the patient receives Cardio Pulmonary Resuscitation (CPR) after occurrence of VF, his/her chances of survival increases dramatically [4]. In addition since circulation is sustained through CPR, the amount of damage to vital organs such as brain and heart itself also can be decreases substantially. As of today, Defibrillation or the electric shocks, is the only choice of treatment to restore the heart's normal rhythm especially in out-of-the-hospital VF incidents. In fact, one of the challenges the EMS face is to be able to determine when the heart is ready to receive Defibrillation and when to cut off CPR or minister anti-arrhythmic drugs [3]. One way of knowing the best time to apply shock is to determine the level of High-Energy Phosphate (HEP). There should be enough HEP stored in the myocardial so that contractions can happen. Therefore, the best timing would be right before the level of HEP is reduced due to global ischemia [2].

One of the works done in this area has an application in optimizing the defibrillation for cardiac resuscitation [1]. The authors present a wavelet-based feature, Scale Distribution Width (SDW), in order to predict the output of defibrillation for out of hospital patients undergoing cardiac arrest. The feature can be incorporated in the devices used by the EMS that are at the scene by the patient's side and can be used to provide real-time feedback as to determine whether the shock outcome will be successful or unsuccessful. The information can be used to decide the optimal treatment for the patient. The application also can be used for diagnosis purposes.

Heart rate prediction techniques are also used in diagnosis as well as prevention for treatment of VF and VT. As an example the application in stress-test procedures can be mentioned; where HR prediction can be used as a sensing system to indicate possible abnormal HR behavior related to probable incidents of VT or VF.

1.2 Why VT/VF Prediction Matter

There are many applications to VF/VT prediction, classification, and characterization. As mentioned earlier, defibrillation is the only choice of treatment especially for out-of-the hospital VF incidents, in restoring the heart to normal rhythm. During the process of resuscitation it would be of immense help if the EMS personnel could have a real-time feedback on the electrical state of the heart so that they could choose the right combination of therapies before applying the shock [3]. From a practical point of view -at least for the time being- the applications of VF analysis could be listed as follows:

- Almost always VT is followed by VF incidents which is highly fatal due to lack of blood delivery to the important organs such as brain. Therefore if occurrence of VT is detected, subsequence VF occurrence may be predicted and ultimately prevented [2].

- Defibrillation output prediction based on information available on heart's physical status before applying shock. There are several researches conducted in predicting the success of defibrillation outcome. Of the most successful ones we can mention Brown and Dzwonczyk [5] (1996), Sherman et al. [6] (2008), Jagric et al. [7] (2007), Watson et al. [8] (2005) and many others.

- Monitoring the CPR Performance by invasive real-time and online observation on the physiological activities of cardiac muscle and overall changes in surface ECG signals during CPR (i.e. such real-time feedback may be used to measure heart's state as to determining its readiness to receive shock). The success of defibrillation and application of CPR are directly proportional according to Baker et al. [9] (2008).

- The CPR process can be monitored and its effectiveness can be measured through real-time feedback of surface ECG signals. An example is the CPR gloves designed in 2007. The gloves are worn by whoever is performing CPR and the effectiveness of their performance (i.e. number of compression per minute and the amount of pressure applied) may be determined during the whole procedure.

Characterizing VF and VT signals and developing a practical classification system to discriminate VF and VT signals from one another is the first step in predicting incidents of VF or VT before serious damage is done to vital organs; in order to carry out successful signal prediction, the signal characteristics must be known. Ventricular arrhythmia has been the subject of study for decades now. The motivation in attempting to characterize these signals covers a wide range of application from understanding the origin of VF and VT for diagnosis purposes to treatment and rehabilitation options. In the next section some of the signal-processing approaches attempted in the last decade in understanding aforementioned signals are summarized.

1.3 Thesis Contribution

The objective of this thesis is to investigate underlying characteristics of VT and VF surface ECG signals which can assist cardiologist in efficiently classify these signals. In particular VT and VF signals are studied closely through CWT decomposition techniques. For the purpose of this project the energy of the VT and VF signals are targeted. The choice is due to the fact that the features which are derivatives of energy can also explain physiological behaviour of the cardiac muscles. The motivation in performing PCA is to both to reduce the complexity of the data or feature vectors and also to obtain a feature vector as the project of the energy components to new coordinates. It was found that the number of the Principal Components needed to describe VT and VF signals are different. It takes more components to characterize VF signals than VT signals. This is due to the fact that the VT signals are more organized that VF signals and therefore it takes less. Lastly, the performance of the two features along with SDW [1] is determined by passing the feature vectors though FFNN for classification results.

1.4 Thesis Organization

In chapter 2 a brief survey of the previous studies on characterizing VF and VT signals is presented. Chapter 3 explains the theory on which this thesis is based on. The feature vectors are

described in chapter 4 followed by the classification methods in chapter 5. The results are summarized in chapter 6 and a conclusion is made in chapter 7.

Chapter 2

Literature Survey

2.1 VF-VT Classification and Prediction Techniques

There are set of codes and international regulations when dealing with cardiac related diseases. For example the EMS staff must follow certain rules when treating patients undergoing cardiac arrest caused by onset of VF. Most of such regulations are merely based on experimental results; however, the need for tested algorithms developed by studying the surface ECG signals leading to cardiac arrest is becoming evident. Having real-time and non-invasive feedback on VF or VT signals will provide EMS staff with reliable information on which they can make a practical decision on choosing from the available treatment options.

Many of the recent studies involving VF signals are directed towards predicting and optimizing the output of the defibrillation. As a developed convention, Fourier transforms are used for signal processing and decomposition since time series analysis is usually very complex and computationally expensive. Frequency domain contains underlying information about such signals. Here, some spectral features used for VF-VT signal prediction/classification is highlighted.

In the recent years, the focus has been directed towards Wavelet-Based signal processing techniques, especially when dealing with bio-signals. Practice confirms that Wavelet Transform (WT) approaches are suitable for analyzing VF signals due to their nature being random, noisy, chaotic, and unstructured. For the application of this project, it is known that WT techniques allow the identification of coherent structures in the VT-VF waveform, especially where VF contains high frequency spikes [16, 17]. It is once again stressed that due to its fixed window size, STFT is unable to provide good time resolution for high-frequency signals and vice-versa. I

addition, WT provides time-frequency analysis spontaneously without losing information on either.

In this section, the intension is to provide a collective review of the successful techniques and features used for VF-VT classification and prediction

2.1.1 Spectral Analysis Approach

In trying to establish real-time and online feedback for physicians or EMS, H. Strohmenger et al. [11] studied frequency components of VF signals leading to cardiac arrest. They used FFT to decompose VF signals and extracted feature vectors such as Median Frequency, Dominant Frequency, Spectral Edge Frequency, and Amplitude for successful and unsuccessful counter-shock outputs; where they propose that amplitude is the best discriminate feature between successful and unsuccessful counter-shocks.

Brown et al [5] examined a combination of Centroid Frequency (CF) and Peak Power Frequency (PPF) on VF signals could predict ROSC with good sensitivity measures. Their method was questioned by T. Eftestøl et al [4] due to their small database and their method in determining the specificity and the efficacy of their results since they have chosen the same data-set for both training and test sets. In addition to the CF and PPF features used by Brown et al [1], Eftestøl considered two features: Spectral Flatness Measure (SFM) [12] and Frequency Band–Limited Energy Measurements (ENRG) which are all calculated from Power Spectrum Density (PSD). The features are then de-correlated using PCA [13]. Their method shows that the specificity increased with number of bins and decrease with increased kernel width. They conclude that performing CPR increases spectral flatness measure, centroid frequency, and amplitude spectrum relationship. In addition, they found that the probability of ROSC grows higher if CPR is performed more than 3 minutes.

2.1.2 Wavelet-Based Approach

One of the first groups investigating VF signals using Wavelet Transform are the "Cardio-digital Ltd, 18, Blantyre Terrace, Edinburgh, Scotland" [14] with the application to predict the successful DC counter-shock from surface ECG recorder while patients undergo VF. The authors find a correlation between the Power Spectrum Features obtained from CWT to the Return Of Spontaneous Circulation (ROSC). The Scalogram of the pre-shock VF signals are calculated which are then used to obtain the wavelet-based power spectrum of the signals. In order to determine the power spectrum of the signal, the characteristic frequency of the wavelet is calculated given the scale and central frequency of the wavelet used for decomposition. Some of the features used as marker of the shock outcome include Median Frequency (MF) and Peak Power Frequency (PPF). To classify the VF signals, Probability Density (PD) of feature vector was calculated. To fine-tune and improve the results, Principal Component Analysis (PCA)-which is explained in the methodology section III-is used. This research also implies that classifications based on individual features are best carried out with WT since Fourier based analysis have fixed windows.

One of the recent investigations of VF signals is carried out with the research group from Ryerson University and St.Micheals hospital [1]. Their motivation is to determine the best combination of treatment for out of hospital patients experiencing cardiac arrest followed by series of VF incidents. As mentioned before, real-time feedback and shock outcome prediction provides the EMS with the knowledge to assist them optimize their treatment options. They have extracted features such as Wavelet Energy, and Scale Distribution Width [1] (SDW); which is implemented in the results section.

Investigation on VF signals for the same application as the one described in [1] was later expanded for tree different categories of shock outcome, namely successful, unsuccessful, and Refibrillation-where aftershock up to 10 normal rhythms are observed followed by reoccurrence of VF [3]. In addition to SDW, Central Scale was also examined in this work. These feature vectors are then classified using a Linear Discriminate Analysis (LDA) function where SDW proved to yield more accurate results.

James N. Watsona et al [15], also describe multiple features among which Entropy measures yield the best result in predicting ROSC. The time-frequency components of VF signals are examined using wavelet transform techniques. The feature vectors were then classified using multidimensional histogram and Gaussian kernel smoothing techniques. Two cross validations were performed using ROSC and No-ROSC as training and test sets alternating. The five features are Peak Frequency, Energy, Entropy, and Spectral Flatness. The principal component of the five markers is also applied to create 1D and 2D Probability Density Functions for classification. The result can be seen in Fig.1 where Entropy shows better discrimination between ROSC and no-ROSC.

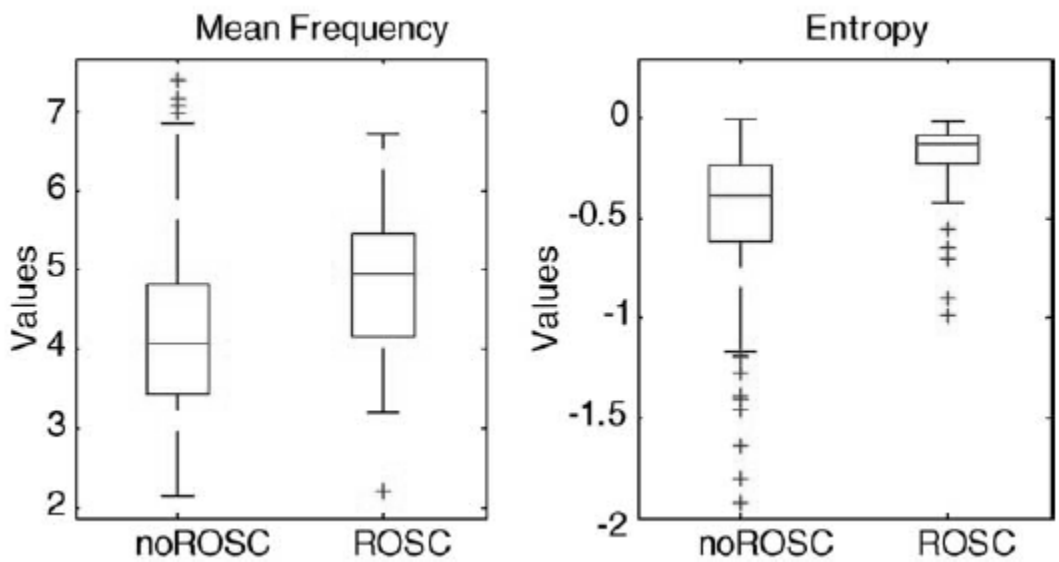

Figure 1. ROSC Prediction Results for MF and Entropy [15]

R.Abbbas and W.Aziz [18] propose a method in their paper to characterize VF signals prior to its onset in order to prevent the patient from going through fibrillation. A combination of Continuous Wavelet Transform techniques and Neural Networks is used in classifying VF, VT and Normal Sinusoidal Rhythm signals (NSR). They argue that almost always VT incidents are followed by VF onset. Therefore if VT signals can be characterized and then classified, then the

onset of VF can be predicted and ultimately prevented. The authors have used three different mother wavelets to generate 2D and 3D wavelet coefficients for VF signals from MIT-BIH PhysioNet [22] database. The coefficients are then used to train a 2layer Generalized Regressive Neural Networks (GRNN) -yielding best results- and a 2layer Linear Vector Quantization Network (LVQN). As soon as a VT period is detected, it is predicted that a VF incident is about to happen and therefore necessary care can be taken by the physicians to prevent it.

Chaotic and nonlinear methods are also promising in detecting and classifying VF/VT signals with high accuracy; such as trajectory analysis, approximation entropy and phase space reconstruction. In 2006, A.Fahoum1 [21] and colleagues employ Reconstructed Phase Space (RPS) and used the results from different form of rhythms as a classifying feature. Their procedure is shown in the flowchart provided below:

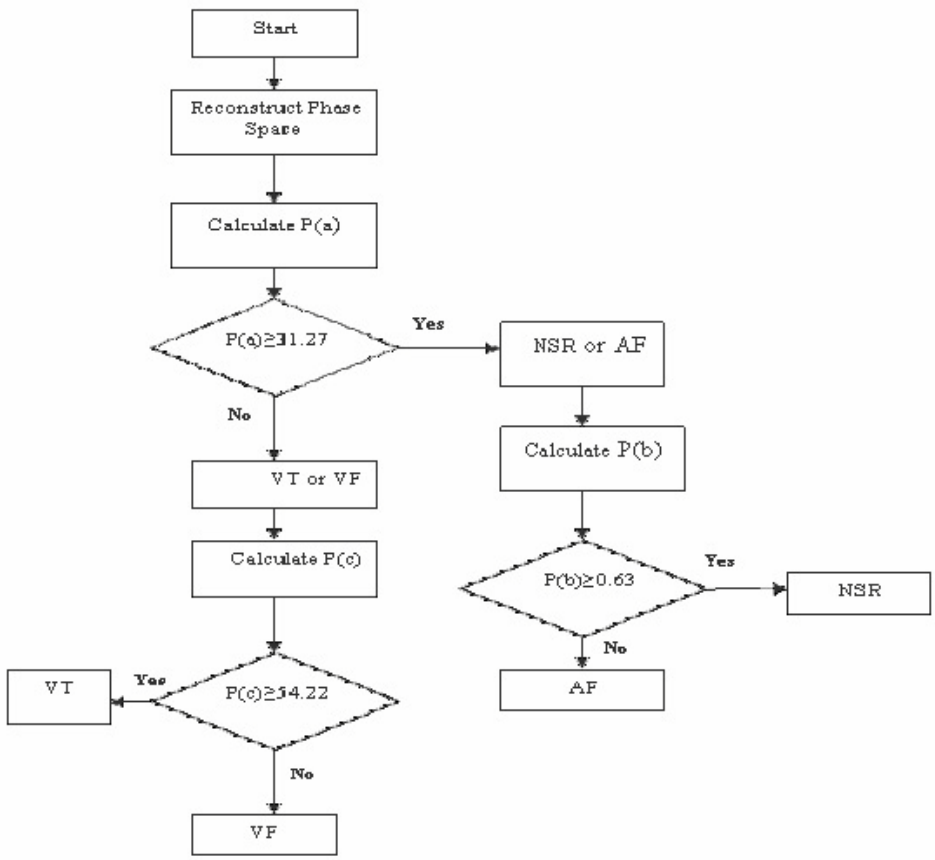

Figure 2. Reconstructed Phase Space Classification Technique [21]

Chapter 3

Theory and Methodology

3.1 Continuous Wavelet Transform

When it comes to signal analysis and signal processing, Fourier Transform (FT) has proved to be effective and widely used for the last 150 years. FT was first developed by Joseph Fourier for periodic signals and then after series of modifications has been used for non-periodic and also discrete time series signals. Although FT provides inclusive information in frequency domain, it has shortcomings in providing compact information in time domain and hence not suitable when dealing with non-stationary signals. The spectral characteristic of non-stationary signals change with time; therefore a time-frequency representation is needed to analyze non-stationary signals and that is when the Short Time Fourier Transform (STFT) was developed. Using STFT the function/signal can be time-localized by segmenting the signal into small windows of interest.

The only shortcoming of STFT and its other modifications was the fact that when a window size is chosen, the entire signal is analyzed using the same window [19]. STFT was able to analyze either high frequency components using narrow windows (wideband frequency analysis), or low frequency components using wide windows (narrowband frequency analysis), but not both [19]. In 1970's, J.Morlet came up with the idea of using different window function to analyze different frequency bands. He generated different windows by dilation and compression of a basis function called mother wavelet. In the last decade, WT has been used widely in different fields of mathematics, physics and engineering. Some of WT application can be summarized in data compression, de-noising, source and channel coding, biomedical

engineering, non-destructive evaluation, numerical solution of PDEs, and Wavelet Networks. Wavelet Transform is a suited tool in studying ECG-VF signal due to non-stationary nature of biomedical signals. WT provides flexibility in extracting morphologically distinct features. Wavelet analysis is also computationally less expensive and can be realized in hardware to provide near real-time feedback. In addition, it provides varying frequency and time resolution incorporating windows of different lengths; the signal is first decomposed to obtain its frequency components and then the time information corresponding to each frequency band is investigated. The method is especially fitting for signals with sharp transitions and slowly varying spectra. For the purpose of this project, Continuous Wavelet Transform (CWT) is used and explained which can be obtained from the following formula:

$$T(a,b) = {}^{1}/_{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\varphi * \left(\frac{t-b}{a}\right); \quad for\ all\ \ a > 0 \qquad [1]$$

The Orthonormal wavelets are used for DWT which requires the dilation levels to be set in the form of octaves or integer powers of two. The advantages of DWT are fast signal decomposition, energy conservation and exact signal reconstruction. The disadvantages include its limitation through loss of frequency resolution due to the incremental doubling of the level associated frequencies. On the other hand, CWT provides high resolution. Thus, proper use of wavelet analysis demands identification of the on correct wavelet and transform type for the given application [14].

3.2 Dimensionality Reduction

3.2.1 Principal Components Analysis (PCA)

PCA is a method of multivariate data analysis in classification problems where the data complexity is considerably reduced using prior knowledge of the data, increasing smoothness of the function and reducing the dimensionality. In general, dimensionality reduction involves discarding a minimum number of data that if incorporated in the analysis, the performance of the classifier would rather degrade than improve. The data discarded results in a lower-dimensionality which reduces the complexity of the computation plus a more accurate mapping n the lower-dimension. In other words, the more complex the target function becomes, the higher the sample density needs to be in order to learn from it efficiently. The classifier performance and the number of dimensionality are related according to the following graph:

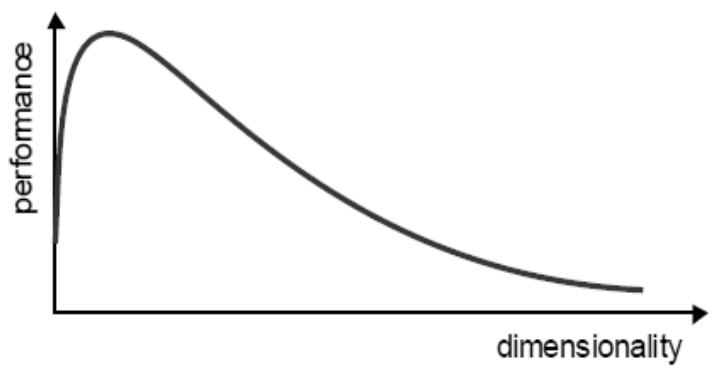

Figure3. PCA Performance graph

If data are represented by X of N-Dimension vector as a linear combination of Orthonormal basis vectors F_n for n=1, 2…N; in mathematical form:

$$X = \sum_{i=1}^{N} k_i \emptyset_i \qquad [2]$$

Then random vector $X \in R^{N,}$ can be approximated by a linear combination of M (M<N) independent vectors which are determined by projecting Vector X onto the eigenvectors F_i; where F_i are corresponding to the largest Eigen-values λ_i of the covariance matrix S_x. PCA does not label data classes but maps the data by rotating coordinate axes in a direction of the maximum. However, this does not mean that the most affective features are aligned in this direction. Dimensionality reduction through PCA can be done in MATLAB by following the following simple steps:

- Calculate the covariance matrix of the data vector; Sx
- Calculate the eigenvector and Eigen-values of the covariance matrix
- Extract the diagonal of the matrix as a vector
- Sort the variances in descending order
- Finally, project the original data onto the sorted vector

3.2.2 Singular Value Decomposition (SVD)

Dimensionality reduction techniques can be done through SVD. The general idea here also is to approximate high-dimensional data set with a lower-dimensional one. SVD can be performed on any matrix A_{nxp}; the Principal states that A can be decomposed into the following matrices:

$$A=UWV^T \qquad [3]$$

Where U_{mxn} and V^T_{nxn} are Orthonormal matrices and W_{nxp} is a diagonal matrix. U and V can be considered as rotating matrices. When matrix A is decomposed as above and through mean elimination whitened, then V_ks columns are principal components and W_is are the weighted importance of each component. SVD can be easily performed in MATLAB using the following syntax: [U, W, V] = SVD (A, 0);

3.3 Data-Base and Pre-processing

The data used for this project are obtained from "Spontaneous Ventricular Tachyarrhythmia Database Version 1.0 from Medtronic, Inc" provided by PhysioNet [20]. As explained in the data collection information from MIT-BIH online directory, the database contains episodes from 78 patients who experienced at least one VT or VF episode. Some patients experience both a VT and a VF episode. The signals are sampled at 250 [Hz/sec]. For this project 4 (s) of each data is used resulting in 1000 sample points. The spontaneous VF, VT time series data may contain several normal rhythm beats as well. For this project the data are studied in Audacity software in order to find the minimum duration of consistent VF before encountering a normal and VT; taking this numbers as references, the data used in this project are extracted for the durations mentioned above where VT and VF are consistent with no interruption or return of normal rhythm. The data are then passed through a band-pass filter of 2-12 [Hz] [3]. After this step the data are ready and CWT is performed to extract features which are described in section IV.

Chapter 4

Feature Extraction

4.1 Dominant and Central Scale

Analogous to dominant frequency and central frequency, dominant Scale and central scale also are the scale at which the most energy of the signal is preserved and the dominant scales of the normalized distribution of the energy for a range of scales [3]. The syntax is available in MATLAB.

4.2 Wavelet Energy

The energy of the signal for each scale using CWT can be obtained from the following formula:

$$E = \left(\frac{1}{C_g}\right) \int_{-\infty}^{\infty} |Tx(a,b)|^2 db \qquad [5]$$

The Energy matrix is obtained for each set of signals for both VF and VT signals. The Energy matrices are then used as feature vectors which are then passed through a FFNN and LOOM classifier. The results are then compared for the two classifier systems. The energy of the signals indirectly can be used as an indicator of the complexity and its composition. If E is the total signal energy and a_1 to a_n are the scales used in the wavelet analysis that could model the signal completely, then it can be written as [1]:

$$E_{sig} = E_{a1} + E_{a2} + \ldots + E_{aN} \quad [6]$$

The energy matrix is then processed for dimensionality reduction with both PCA and SVD methods described below in order to extract another feature.

4.3 Number of Top 90% Energy (NTE-PCA)

After performing PCA on the energy matrix feature, the number of the top 90% of the data contributing to the target function is chosen as a feature which is then used in classification between VF and VT signals.

4.4 Scale Distribution Width (SDW) [1]

Scale Distribution Width (SDW) is the width of the normalized distribution of the energy captured by the scales measured around the dominant scale at half the height of the distribution [3]. The amount of energy captured by each of the scales E (a) depends on the signal characteristics and thus the normalized energy distribution of the scales is representative of the signal content. The width of the distribution indirectly provides us a measure of signal composition, for example the degree of multi or mono component nature of the signal. Due to the inverse relation between scale and frequency, SDW can be seen as a function of frequency and bandwidth of a signal. [3]

The Energy for all scales is normalized over the entire scale domain and then SDW is extracted as a feature. SDW feature vector are then passed through the same classifier systems at which the Energy signals were passed on. The results are then compared with the results

obtained from the energy features. The results of classification for each of the features obtained are then compared for the best results. In addition a comparison will be done to conclude which of the energy distribution techniques is the better indicator of the distribution of the energy of CWT for different scales.

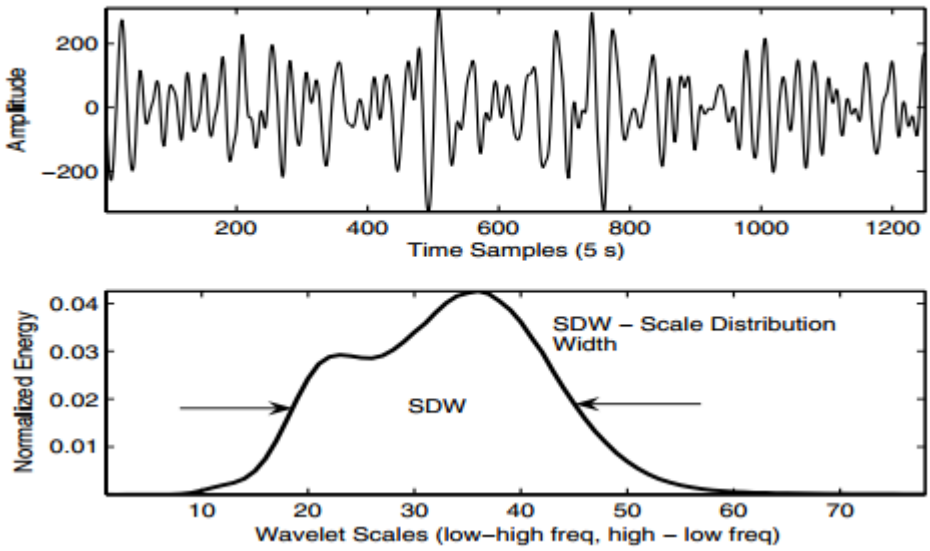

Figure 4. VF Signal and its corresponding Scale Distribution Width plot [1]

SDW is considered an efficient feature not only because it yields good classification results for shock prediction but also because it can be used to explain the physiological behaviour of the cardiac muscle. Given that frequency and scale are inversely proportional, SDW indirectly provides spectral information of VF or VT signals and also a measure of signals composition [2].

Chapter 5

Classification Methods

Signal prediction is a major area in Signal Processing. There are many techniques and models developed for signal prediction. In general, prediction models can be linear such as Auto-Regression Model or non-linear such as Neural Networks, single step or multi-step. Single step prediction models such as two layers NNs pass set of inputs through a hidden layer in the NN which is usually trained with Back Propagation.

5.1 Fast Forward Neural Networks (FFNN)

Artificial Neural Networks (ANNs) are classification and pattern recognition systems whose structures are based on the nervous system in the brain. They are capable of parallel processing large amount of data in short amount of time which has made them very popular. The pattern recognition and classification is performed through training and is not based on memory. Neural Networks can learn through a supervised learning process or an unsupervised process. In supervised learning the system learns from a target function which is used to predict the values of a certain class; where the data to be analyzed are labeled to pre-defined classes. Such network is sometimes referred to as inductive learning. On the other hand, in unsupervised learning the class labels are not defined and the function of the network is to determine if a class or category exists. A simple ANN is consisted of an input layer, an intermediate layer (Hidden Layer) and an

output layer. The hidden layer usually incorporates a thresholding function (i.e. Sigmoid Function) through which the input data are passed and classified according to the weights assigned to each input data in the hidden layer. The following figure depicts a simple Feed Forward Neural Network configuration. The network consist of an input layer- usually considered as the 0th layer- the feed forward adjective emphasizes the fact that all the connections between layers and neurons start at the input layer and end at output; there are no connections from outputs back to hidden layer, or to the input layer.

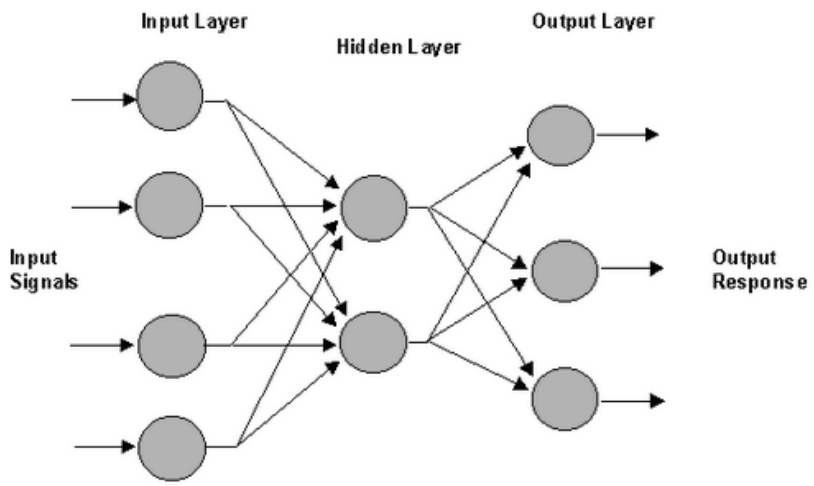

Figure 5. Feed Forward Neural Network diagram

There are many techniques developed for training FFNN of which Back-Propagation technique is the most popular one. Back Propagation method requires a training set (input and output pairs) and uses Gradient Descent Algorithm as its convergence method.

5.2 Leave One Out Method (LOOM)

LOOM is a cross validation, classification method in which data size of l is divided into l partitions of size 1 and the Leave One Out Error (LOOE) is the average error over all partitions. A single observation is made from the data sample with which the remaining of the data is

trained. This method also follows a supervised learning process where the categories are pre-defined for the machine. The challenge in LOOM algorithm is to find a reasonable regularization parameter. The method is expensive when dealing with large data; however it is also very accurate since the training process is repeated as the number of data. The classification performed done in IBM-SPPF software available on the Ryerson Virtual Application Webpage.

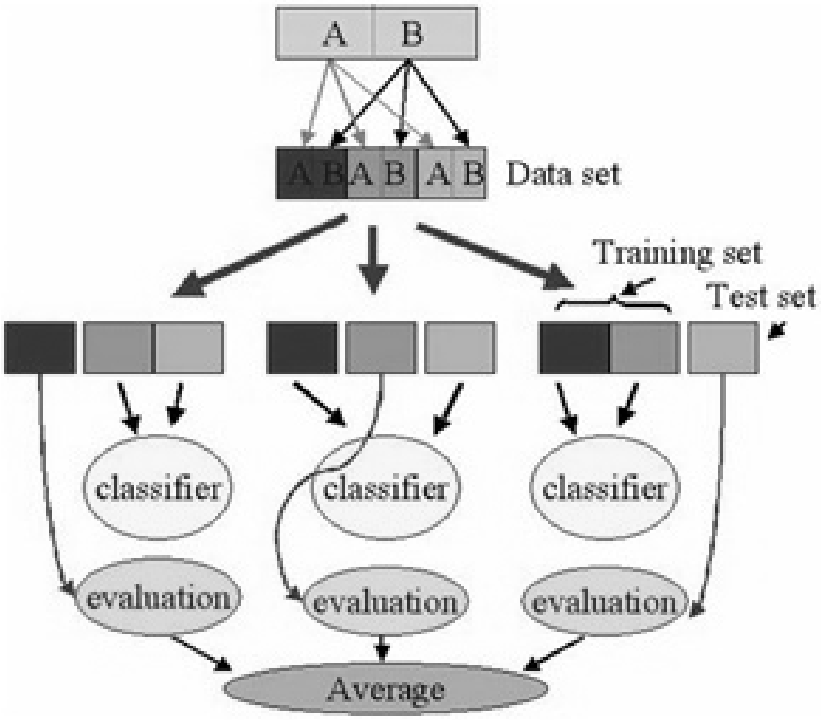

Figure 6. Leave One Out Method diagram

As you can see in Figure 6, each time, one of the input data is ignored and the rest of the data is cross validated. The final result is the average of the entire cross validations done by selecting out one data at a time.

Chapter 6

Results and Discussion

6.1 VF/VT original and filtered signal samples:

In this section is a step by step demonstration of signal sample acquisition, signal preprocessing, and frequency spectrum analysis. Figures 7-10 show the original ECG signal obtained from PhysioNet [22], made available through MIT-BIH Data-Base. Part (a) of each graph depicts 4(s) of signal sampled at 250 [Hz] which results in 1000 samples. Part (b) depicts the filtered signal with a Butterworth band-pass filter which frequency width of [2 12] [3] Hz. The range of filter is chosen in this manner since the most important frequency components of ECG happen at these frequencies which withhold most of the valuable information. In addition, FFT of the signals were determined in order to obtain some perspective on the signal behavior; it was observed that a peak PSD value was obtained at zero for most of the signals which confirms the appearance of noise in lower frequencies. Figures 7-8 show VT signal samples and 9-10 show VF signal samples:

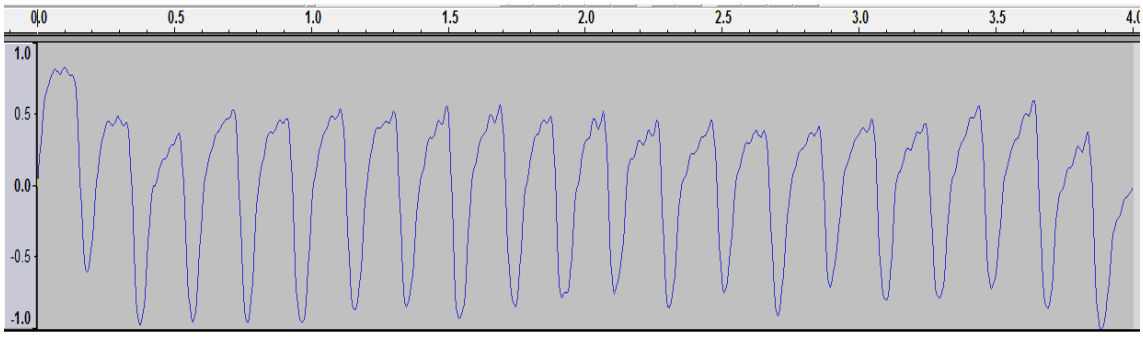

Figure 7. Sample VT (vt5) signal [fs=250; time=4s]

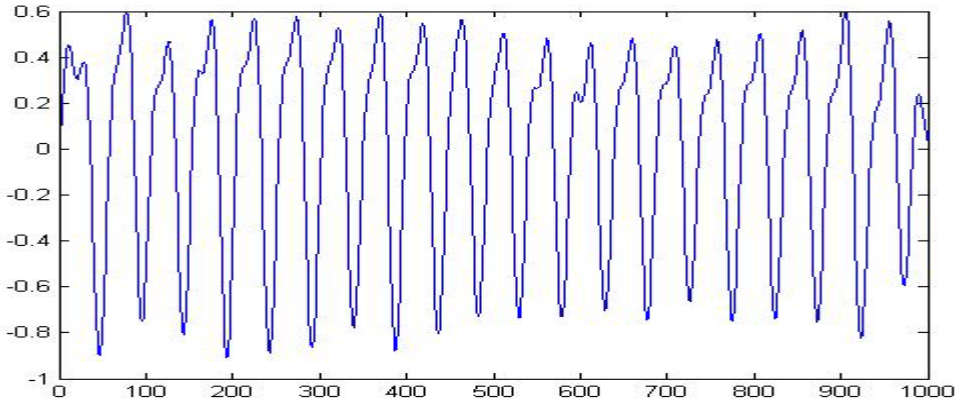

Figure 8. Filtered VT (corresponding to Fig5) signal @ [2 12]

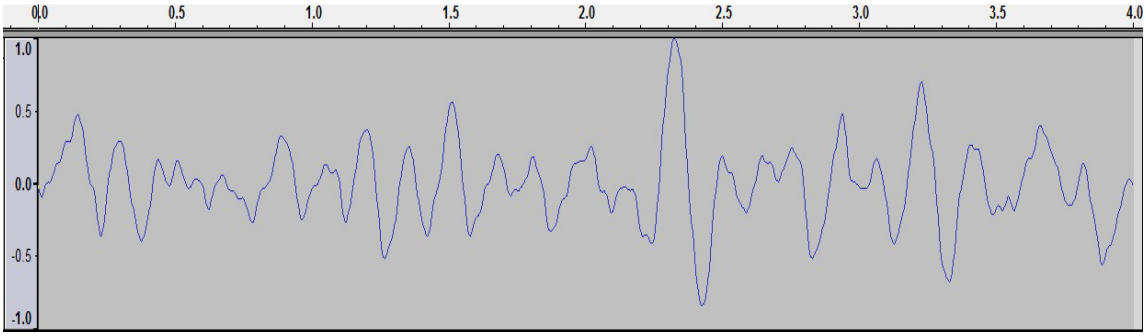

Figure 9. Sample VF (vf5) signal [fs=250; time=4s]

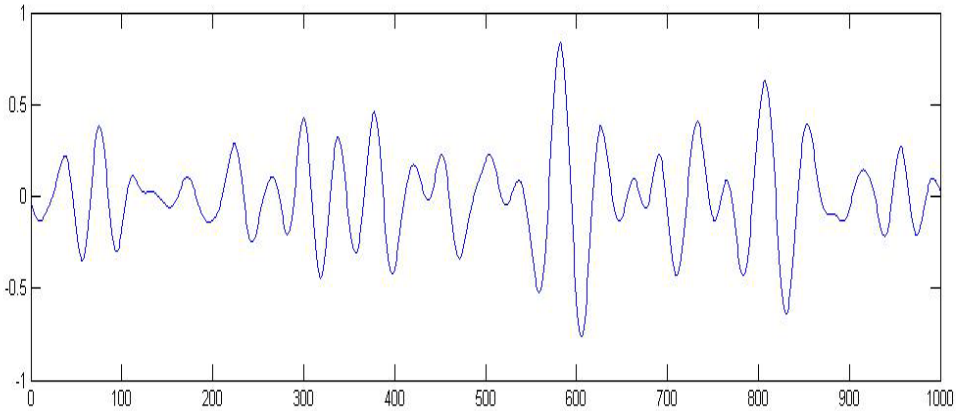

Figure 10. Filtered VF (Corresponding to Fig7) signal @ [2 12] Hz

It is evident from the signals plotted above that the VT signals show some rhythm while the VF signals demonstrate fast which lack any rhythmic behavior. This can be explained according to the origin of each signal. As mentioned in the background section, VT signals are generated when the Atrio-Ventricular Node has changed its position from its normal spot, which is on the ventricles; however, the node is stimulated in a rhythmic fashion. On the other hand, when heart is in the VF state, the Atrio-Ventricular Node constantly is changing its position to random spots and also stimulates muscle contraction very fast. That also explains why the VF signals have relatively higher frequencies than VT signals.

6.2 Power Spectrum Density (PSD)

In order to gain some perspective on the behavior of the VT and VF signals and to recognize their differences, PSD of the signals were obtained using Welch method. The Welch method takes the Discrete FTs of the signals by divining the signals into number of blocks and averaging the squared of its magnitude according to the following formula:

$$\hat{R}_x(\omega_k) = \frac{1}{M}\sum_{m=0}^{M-1} |DFT_k(x_m)|^2 \triangleq \left\{ \left| X_m(\omega_k)^2 \right| \right\}_m \qquad [4]$$

The signal averaging is done inside the braces {}. The PSD can be determined using MATLAB Signal Processing toolbox.

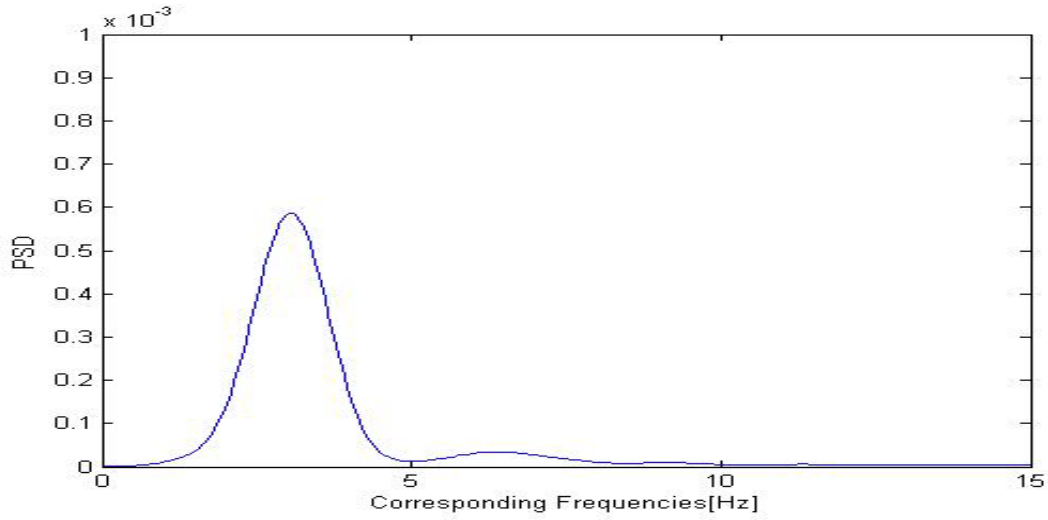

Figure 11. VT PSD with Dominant Frequency at 3.05 [Hz]

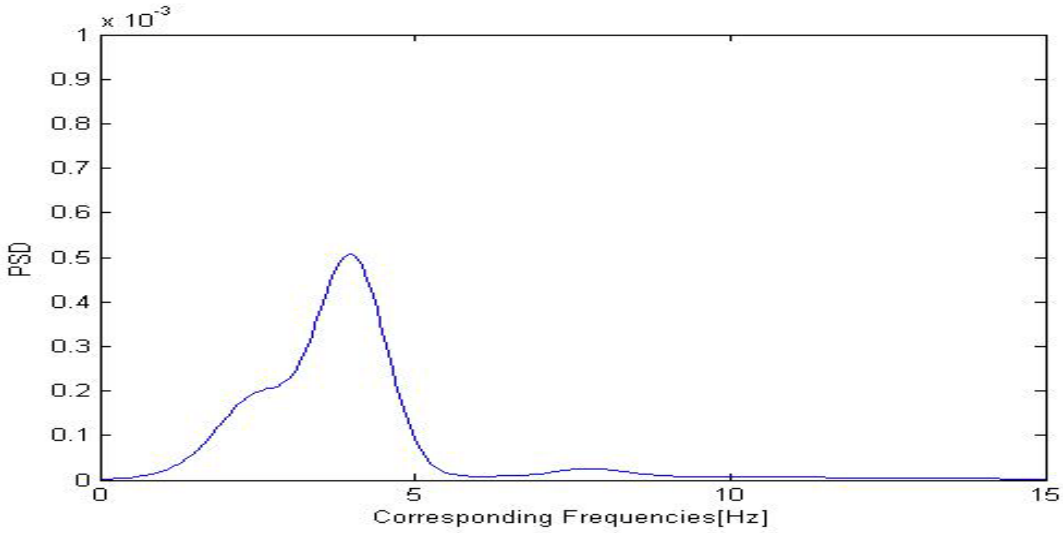

Figure 12. VF PSD with Dominant Frequency @ 4.5 [hz]

The following table contains the Dominant Frequencies for VF and VT signals at their maximum power magnitudes. The average DF for VT and VF are 3.38 [Hz] and 4.79 [Hz] respectively.

Dominant Frequency [VT]	Dominant Frequency [VF]
4.089355469	3.845214844
4.089355469	5.737304688
5.126953125	4.943847656
2.685546875	9.094238281
2.807617188	6.34765625
2.9296875	4.638671875
3.967285156	4.760742188
2.258300781	4.699707031
2.258300781	4.028320313
2.807617188	6.042480469
2.685546875	3.784179688
3.295898438	3.662109375
4.638671875	5.249023438
4.516601563	3.90625
2.014160156	1.892089844
1.647949219	5.004882813
4.39453125	5.432128906
4.211425781	4.943847656
3.723144531	4.577636719
3.723144531	4.821777344
3.051757813	4.028320313
	3.967285156

Table 1. PSD of VT and VF Signals

It can be concluded from the DF values that the frequency components of the VT and VF signals are distinguishable. This encourages that the energy components of the two signals also contain information which can be used in discriminating them. As mentioned in the theory section of this project, Wavelet Transforms will be used in analyzing the Energy components of the signals due to their flexibility in providing both frequency and time information

simultaneously. The following results are obtained by performing CWT of the signals in MATLAB.

6.3 Continuous Wavelet Transform Analysis (Wavelet Basis: 'Gauss6')

CWT uses an analyzing function which is referred to as the mother wavelet. The original signal is compared to the mother wavelet through a series of inner products. In order to obtain information about time and frequency of the signals, the Mother Wavelet is shifted and compressed/stretched by selecting different scales and locations. The process is referred to as dilation or. The result is a function of two variables, namely a, and be; scale and location respectively.

Two different Mother Wavelets were examined to WT analysis: Morlet and Gauss6. From the classification results carried on later in the results section, it was concluded that the Gauss6 wavelet yield better results in discriminating VF and VT Signals. Gaussian Wavelets are obtained from i^{th} differential of a Gaussian function. In this study the Energy components of the signal are being observed. The goal is to discover a pattern in the energy spectrum of the signals and to find its correlation with different wavelet scales. Gaussian Mother Wavelets are based on the Mexican hat and due their nature are suitable in capturing the high energy peaks; and this in one of the reasons why Gaussian Mother Wavelets perform well for the purpose of this project. Morlet Wavelet consists of complex exponentials which is multiplied by a Gaussian window and performs best in bio-signal analysis related to hearing and vision which is due to its similarity to the AM modulation of such bio-signal.

Figures 14-19 depict the CWT of VT and VF signals using 'Gauss6' Mother wavelet. It can be easily seen that the most of the energy percentages are presented in the scales 1:100. However, the location at which the highest energy percentages are evident is different for VT and VF. This suggests that the Energy Distribution is diverse for VT and VF which in turn encourages focusing on wavelet energy components in order to find a discriminating function in classifying the signals.

6.4 Feature Extraction Process

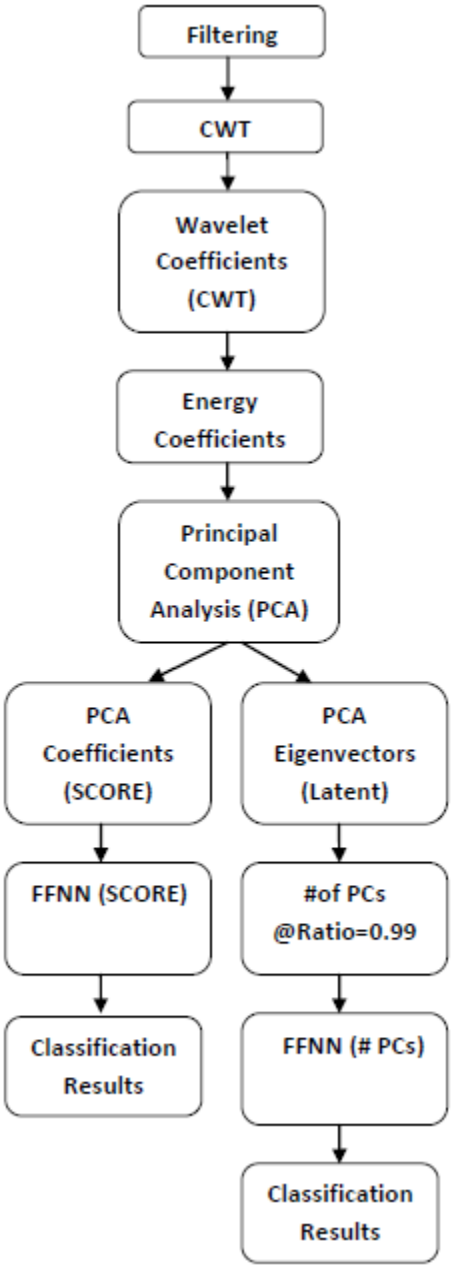

Figure 13. Feature Extraction Flow Chart

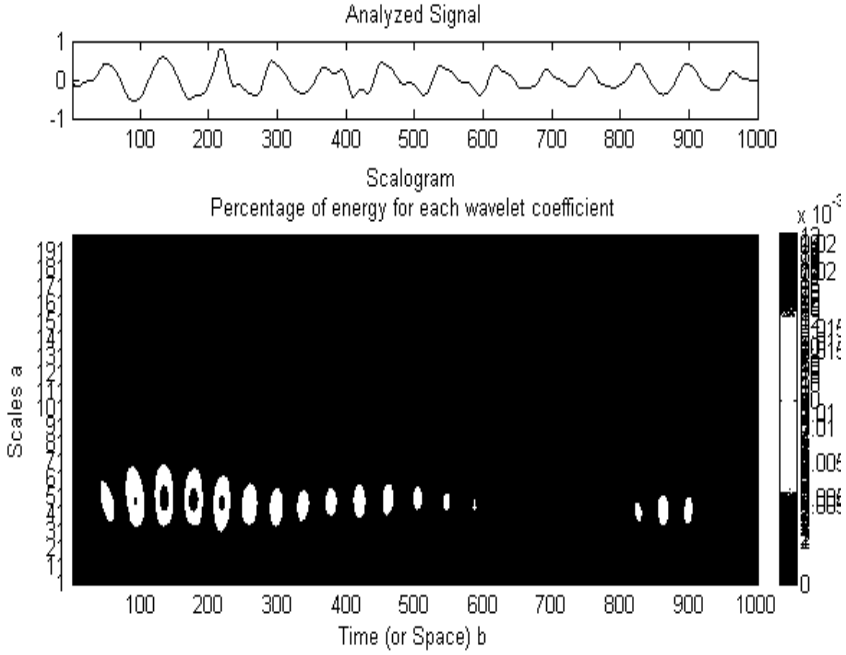

Figure 14. VT Signal CWT plot for scales 1:200.

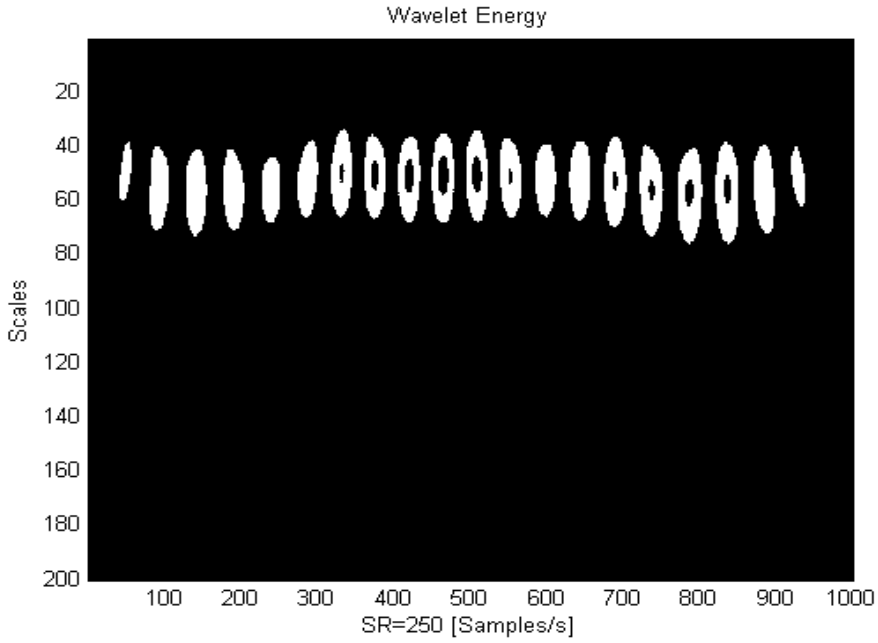

Figure 15. VT Wavelet Energy for scales 1:200

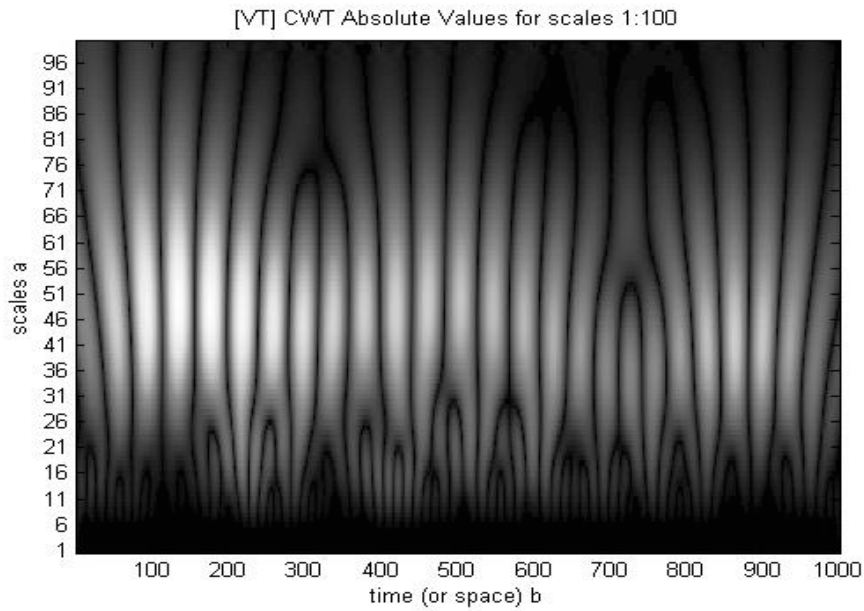

Figure 16. VT Signal Wavelet Scologram for scales 1:100.

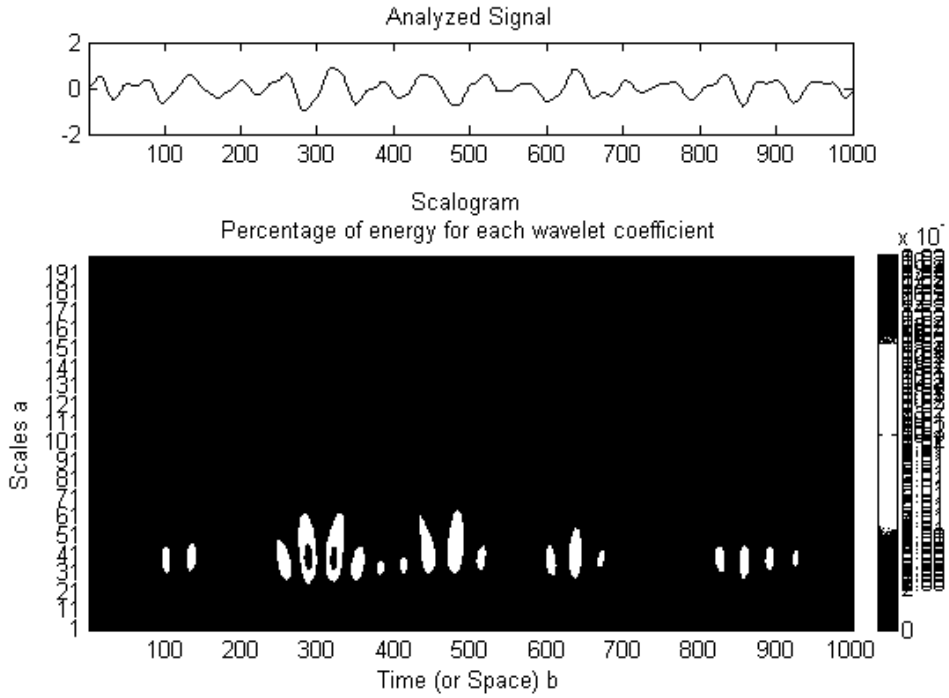

Figure 17. VF Signal CWT plot for scales 1:200.

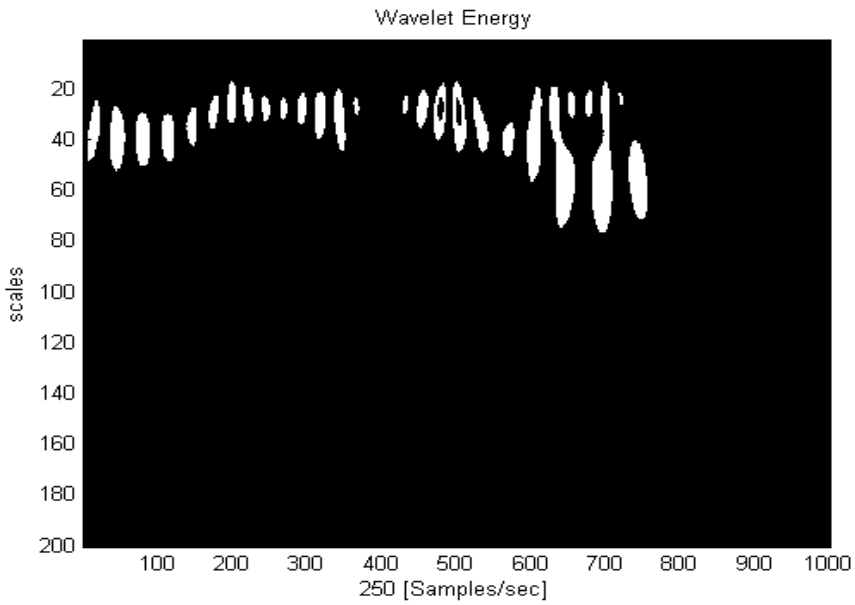

Figure 18. VF Wavelet Energy for scales 1:200.

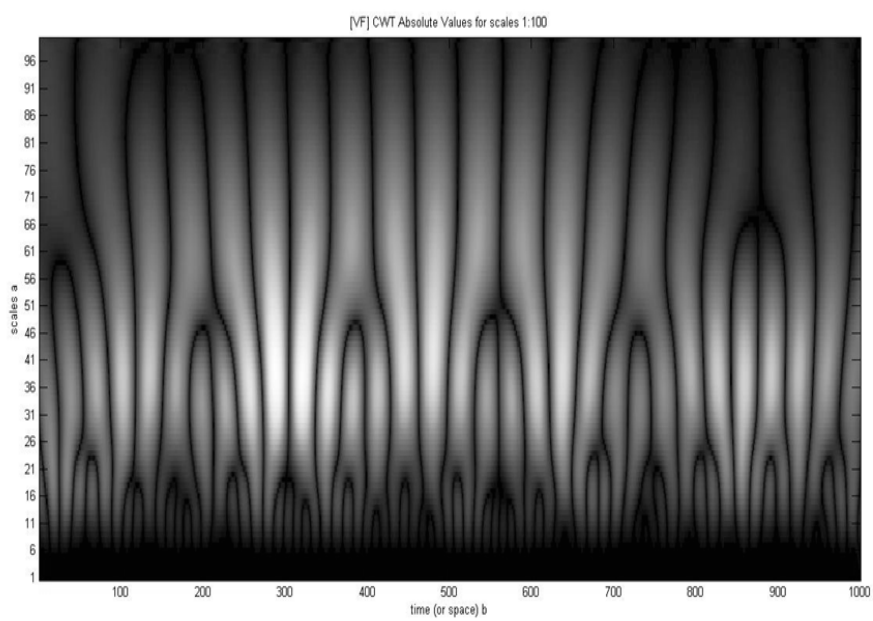

Figure 19. VF Signal Wavelet Scologram for scales 1:100.

6.5 Scale Distribution Width [1] (SDW)

As it was concluded from figures 14-19, the distribution of energy is a potential feature in discriminating VT and VF signals. The feature explained previously is SDW [1] which was introduced by K.Umapathy and group at the TGH. The feature was implemented in MATLAB to examine its competence. The feature is obtained as follows: first the CWT of the signal is obtained at different scales; here for scales 1:200. Then the Wavelet Energy of the signal is calculated at each scale which results in a matrix containing energy components. Then the average of the energy components along each scale is obtained as an integer. This number represents the distribution of energy over a range of scales. The box plots of the SDW values for VF and VT are shown in the next page.

The SDW box-plots, Figure 20, have little overlap which suggests SDW is an efficient feature for VT and VT classification. The box represents 75% of data with the red line as its median value.

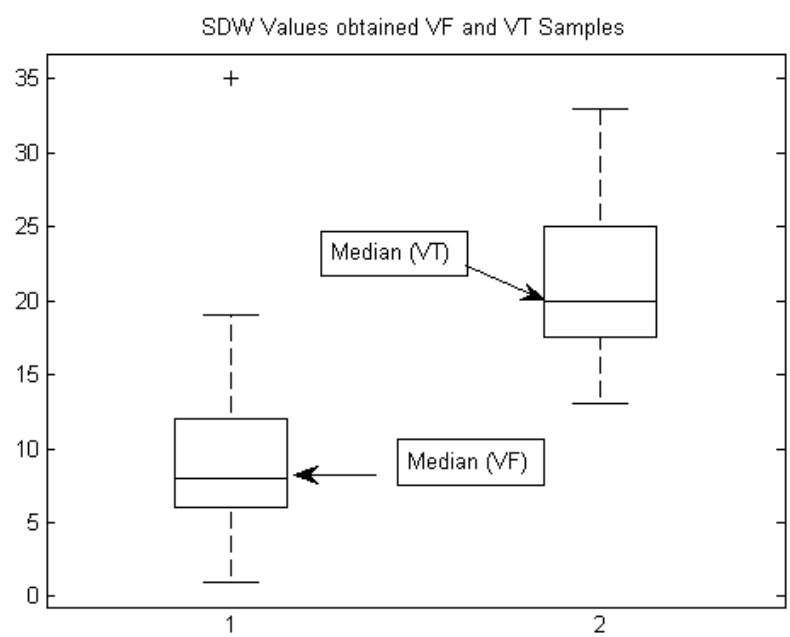

Figure 20. Scale Distribution Width measure for VT & VF signal

6.6 Principal Component Analysis:

PCA was performed on the Wavelet Energy Matrices of signals. The dimensionality reduction yields three components: The Coefficient Matrix which contain the eigenvectors of the data projection to the lower dimension. The Latent Matrix, which contain information about the direction of the eigenvectors. The last component is the Score components which are the actual energy components on the new dimension.

Two different features are extracted through implementation of PCA for this project. One is the Number of Top 99% Energy Components (NTE-PCA) which is obtained by extracting the number of components for each signal from the generated Score Matrix. The second feature is the actual Score values generated. The number of principal components for VF and VT are different as shown in Figures 21. This number is higher for VF class and fluctuates between 2 and 3 for VT class. In order to be consistent, the top-two most important principal components for each class are used as an input to the classification algorithms. The features are later passed through LOOM and FFNN for classification and the results is compared with SDW and Energy Matrix feature.

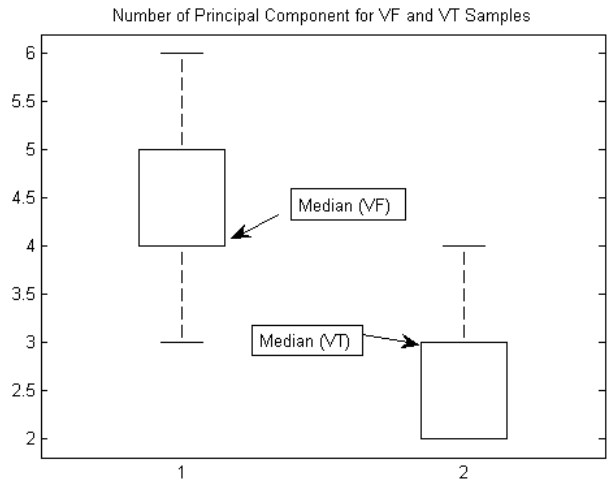

Figure 21. NTE-PCA box-plot for VF & VT Signals

The NTE-PCA values for all the signals in each class are listed in the table below along with the SDW values.

Number of top 99% Principal Components of Wavelet Energy		Scale Distribution Width	
PCA for [VT]	**PCA for [VF]**	**SDW [VF]**	**SDW [VT-LOOM:2]**
2	**5**	**1**	**18**
2	**4**	**6**	**18**
3	**4**	**12**	**13**
2	**6**	**35**	**25**
2	**4**	**6**	**25**
2	**4**	**12**	**24**
4	**4**	**8**	**19**
2	**5**	**6**	**32**
3	**4**	**7**	**32**
2	**5**	**16**	**25**
2	**3**	**11**	**26**
3	**4**	**12**	**20**
3	**5**	**7**	**15**
3	**3**	**11**	**15**
3	**4**	**12**	**33**
3	**4**	**5**	**20**
3	**5**	**7**	**16**
4	**6**	**19**	**16**
3	**3**	**13**	**19**
3	**5**	**4**	**18**
3	**4**	**7**	**21**
-	**3**	**13**	**-**

Table 2. Values for PCA and SDW of Wavelet Energy matrix.

6.7 Classification Results (LOOM + FFNN)

6.7.1 Leave One Out Method (LOOM)

The IBM-SPSS software was used for cross validation classification technique. The data are fed into the system and then manually a class is assigned to VF and VT classes. In this method the input data is divided into two groups of 10% and 90% sections, for every iteration. For each epoch, a classification tree is built for the 90% section while holding the 10% out as test samples. This process is performed for a number of any iterations until a set of mutually exclusive 10% sections are used as test values. The final cross-validation value is an average of the cross-validation of all the previous iterations.

Cross Validation	Class VF	Class VT	Total
# Class VF	19	3	22
# Class VT	5	16	21
% Class VF	***% 86.4***	%13.6	%100
% Class VT	%23.8	***%76.2***	%100

Table 3. LOOM Cross Validation Analysis for SDW Values

Table3 shows the classification results of LOOM method on SDW features. According to the table VF class is classified with 86.4% accuracy and VT class is classified with 76.2%

accuracy. Overall 86.0% of original classes are correctly classified with 86.0% accuracy for the cross-validated cases.

Table4 shows classification results of LOOM on NTE-PCA values listed in table2. The overall accuracy for cross-validation obtained is 86% with 90.5% of VT classes and 81.8% of VF cases classified correctly. The results are improved by approximately 6% for NTE-PCA features.

Cross Validation	Class VF	Class VT	Total
# Class VF	18	4	22
# Class VT	2	19	21
% Class VF	***%81.8***	%18.2	%100
% Class VT	%9.5	***%90.5***	%100

Table4. LOOM Cross Validation Analysis for NTE-PCA @0. 99

Tables 5 and 6 depict classification results which are obtained using Multilayer Perceptron Networks available through IBM-SPSS software. The flexibility to change the Perceptron Network settings was limited in using the software and the results obtained are not very satisfactory; however, they are being represented here for the comparison purposes. The Network consists of one hidden layer with five neurons and it uses a Hyperbolic Tangent activation function to adjust its weighs.

Cross Validation	Class VF	Class VT	% Classification
Class VF (Test)	14	0	%92.3
Class VT (Test)	1	12	96.3%
Class VF (Training)	5	1	83.3%
Class VT (Training)	2	5	71.4%
OVERALL CLASSIFICATION PERCENTAGE: ***76.9%***			

Table 5. Neural Network (Perceptron) Classification Result for SDW

The following three tables depict the classification results obtained from IBM-SPSS software using Radial Basis Networks and ML Perceptron analysis with the same Network configuration as above.

Cross Validation	Class VF	Class VT	% Classification
Class VF (Test)	11	2	84.6%
Class VT (Test)	1	12	92.3%
Class VF (Training)	7	2	77.8%
Class VT (Training)	1	7	87.5%
OVERALL CLASSIFICATION PERCENTAGE: ***88.5%***			

Table 6. Neural Network (Perceptron) Analysis for NTE-PCA

It is evident that the classification results for VT signal samples yields better results for all the classification methods used. Since the signal analysis is performed on the Energy Matrices of the signal samples, this suggests that VT energy components have a more organized nature than that of the VF.

6.7.2 Feed Forward Neural Network Classification

From this point forward, the classification results obtained from FFNN is presented. The MATLAB Pattern Recognition ToolBox was used to carry out this section. The following graph shows the two-layer FFNN configuration used which has one hidden layer with twenty neurons- The number of neurons were increased to examine its effect on the system; however, the overall result did not improve as much while the training time was increased . Therefore, in order to simplify the network, the numbers was fixed at 20 for all the cases.

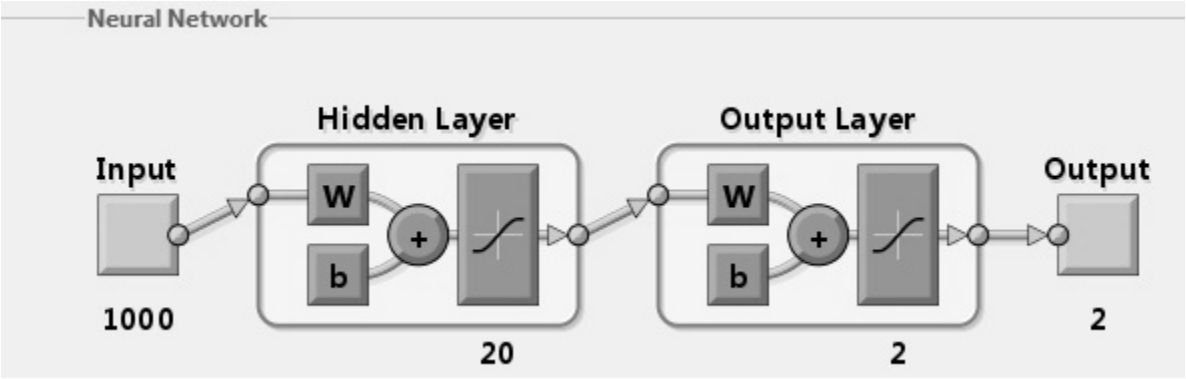

Figure 22. Feed Forward Neural Network Configuration

The network is trained by Back Propagation supervised technique based on a Gradient Decent technique. The Pattern Recognition and Classification toolbox is initiated by typing the command ‘nprtool’ in the command window. The first step is to choose the input matrix that is to be analyzed which contains all the feature cases to be classified. Next, a target output must be

created which is used to assign a class to each one of the feature values in the input matrix. As an example, the 'Score' feature is a 1000x86 matrix. The first 44 columns correspond to the VF class, marked as class 1 and the rest of the 42 columns are features corresponding to VT class. The target matrix must have the same number of columns as the input matrix. The ith column of the target matrix determines which class the ith input belongs to. A sample target matrix for 'Score' features can be a matrix like […] $_{2x86}$ where the first row of the 1st 44 columns are ones, the rest zeroes. On the second row, the 1st 44 columns are zeros and the rest are ones. The selection can be done in the following step:

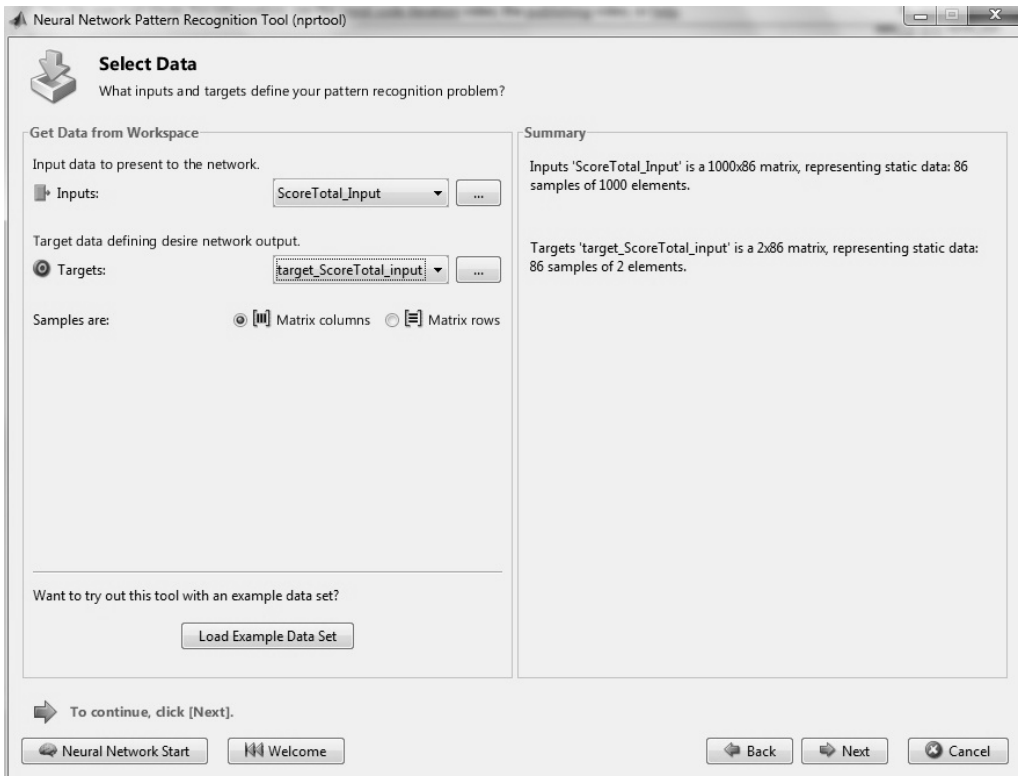

Figure 23. Classification Toolbox-Input selection

In the next step, the input matrix is divided into three groups of samples, test and validation as percentages. The testing group determines system performance in terms of its ability to perform accurately on a new set of input data-set after one training, and then the

consequence trainings. In the next step, the Network configuration is determined. The number of Hidden layers and the number of neurons in the hidden layer.

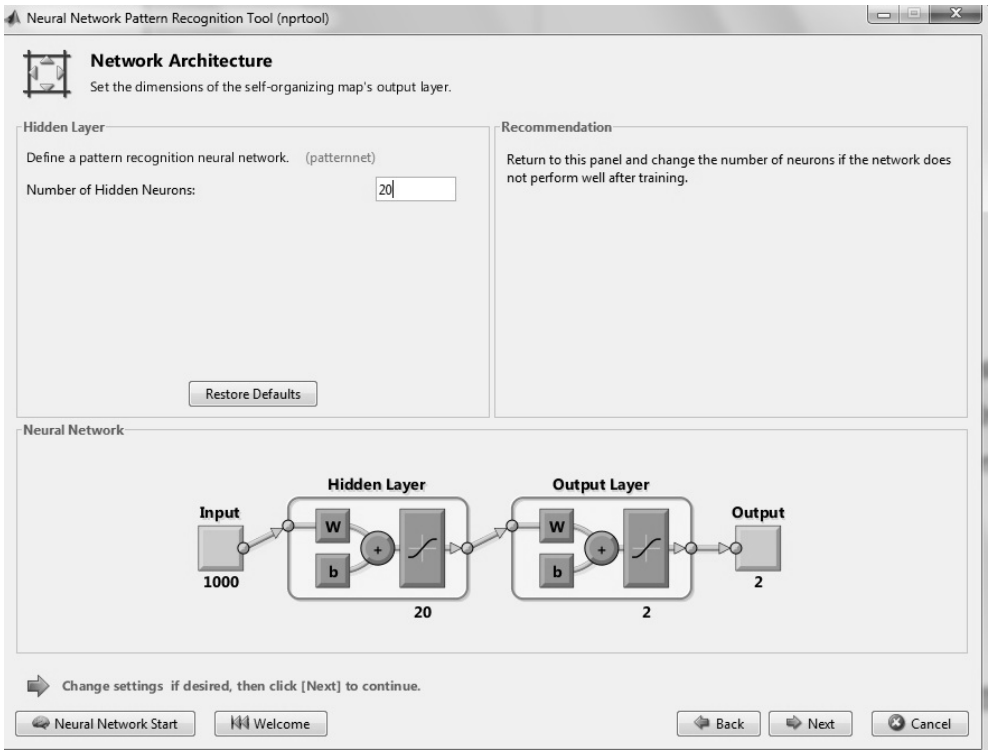

Figure 24. Network Configuration setting

Next, the system is trained and the cross-validation table plus the training performance can be plotted.

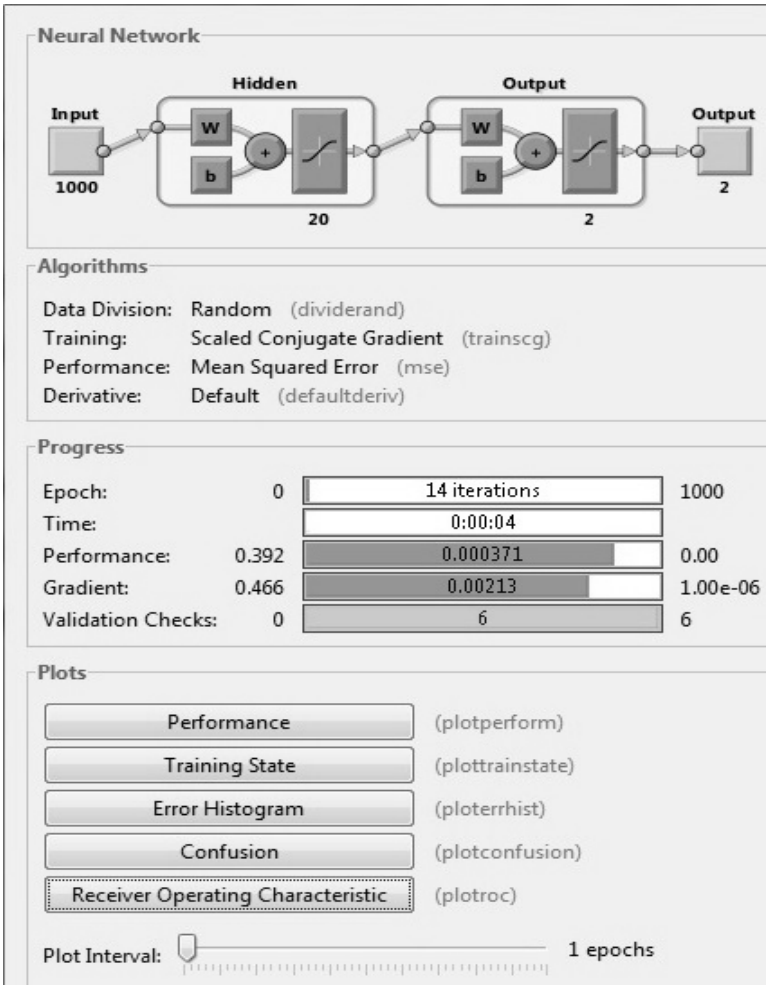

Figure 25. Training results: Best performance at epoch #8

Figure26 shows the confusion plot for the TNE-PCA values. The overall classification result is 86% which is close to the percentage obtained using LOOM. The training yielded the best results at 25 epochs.

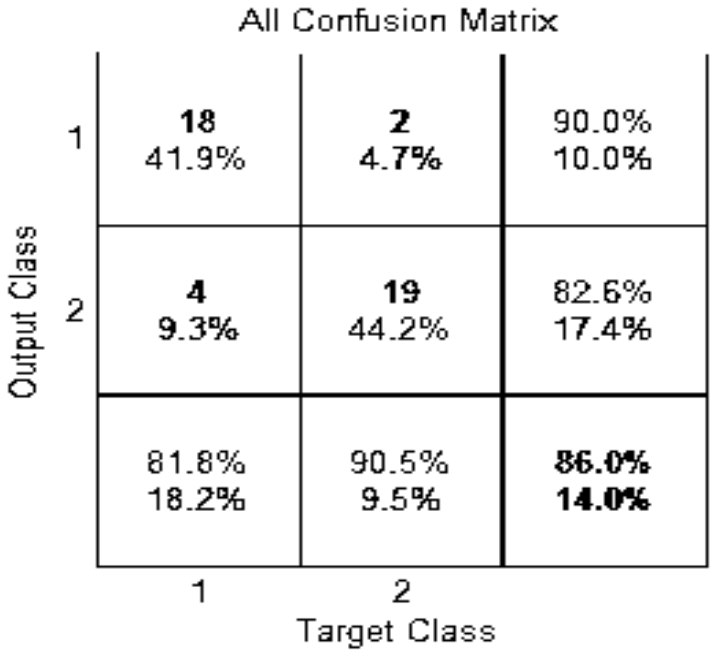

Figure 26. FFNN Classification results and confusion plot for 'q' values

Figure 27. FFNN Classification results and confusion plot for 'SDW and q' values

Figure27 shows the results from the same configuration when the input are both SDW and q values. It can be seen that the two features combined yield a classification result of 97.2% which is a very promising result. The best results were however obtained when the actual Score values were used as input to the FFNN. The top two components of each Score value were selected and then were passed on to the FFNN which resulted in 98.8% classification results. The confusion matrix displays the numbers of cases actually belonging to each class, and the assigned classes by the FFNN to each class. The blue squares represent the overall accuracy of the system. Figure 28 is the confusion matrix for Score Vector which yields the highest classification results.

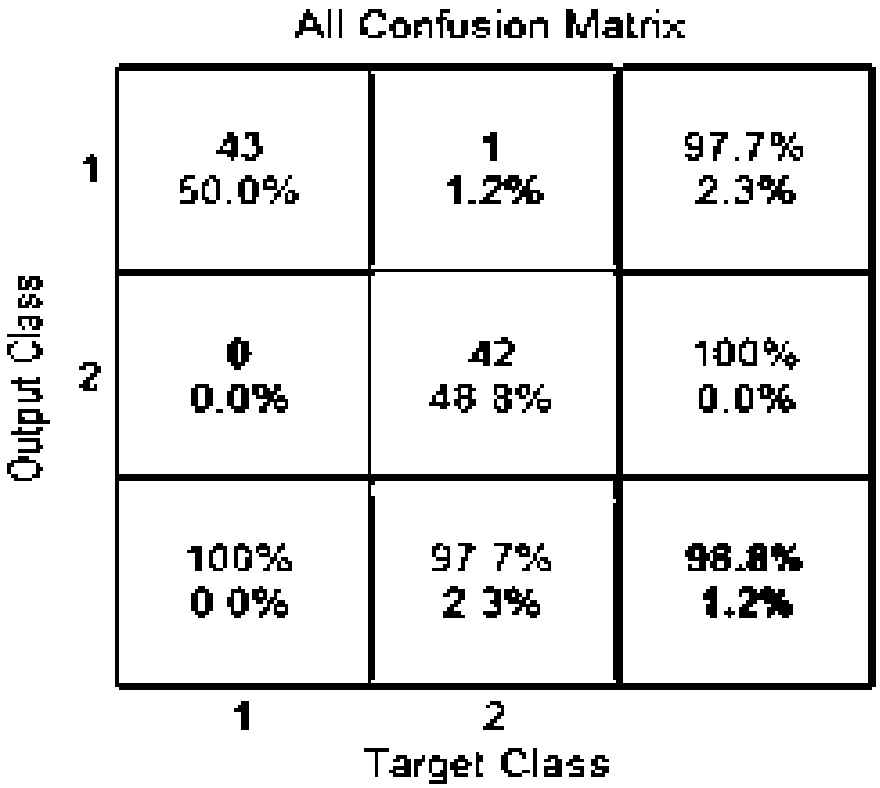

Figure 28. Classification results and confusion plot for 'Score' values

Figures 29 and 30 show the performance of the FFNN for the Score Matrix, and SDW & q values at 38 and 22 epochs.

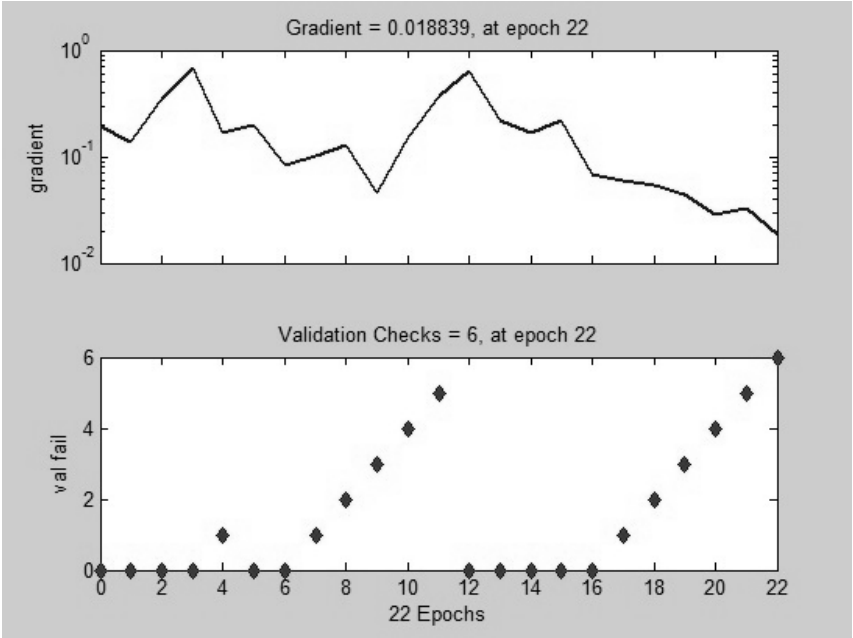

Figure 29. FFNN Training state for 'q and SDW' features

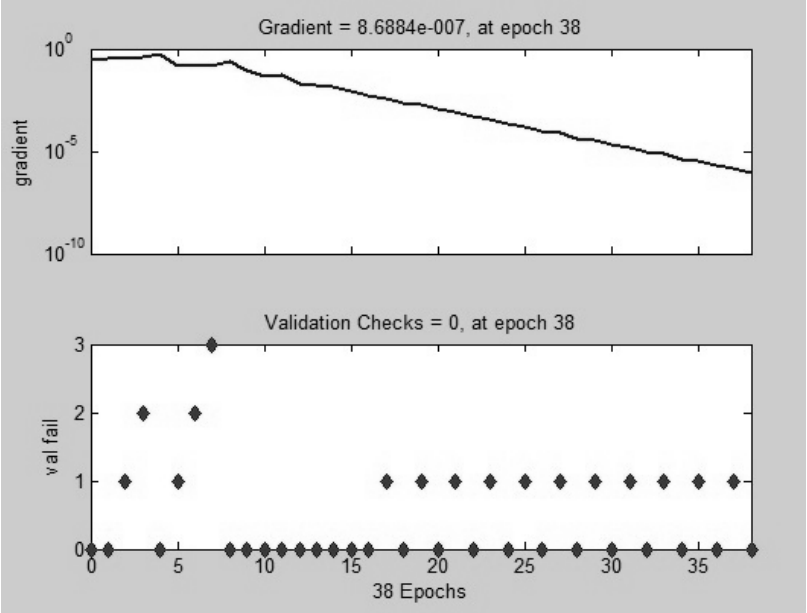

Figure 30. FFNN Training state for 'Score' features

Chapter 7

Conclusion

Surface ECG signals are one of the most important biological signals to study since they contain valuable information which can assist cardiologists in diagnosis of cardiac diseases as well as treatment and rehabilitation. Continuous Wavelet Transforms have been used intensely on the past decade due to their flexibility in analyzing time and frequency information simultaneously. This project has aimed to briefly summarize some of the techniques used in processing ECG-VF and ECG-VT signals. CWT was used to analyze the ECG signals and to examine their energy spectrum. PCA dimensionality reduction technique was then performed on the energy matrices in order to both extract new features for discriminating VF and VT cases and to decrease the complexity of the computation. It is concluded that the Score values obtained from PC analysis of the Energy matrices yields the highest classification results. However, the NTE-PCA combined with SDW values also yielded classification results of higher 90% which is a very promising number. CWT proved to be a suitable tool in analysis bio-signals and has opened many doors in many diagnosis and treatment applications. The best result was obtained using `Score` features in combination with Feed Forward Neural Network classification method. The overall classification accuracy of 98.8% was achieved.

Bibliography

[1] K. Umapath, S. Krishnan, S. Masse, X. Hu, P. Dorian, and K. Nanthakumar "Optimizing cardiac resuscitation outcomes using wavelet analysis," *in 31st Annual International Conference of the IEEE EMBS, Minneapolis*, 2009.

[2] R. Abbas, W. Aziz, M. Arif, "Prediction of ventricular tachyarrhythmia in electrocardiograph signal using neuro-wavelet approach," *in National Conference on Emerging Technologies, Islamabad*, 2004.

[3] E. Afatmirni, K. Umapathy, E. Masse, K.Nair, T.Farid, S.Krishnan, P.Dorian, "Predicting refibrillation from pre-shock waveforms in optimizing cardiac resuscitation," *Engineering in Medicine and Biology Society,EMBC, 2011 Annual International Conference of the IEEE*, 2011.

[4] T. Eftestøl, L. Wik, K. Sunde, PA. Steen, "Effects of cardiopulmonary resuscitation on predictors of ventricular fibrillation defibrillation success during out-of-hospital cardiac arrest," *Circulation*, vol. 110, pp. 10-15, 2004.

[5] CG. Brown, R. Dzwonczyk, "Signal analysis of the human electrocardiogram during ventricular fibrillation: frequency and amplitude parameters as predictors of successful shock," *Annual Emergency Medicine*, vol. 27, no. 2, p. 436–437, 1996.

[6] LD Sherman, TD Rea, JD. Waters, JJ. Menegazzi, CW. Callaway, "Logarithm of the absolute correlations of the ECG waveform estimates duration of ventricular fibrillation and predicts successful defibrillation," *Resuscitation*, vol. 78, no. 3, pp. 346-354, 2008.

[7] T. Jagric, M. Marhl, D. Stajer, S. T. Kocjancic, M. Podbregar, and M. Perc, "Irregularity test for very short electrocardiogram (ECG) signals as a method for predicting a successful

defibrillation in patients with ventricular fibrillation," *Translational Research*, vol. 149, no. 3, pp. 145-151, 2007.

[8] J. Watson, P.S. Addison, G. R. Clegg, P.A. Steen and C.E. Robertson, "Wavelet transform-based prediction of the likelihood of successful defibrillation for patients exhibiting ventricular fibrillation," *Measurement Science and Technology*, vol. 16, no. 10, p. L1–L6, 2005.

[9] P.W. Baker, J. Conway, C. Cotton, D. T. Ashby, J. Smyth, R. J. Woodman, H. Grantham, "Defibrillation or cardiopulmonary resuscitation first for patients with out-of-hospital cardiac arrests found by paramedics to be in ventricular fibrillation? A randomised control trial," *Resuscitation*, vol. 79, no. 3, pp. 424-431, 2008.

[10] T. Eftestøl, L Wik, K. Sunde, PA. Steen, "Effects of cardiopulmonary resuscitation on predictors of ventricular fibrillation defibrillation success during out-of-hospital cardiac arrest," *Circulation*, vol. 110, no. 1, pp. 10-5, 2004.

[11] HU. Strohmenger, T. Eftestol, K. Sunde, V. Wenzel, M. Mair, H. Ulmer, KH. Lindner, PA. Steen, "The predictive value of ventricular fibrillation electrocardiogram signal frequency and amplitude variables in patients with out-of-hospital cardiac arrest," *International Anesthesia Research Society*, vol. 93, no. 6, p. 1428–33, 2001.

[12] J. a. P. Addison, J.N. Watson, G.R. Clegg, M Holzer, F Sterz,, C.E. Robertson, "Evaluation of arrhythmic ECG signals using a novel wavelet transform method," *Resuscitation*, vol. 43, no. 2, p. 121–7, 2000.

[13] T. Eftestøl, K. Sunde, S.O. Aase, J. H.Husoy, P.A. Steen, "Predicting outcome of defibrillation by spectral characterization and nonparametric classification of ventricular fibrillation in patients with out-of-hospital cardiac arrest," *Circulation*, vol. 102, no. 1, pp. 1523-1529, 2000.

[14] P. Addison, N .Uchaipichat, J.N. Watson, G.R. Clegg, C.E. Robertson, P.A. Steen, T. Eftestol, "Wavelet power spectrum-based prediction of successful defibrillation from ventricular fibrillation," *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, vol. 2, no. 1, pp. 1812-1815, 2001.

[15] Watson JN, Uchaipichat N, Addison PS, Clegg GR, Robertson CE, Eftestol T, Steen PA., "Improved prediction of defibrillation success for out-of-hospital VF cardiac arrest using wavelet transform methods," *Resuscitation*, vol. 63, no. 1, p. 269–275, 2004.

[16] Watson JN, Addison PS, Clegg GR, Holzer M, Sterz F, Robertson CE., "A novel wavelet based analysis reveals hidden structure in ventricular fibrillation," *IEEE Engineering in Medicine and Biology*, vol. 19, no. 1, p. 83–92, 2000.

[17] Addison PS, Watson JN, Clegg GR, Steen PA, Robertson CE., "Finding coordinated a trial activity during ventricular fibrillation using wavelet decomposition," *IEEE Engineering in Medicine and Biology*, vol. 21, no. 1, p. 58–65, 2002

[18] R. Abbas, W. Aziz, M. Arif, "Prediction of ventricular tachyarrhythmia in electrocardiograph signal using neuro-wavelet approach," *in National Conference on Emerging Technologies, Islamabad*, 2004.

[19] R. Polikar, "The story of wavelets," *in IMACS/IEEE CSCC Proceedings, Durham,* 1999.

[20] Moody GB, Mark RG, "The impact of the MIT-BIH Arrhythmia Database," *IEEE Engineering in Medicine and Biology*, vol. 20, no. 3, pp. 45-50, 2001.

[21] AS. Al-Fahoum, A.M Qasaimeh, “ECG arrhythmia classification using simple reconstructed phase space approach,” *Computers in Cardiology*, vol. 33, pp. 757-760, 2006

[22] Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng C-K, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals. *Circulation*, vol. 101, no 23, pp. 215-220, 2000.