ANALYSIS OF PHONOCARDIOGRAM SIGNAL FOR BIOMETRIC APPLICATION

A Thesis report submitted in partial fulfilment of the requirement for the degree of

Master of Technology

In

Electronics and Instrumentation

By

SHAILESH SINGH BADGHARE

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Department of Electronics and Communication Engineering
National Institute of Technology, Rourkela-769008,
Orissa, India

2014

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Under the guidance of

Dr. Samit Ari

Department of Electronics and Communication Engineering
National Institute of Technology, Rourkela-769008,
Orissa, India, 2014

DECLARATION

I hereby declare that the work presented in the thesis entitled as "***Analysis of Phonocardiograph signal for Biometric application***" is a bona fide record of the systematic research work done by me under the guidance of **Dr. Samit Ari**, Department of Electronics & Communication, National Institute of Technology, Rourkela, India and that no part thereof has been presented for the award of any other degree.

Shailesh Singh Badghare

(Roll no. 212ec3150)

Department of Electronics and Communication Engineering

National Institute of Technology

Rourkela-769008

CERTIFICATE

This is to certify that the thesis entitled "**Analysis of Phonocardiograph signal for Biometric application**" submitted by **Mr. Shailesh Singh Badghare** in partial fulfilment of the requirements for the award of **Master of Technology** Degree in Electronics and Communication Engineering with specialization in "Electronics and Instrumentation" during the session 2012-2014 at **National Institute of Technology, Rourkela** is an authentic work carried out by his under my supervision and guidance.

Date:

Place:

Dr. Samit Ari

Department of Electronics & Communication Engineering

National Institute of Technology, Rourkela

ABSTRACT

Heart sound is distinctive in nature. Earlier work reported that, it can also contribute a lot to recognize a person by their heart sound. A novel technique is described in this thesis for the identification and verification of the person using energy based feature set and back propagation multilayer perceptron artificial neural network classifier (BP-MLP-ANN) is used in this thesis. PCG signal is invariable, unique, universal easy to accessible and unique in nature. Heart samples were collected through ten volunteers as ten data (i.e. heart sounds) per individuals. Before feature extraction, pre-processing involves extraction of cycles, alignment, and segmentation of primary heart sound S1 and S2. This Segmentation contributes to the features extraction based on energy taken 30 windows at a time. Classification was done, using BP-MLP-ANN. 69 % of total numbers of heart sound signal were used as Training and remaining 31 % of heart sound signal were used for Testing. The identification results show 63.3824 % of performance accuracy.

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Shailesh Singh Badghare

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CHAPTER-1

INTRODUCTION

1.1 BIOMETRIC SYSTEM

Biometric system is the system in which a person is identified by means of his distinguishing characteristics or quality basically one belonging to a person. Recognizing humans using computers not only provide some best security solutions but also help to efficiently deliver human services. This computer based human identification systems are known as biometric systems. Present day we encounter biometric systems in offices, laptops, cars, lockers and many everyday items. Biometric authentication system associate behavioural or physiological attributes to identify or verify a person. Physiological characters are based on bodily features, like fingerprint, iris, and facial structure etc. Behavioural traits are based upon unique behavioural characteristics of an individual, like voice, signature etc. Heart sound comes under physiological traits because it is a natural sound created by the opening and closure of valves present in the heart. Generally biometric itself means related with living thing as we human being , although we are having different types of biometric traits such a heart sound, Iris, Retina, face, finger-print etc. All biometric attributes are playing dissimilar role for their recognition. No such human being having same biometric traits. Sometimes same feature of Iris, face, but Heart sound is uniqueness in nature, no others can resemble it [1] [2].

A physiologic biometric is the scientific study of the biological functions in the living system, which should be identify by iris scan, DNA or fingerprint [3]. More old-fashioned means of getting at control including the nominal-based identification systems, such as identity card and driving license [4] [5]. It is the most secured and honest in confirming identity than knowledge and token-based methods.

Biometric authentication processes consist of two modes. In first mode, feature sets are extracted from the heart sound samples and the database is prepared. Whereas, in the next phase the extracted feature sets are matched with the feature templates stored in the database to find a match [6] [7].

1.1.1 Identification

In present scenario, crime is increasing vigorously in our world. To identity the suspect behind it, we have to identify through by our memory based picture which comes to our mind instantly or by any other means of photograph, and through different person claiming for that. These types of systems are already present in police department for thief to detect. If we make the data base of all the previously detected thieves with their every means of biometric identification i.e. Fingerprint, Face, iris, and DNA etc.

The process of identification is seemed to as the matching of the current data to the stored data. If it resembles then it result as identified otherwise unidentified. Just like in case of C. I. D in which, as the criminal is detected , first it is compared to the stored data's of all criminal they possessed, the process includes as face picture recognition system, iris recognition system, DNA matching, finger print recognition . If there is not matching then criminal's data's are taken for the new record.

1.1.2 Verification

The process of verification is different from that of identification. In verification, the system examines the extracted features and has to take a verdict that if the feature is good enough to be labelled as the identity it claims to be or not. Here the systems are supposed to take a decision between true and false. It means identified individual is right or wrong.

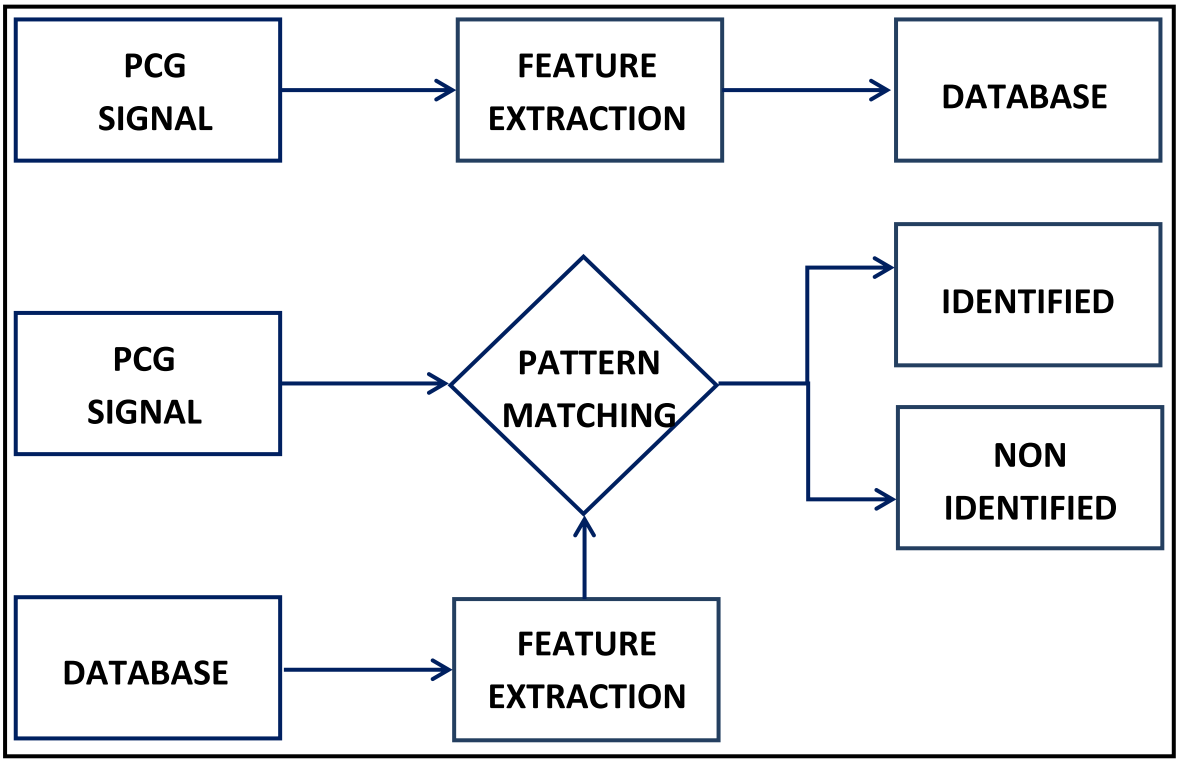


Figure 1.1:Two phases of Biometric Authentication System [2]

1.2 SIGNIFICANT FEATURES OF HEART SOUND AS BIOMETRIC

Following are the factors which differentiate hear sound from other physiological properties [8]

i. ***Universality***: It is universal in nature.it means it is present in every individual's heart.

ii. ***Easy accessibility:*** This physiological property is easy to access at the time of data collection an also at the time of the Authentication system.

iii. ***Invariability:*** It is invariant in nature, because it is somehow depend upon the height and weight of the body and the anatomy of the heart.

iv. ***Accuracy:*** Accuracy plays an important role in the biometric with minimum False Accept Rate (FAR) and high True Accept Rate (TAR).

v. ***Speed:*** A quick response is very desirable for a biometric system. This includes quick data acquisition, quick enrolment of inputs and processing.

vi. ***Reliability:*** There are not any chances of the forgery, because to steal the heart sound a concealed device has to be placed at chest.

vii. ***Usability:*** It is totally a time saving, a person can send a signal from several meters also.

viii. ***Permanent:*** It cannot change over a time.

1.3 PHONOCARDIOGRAM AS A PHYSIOLOGICAL CHARACTERISTIC FOR BIOMETRIC SYSTEMS

PCG signal contains the information of individual’s cardiac system. Physiological characteristics are unique and invariant (for instance face, iris, geometry of hand) unlike behavioural characteristics which is variant in nature for example way of walking, voice signature. So PCG here is taken as physiological trait. Heart sound contains s1 and s2 segment which is also known as “lub” and “dub” respectively as well as first and second hearts sound also. The reason for choosing heart sound is that it is distinct and most secured, because it is almost impossible for any forger to reproduce these heart sounds. For reproducing these signals it requires the heart of same anatomy, same structured. There is an advantage of digital stethoscope which are capable of acquiring cardiac source samples can be stored in a computer, and various storage devices. S1 & S2 are the sounds generating from the contraction and relaxation of valves which are varying from person to person.

1.4 MECHANISM OF HEART SOUND

The mechanism of heart sound production is very complex and there is not yet as a consensus find for contributing to form a single component. The mechanism includes two *viz*: sounds and murmurs

- *Sounds*: sounds are the vibrations produced by the closure of the valve and by the tensing of the cardiac muscle.
- *Murmur*: it is also a sound, it produced due to the turbulence in the flow of the blood from narrow of the cardiac valves or by flowing again from the atrioventricular valves.

Mainly, there are two louder sounds named as S1 & S2, which are easily audible in nature, and the time duration is around 150 ms & 120 ms. It ranges from 20 to 150 hertz. Heart sound S1 is associated with the closure of the mitral-tricuspid valve, it occurs during the isovolumetric contraction of the ventricles. And whereas, Heart sound S2 is related to the aorticpulmonary valve at the time of the isovolumetric relaxation of the ventricles.

Heart sound S3 and S4 are very light sound i.e. almost inaudible in nature. S3 and S4 are very low frequency sound .S3 is not originated from the valve although it happens at the beginning of the diastole that’s why it is also known as Proto-diastolic sound. Bulk of blood is flowing into the left ventricles cause vibrations in the valve. It is found generally in the children’s and young adults, and usually it disappear in the middle age. But if it occurs in the late age then there may be a chances of Proto-diastolic gallop, which is in pathological state, a sign of failing of left ventricles.

Heart sound S4 is mainly found in the healthy children’s; it is not found in adults but when found it is called in pathological term as presystolic gallop.

1.4.1 Diastolic Period

During this period the ventricle relaxes and thus the pressure inside ventricle drops. When the pressure drops below the pressure in the atrium, the Mitral and Tricuspid valves are open and blood flows into ventricles from the atrium.

1.4.2 Systolic Period

During this period, the ventricles get contract. The sudden increase in pressure closes the Tricuspid and Mitral valves opens the Aortic and Pulmonary valves and pump-out the blood.

1.5 AUSCULTATION PROCESS OF HEART SOUND

Auscultation is the process of hearing the sounds produced in the body, usually with a digital stethoscope. There are four auscultation sites in the chest region. These are Aortic, Pulmonary, Lower Sternal Border and Mitral.

Two major heart sounds are the S1 or lub and S2 or dub. S1 sound is produced by the impulsive blockage of blood flowing in the reverse direction due to the closing of the Atrioventricular valves, i.e. Bicuspid valves consisting Tricuspid and Mitral valve (at the commencement of Systole or ventricular contraction. S2 sound is produced by due to the flowing of the blood with an impulsive blockage, due to closure of the Semilunar valves at the ending of ventricular systole, i.e. at the commencement of ventricular diastole [9-12].

1.6 CARDIAC DATA RESOURCES COLLECTION

For the identification of human it is mandatory to collect the PCG signals from the human. Therefore, there is 10 volunteers are randomly selected for this process these volunteers are in under the age group of 25 years to 40 years, provided that they are medically fit and ensure that their heart is in well condition [13],(or no any sign of the heart disease). With the help of Digital Stethoscope with good sensitivity and noise rejection, manufactured by HD Medical Services (India) Pvt. Ltd, was used.

Because Heart sound is not easily available in a large scale just like as that of face, iris and, geometry of hand [14]. So Database is created .As there is advent in the technology so these physiological data can be easily stored in the PC and Disks through the USB CONNECTIVITY. It can be used further for the training and testing of the data samples, all data's are stored in the Waveform Audio File Format, also known as "WAV" format easily accessible to the MATLAB.

1.7 ADVANTAGES OF PCG SIGNALS

Followings are the advantages of the PCG signals:

1. It is the perfect physiological trait for the identification.
2. It helps to examine the condition of the heart.
3. It helps to know about diastolic and systolic behaviour.
4. If the disease presystolic and proto-diastolic gallop is present in heart ,which is the sign of the failure of the left ventricles ,it can be easily detected
5. It shows tachycardia, it shows the exceed heart rate than the normal heart-rate [15-17].
6. It shows bradycardia ,which is the resting heart beat rate of under 60 BPM (Beats Per Minute)

1.8 HEALTHY PCG SIGNALS

The Healthy signals are the signals which have a clear sound of S1 & S2 and almost negligible sound of S3 & S4. Healthy heart sound contains heart sound segment S1 and S2, which gives information of functionality of heart sound [18]. Unhealthy Heart sound are unsynchronised in nature which give rise to the disease known as tachycardia and bradycardia i.e. High heart beat rate and Low heart beat rate respectively. Sometimes also results the failure of Bicuspid and Tricuspid valve which regulate the blood in human body with irregular times [19-20].

1.9 LITERATURE REVIEW

In 2007, the first time F. Beritelli & S. Serrano introduced the system in depth that depicts the usage of the PCG signals, for the identification of the person by using

CZT (Chirp Z transform) of the sound that is originated by the opening and closing of the valve which is S1 & S2. The authors creates the identity samples using feature vectors and check whether the identity of the individuals statement is true by calculating the Euclidean distance between the stored samples and the features extracted samples during the process of verification.

In 2008, the authors designate a different method to heart-sounds biometry. In spite of doing a operational analysis of the input cardiac signal, they use the whole sequences of the signal, serving them to two recognizers constructed using Vector Quantization and Gaussian Mixture Models; the GMM evidences to be the more precise systems.

In 2009, Spadaccini & Beritelli, the authors promote the system described in Beritelli & Serrano (2007), estimating its presentation on a larger storage database, selecting a more proper input feature vector set LFCC.

1.10 THESIS OBJECTIVE

In this thesis, we will focus on how to recognize a person from their heart sound. A novel technique is described in this thesis for the identification and verification of the person using energy based feature set and back propagation multilayer perceptron artificial neural network classifier (BP-MLP-ANN) is used in this thesis.

As every segment of heart sound possess a redundant data in it, so special characteristics or features are extracted from the heart sounds by means of energies of the data collected from the cycle extraction. Then Classification is done, using BP-MLP-ANN where 69 % of total numbers of heart sound signal as Training and remaining 31 % numbers of heart sound signal as Testing are applied.

1.11 THESIS OUTLINE

- **Chapter 2** depicts about Feature Extractions. Feature extraction is carried out by dividing the thirty windows / frame per cardiac cycle. Energy of the frame is calculated. This process involves *Normalization, Extraction of Heart cycle, Alignment of the extracted Cardiac cycle, Segmentation.*
- **Chapter 3** we describe the Classification Process, Back Propagation Multilayer Artificial Neural Network as our Classifier, The artificial neuron acts like as Natural neuron of the Brain. Here 69 % samples used as a Training and remaining 31% samples as Testing. The Identification Results shows only 63.3824 % efficiency.
- **Chapter 4** describe the Conclusion and Future works, here a better results can be obtained from support vector machine. Heart sound as biometric also can be used as attendance system in college and R&D area

CHAPTER-2

SEGMENTATION OF PCG SIGNAL

2.1 INTRODUCTION

Segmentation of the primary heart sounds S1 and S2 came into existence when the aligned input data is given to any process or algorithm. After the aligning process is over the *segmentation* process becomes easy because now the S1 and S2 lies in the same locations of the block compared to the first cycle block. So in the next step of segmentation we only find out the locations of S1 and S2 for the first block and since all the blocks are aligned according to the first block we apply the same location values to determine the beginning and the end of S1 and S2 for all the blocks of this sample.

2.2 PRE-PROCESSING

It is similar to cleaning and cutting the vegetables before actual cooking begins. This process consists of several processes:

- Normalization
- Extraction of Heart cycle
- Alignment of the extracted Cardiac cycle
- Segmentation

2.2.1 Normalization

Normalization of the signal should be carried out before passing through filtering. This is the simplest normalization technique to make the signal vary between -1 to +1. It can be done in two steps. In the first step we find out the extreme absolute value of the signal and in the second step we divide the whole signal by maximum value. The resulted signal will be varying within the range of +1 to -1.

2.2.2 Extraction of Heart cycle

A technique described in [23] and [24] for detection of QRS complex in ECG signal can also provide a cycle extraction technique for PCG signals. Heart cycle is a quasi-periodic signal with normal period is in the range of 0.4 - 1.2 second. The steps followed in this process are described below.

Step 1: Three seconds PCG sample was extracted.

Step 2: A lag index is created ranging from 0.4 to 1.2 second with step of 0.005 second.

Step 3: Now sum of the Autocorrelation of these lag indexes were determined.

Step 4: The position of the peak is determined.

Step 5: The corresponding time of the peak lag index is the determined heart cycle.it gives the duration of the one cycle.

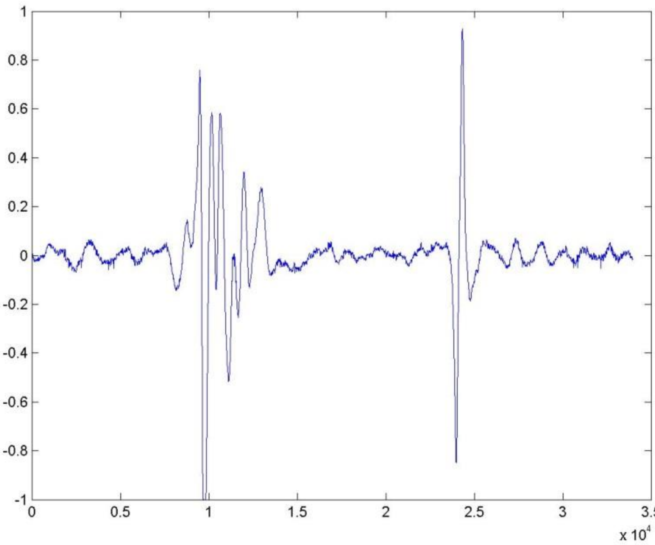
Step 6: The whole sample is divided into cycle blocks.

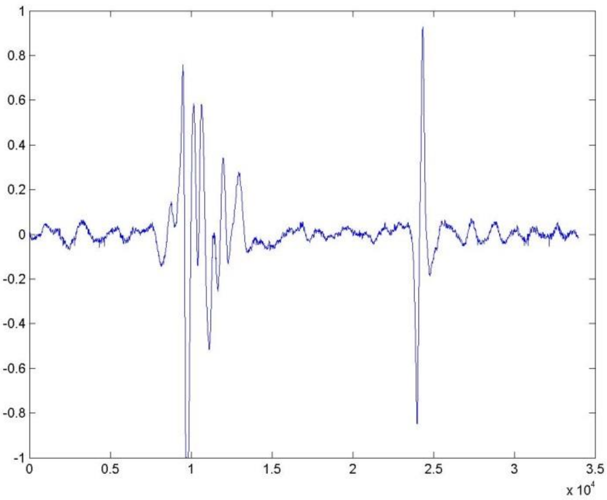
Process is displayed in Figure 2.2. Left side top corner shows the three Sec extracted PCG signal. Right side top corner is the sum of the autocorrelation output of the lag indexes. Right side bottom corner shows the corresponding time of the lag indexes.

2.2.3 Alignment of the extracted Cardiac cycle

Aligning process contributes to the segmentation process. Extracted heart cycle blocks were aligned using cross correlation between two different blocks for a same sample. Figure 2.3 shows two extracted cycle blocks which were correlated. Correlated function will have three regions which are labelled as A; B and C in the figure. Region A in the cross correlation is generated because S2 of second block coming under S1 of first block B because S1 and S2 of the second block coming under the S1 and S2 of the second block C is coming when S1 of second block coming under S2 of the first block.

The peak is coming when the both blocks are perfectly aligned. The distance of the peak from the midpoint point of the correlation window is the amount of shift required to align the two blocks properly.





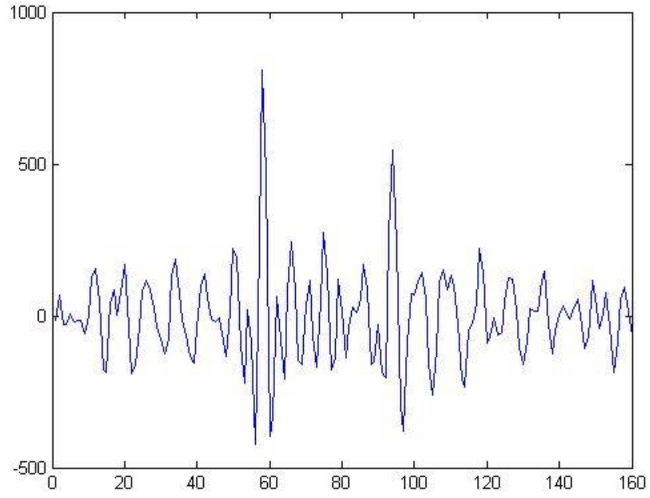


Figure 2.1: Auto-correlated extracted cycle blocks

2.2.4 Segmentation

After the aligning process is over the *segmentation* process becomes easy because now the S1 and S2 lies in the same locations of the block compared to the first cycle block. So in the next step of segmentation we only find out the locations of S1 and S2 for the first block and since all the blocks are aligned according to the first block we apply the same location values to determine the beginning and the end of S1 and S2 for all the blocks of this sample. Figure 2.4 shows the heart cycle before and after aligning and its cross correlation window. At the bottom the first cycle is shown which is taken as standard for aligning all other blocks. Let x(n) is the heart cycle block.

The process of segmentation is described below:

Step-1) Take a threshold of 0.4

Step-2) Applying the mechanism such that, the first maximum point above the threshold level is consider as the peak of S1 marked as M1 matrix, and corresponding location is arranged in P1 matrix

Step-3) Cut the segment of first 50 millisecond signal from the starting of the S1 and append adjacent to the ending of the S2.

And hence, the one cardiac cycle is extracted.

2.3 RESULTS

Segmented cardiac cycle is extracted for the one volunteer is shown as below:

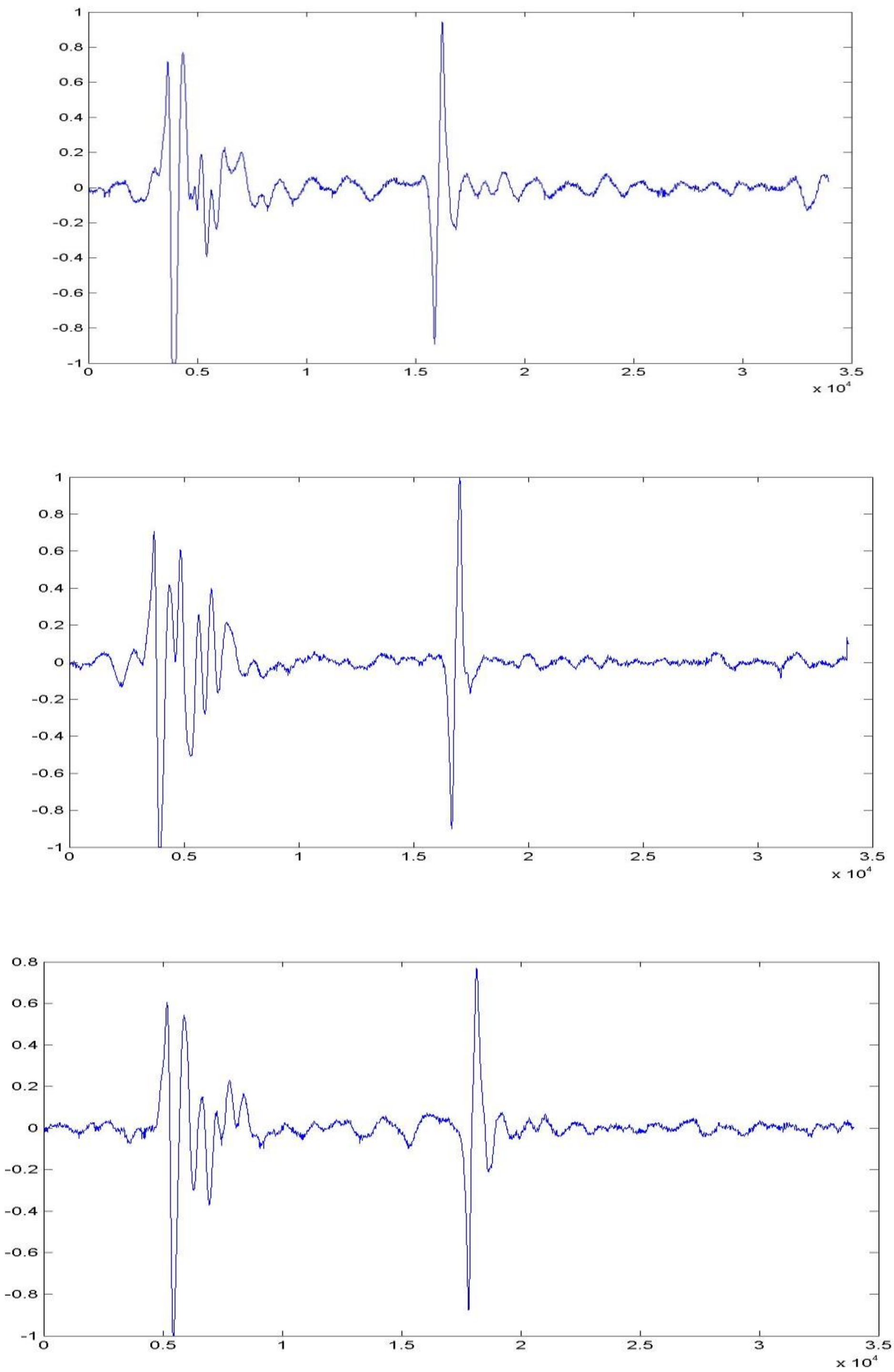


Figure 2.2 : Segmented extracted cycle blocks for one data of a person

CHAPTER -3

FEATURE EXTRACTION AND CLASSIFICATION

3.1 INTRODUCTION

Extraction of features came into existence when the input data to any process or algorithm is too large and notoriously redundant. Then the input data is transformed into the reduced sets which contains the important properties and characteristics of the data. So all the relevant information contained by the data's are also present in the extracted features, which can be process under any algorithm.

Before Feature extraction of the PCG signal it is necessary to extract the cardiac cycle of the one period, so called this process as *pre-processing* because a signal is processed before extracting the features.

Artificial Neural Network is a network containing artificial neurons network. The most basic & principle element of an ANN is called nodes. Nodes act like artificial neurons which is generally same as natural neurons. This concept is initiated by real neurons present in the nervous system of the human body system [10]. ANN for classification of heart sounds and got classification accuracy of 60. 6883%. Classification is executed over normalized features vectors / sets. It was seen by trial and verifies that this method that neural network with 120 hidden nodes is giving the best result.

3.2 PROCEDURE

After having segmented signals we have to perform extraction of the features using this process

1.Feature extraction is carried out by dividing the thirty windows per cardiac cycle

2. Energy of the frame is given by the equation

$$E = \sum X(n)^2 \tag{1}$$

3. By taking the energies as the features we applied it to the classifiers

3.3 MULTILAYER PERCEPTRON

The multiple layer perceptron is the multilayer network consisting of feed forward networks. The network possess three layersi.ie input layer, hidden layers (one or many) , and an outermost layer of computational nodes of the MLP's. Input vector signal is flowing through the input layers in the onward direction, layer by layer and finally computation takes place at the output layer. These are commonly known as MLP's. It trains the whole network in a controlled manner, involving a famous algorithm or a procedure known *as error-back propagation algorithm.* Input and output signals are also known as stimulus and response of the network respectively. The hidden layer of the multi-perceptron consisting of the one or more than one layer of the hidden neurons, which are not the part of the network, however these hidden neurons makes the network to learn the complex tasks.

3.4 ERROR BACK PROPAGATION ALGORITHM

It consists of two passes are as follows:

- Forward pass
- Backward pass

Forward pass: In this pass the set of input signals or vectors are given to the input nodes, and it transmits layer by layer in the network, and finally it reaches up to the computational output nodes. During this session, synaptic weights of the nodes are remained unchanged.

Second pass is a backward pass.

Backward Pass: In this pass, synaptic weights of all the nodes are transformed in synchronization with the error correction rule. Actually the real response of the node is subtracted from the wanted response of the network and hence the error signal is generated, these error signals generated moves the actual response to get nearer to the wanted response. So this is called as *Error Back Propagation System.*

3.5 TRAINING THE FEATURE VECTOR

Training is the process of obtain the desired output when certain inputs are provided. Neural Network weights are corrected according to the error signal rendered. The error can be built in lots of ways. In the easiest form it is the difference between the desired output and actual output.

3.6 ALGORITHM OF BACK PROPAGATION

In training, we alter the synaptic weights in such a way that the overall error rate is reduced. The average squared error energy $\varepsilon_{avg}(n)$ is calculated by adding "(n) overall n and normalizing with respect N. where, N is the size of the set. $\varepsilon(n)$ is the instant value of the error energy obtained from the adding the mean individual error energy of a single node over all neurons in the output layer.

η is called the learning rate parameter of the weight. The smaller it's a value the smaller will be the change in the weight and that means smoother and fine trajectory in the weight space. But the training time will be increase if the learning rate is very small value. Partial derivative

$\frac{\partial \varepsilon(n)}{\partial \omega_{ji}(n)}$ is called the sensitivity factor of weight. It can be shown here:

$$\frac{\partial \varepsilon(n)}{\partial \omega_{ji}(n)} = \partial_j(n).y_i(n)$$

Where $\delta_j(n) = e_j(n)\varphi'_j(v_j(n))$ So we get :

$$\Delta\omega_{ji}(n) = \eta.\partial_j(n).y_i(n)$$

3.7 PERCEPTRON

Suppose we have to train the Artificial Neural Network consisting of an input vector x_j and a desirable output y_k. It is usually +1 or -1 is optimum for the classification of the samples. The learning rule for the perceptron is very easy and robust can be submitted as follows [11].

So begin with the arbitrary weights for the connections in Neural Network. Consider an input vector x_j from the large set of training samples of heart sound.

If $y_k = x_j$ the perceptron will give wrong results, So according to thi,

$$\Delta\omega_{kj} = y_k . x_j$$

4. Go back to 2.

Above, the fundamentals of the Back Propagation Multilayer Perceptron Artificial Neural Network are devoted in the detailed manner. [12][13][14].

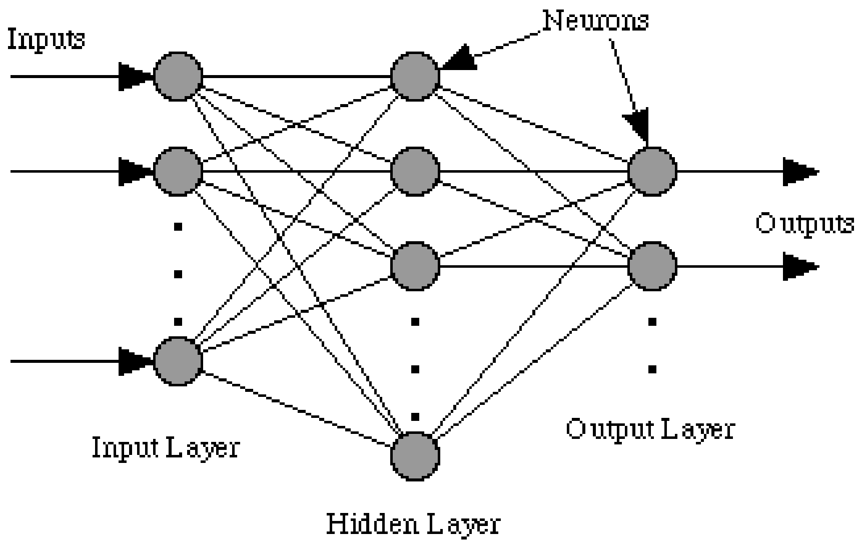


Figure 3.2: Structure of a Multi-layer Back Propagation NN [20]

BP MLP ANN is very popular due to its simplicity and quick and fast processing. MLP ANN is preferred choice of classification for the speech recognition [15]. [16] use ANN for classification of heart murmurs and a classification accuracy of

63.3824 % is achieved. [17] These literatures designate the efficient performance of BP ANN in case of time-frequency domain features to frequency domain.. The same is selected for the classification of the extracted feature in this work. For identification process the Neural Network with 45 hidden nodes was trained using 10 heart cycle features per class. A total of 10 classes of data are used. The Input training vector is allowed for the input nodes. This input values flow in forward direction from the input to the hidden to the output layers to get the desired output values. The output values are equated with desired target values to the generate error E signal. The error signal is then again sent back to changing the weight Wij. This process continues until the error E reaches a permissible optimal value ET. A detailed of Multilayer Perceptron ANN structure and the algorithms are given.[20] Once the training or learning is complete we sent the testing samples in the input nodes for learning and testing, match with the target and finally outputs results.

3.8 TRAINING OF A NEURAL NETWORK

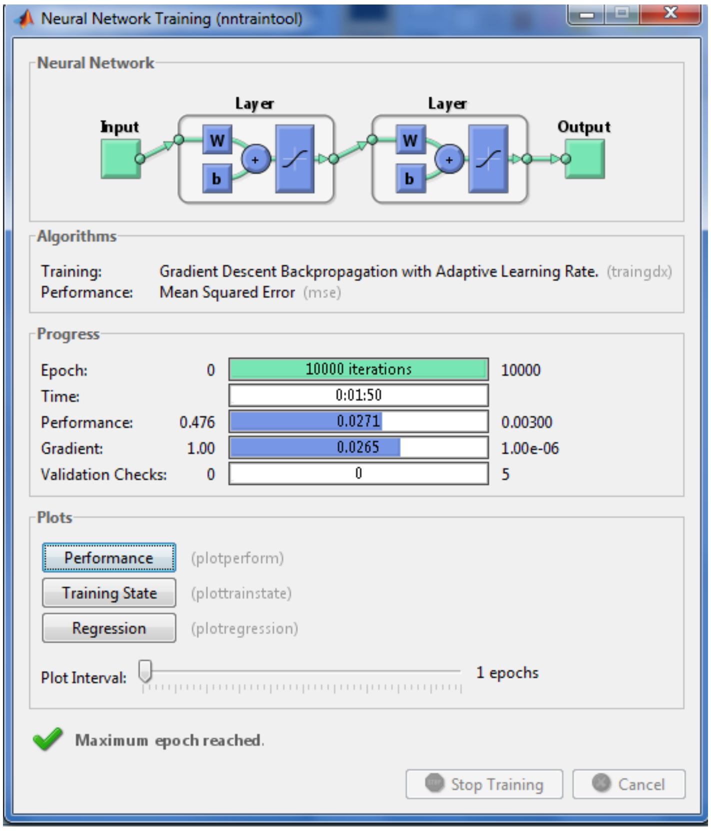
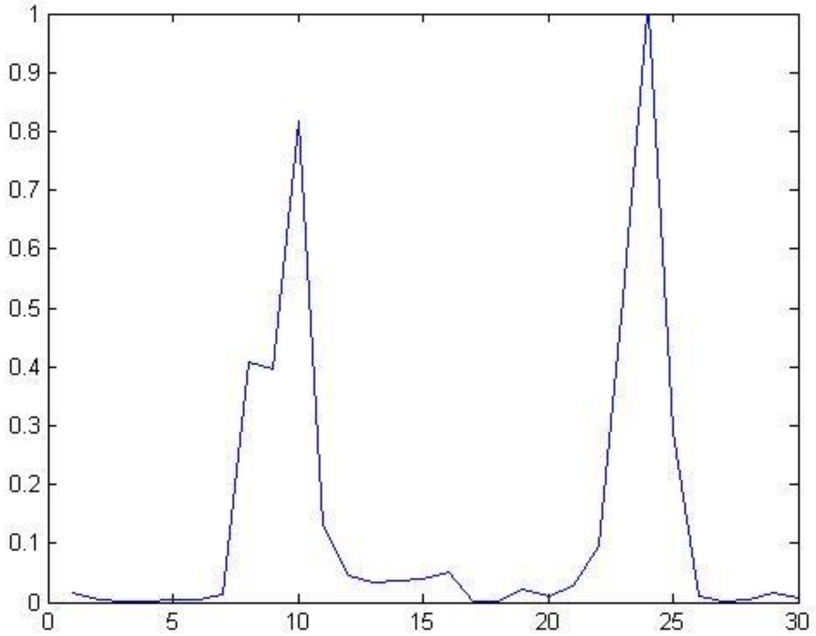
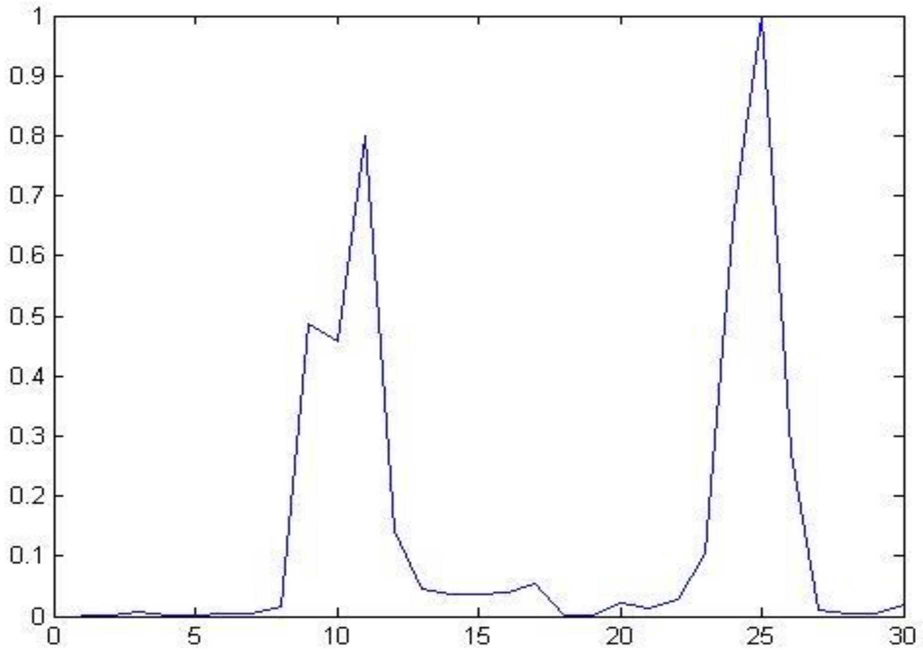


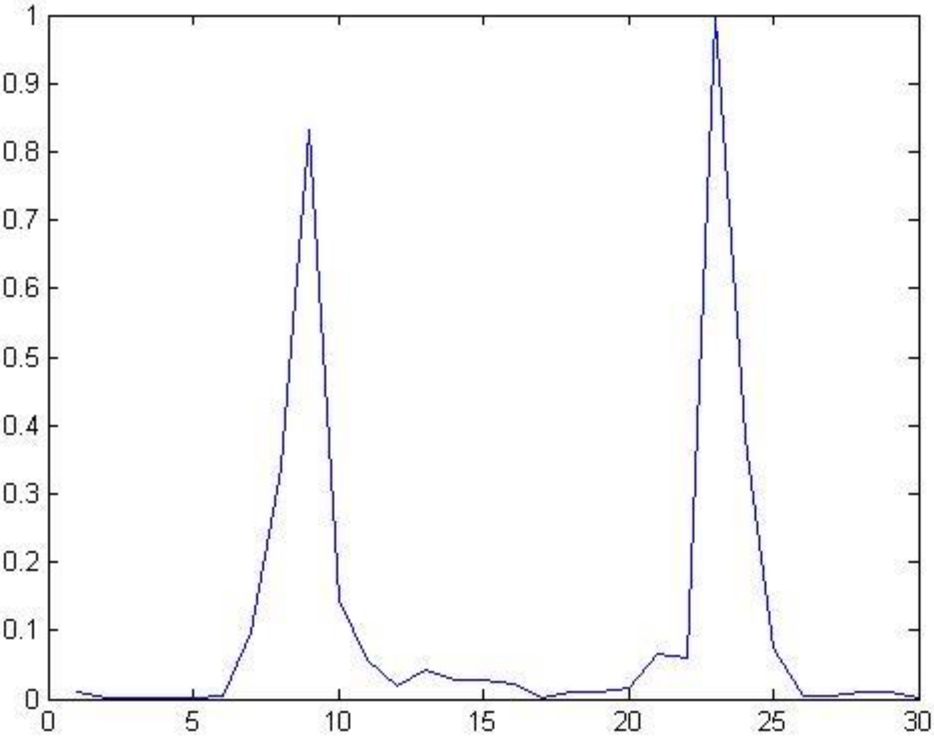
Figure 3.3: Training Of A Neural Network

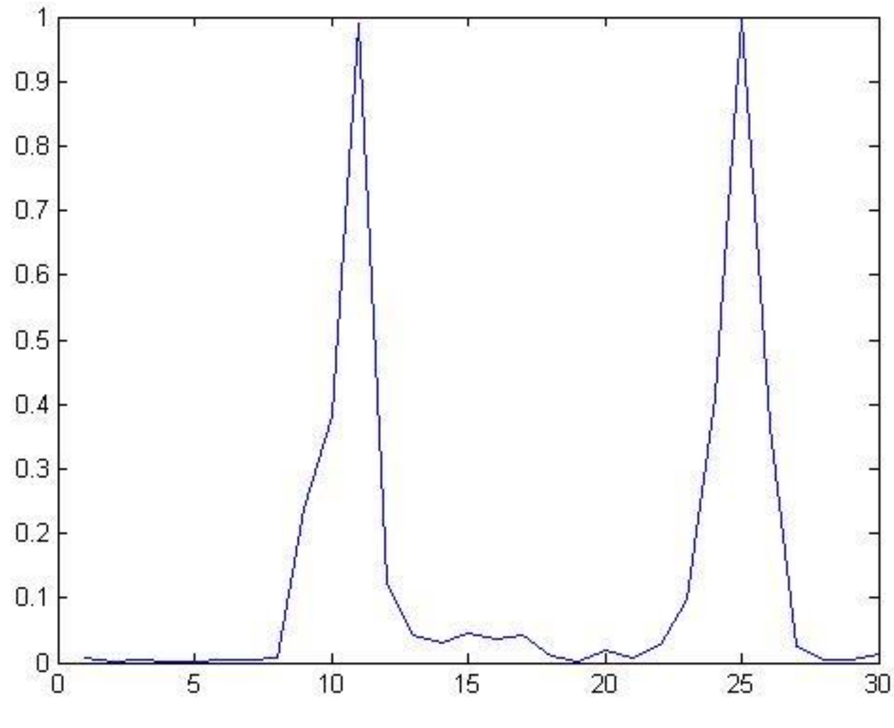
3.9 RESULTS

Extracted features are the energies of the windows having 30 frames in it. It is as shown as below for the set of energies of the five cardiac cycle of a person.






1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
5
10
15
20
25
30


1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
5
10
15
20
25
30

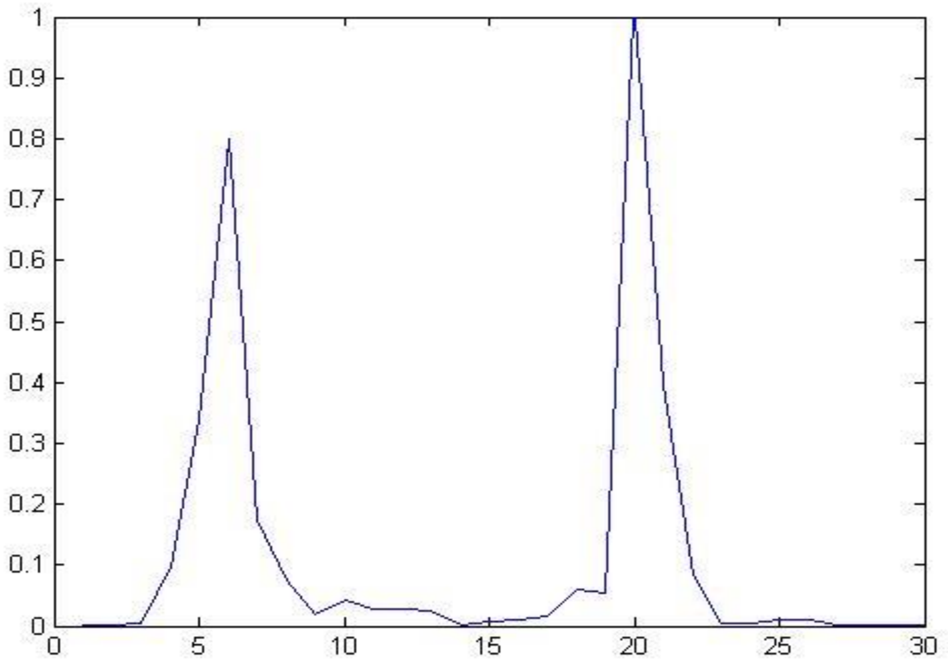


Figure 3.1: Energy based extracted features

The Normalized feature vector from the energy based feature extraction process. Then the Classification is done with feature vector as the input vector for Multilayer Perceptron Artificial Neural Network as Classifier, here we are taking 120 hidden nodes. Identification results shows 63.3824 % efficiency for identifying among the 10 Classes. Classifier help to training and testing operation for identifying the classes we mentioned earlier, here we are using 2 layer with different hidden nodes. Results is shown by the Confusion Matrix

Table 3.1 Confusion Matrix

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
P1	81	4	4	6	1	25	19	1	2	2
P2	3	94	9	5	4	7	8	1	11	1
P3	6	8	105	7	4	10	6	0	19	4
P4	9	3	11	44	0	4	22	0	14	7
P5	4	1	12	0	170	14	3	6	0	0
P6	5	4	7	5	14	109	26	3	5	4
P7	13	14	13	9	2	16	69	0	4	8
P8	3	1	4	4	12	2	3	68	2	1
P9	7	7	31	10	0	5	6	1	102	5
P10	1	10	10	6	4	6	2	7	5	75
ACCURACY=63.3824%										

3.10 IDENTIFICATION RESULTS

The process of the identification system as shown in Figure 4.1 is process of selecting one match from each class among many classes. The Query template is compared with the database of stored heart samples to find a matching. MLP-ANN classifier was trained using 69 % heart feature vector. After training the Identification system was tested using 31 % heart samples. Each of the sample is around 60seconds long sample is 15 heart cycle long. Three second cycle is extracted. Each sample goes through the process of feature extraction and then 30 feature vectors are created for each sample and made a feature vector of dimension 2191x30. Although this feature shows the information we require from the heart sound as much as good. Through segmentation process any transform can be applied to obtain the better results via using different type of classifier for classification mechanism. But sometimes expected results not came due to noisy data taken for identification. The confusion matrix shows the how much the classes are match and mismatch after testing, Due to similar pattern of feature present in the classes 1 to 4. While the other classes shows dissimilar matching, that why accuracy is up to 63.3824 %, i.e. which is very less as according to our expectation.

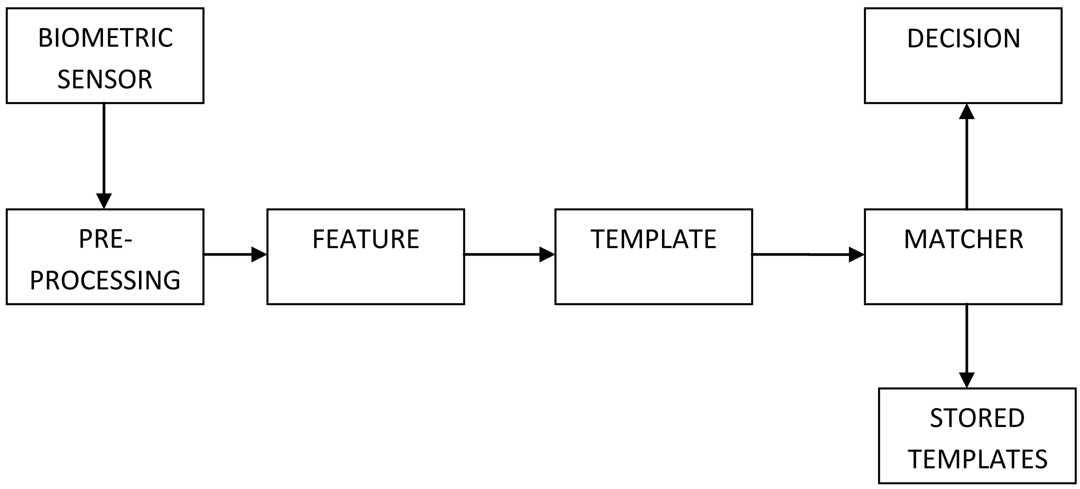


Figure 3.4 : Block diagram of identification process

According to the identification result shows that the class 1, class 2, class 3, class 4 and class 10 of training set are completely match with testing set. But from class 5 to class 9 show improper results while identification simulation process. Accuracy we are getting about 63.3824 % which is very less. Actually the Neural Network wouldn't identify much more among the classes 5, 6, 7 and 8. The patterns of feature vector are very similar that's why Neural Network confused to identify them. However sometimes the iteration gives better results if we increase its count, but if the desired output is not match with the target set for identification process, then the weight of node changes accordingly to improve the output, here we are using 120 hidden nodes for that, Training plays an important role to understanding the pattern of each classes and Testing is done according from the training data.

CHAPTER - 4

CONCLUSION & FUTURE WORKS

4.1 CONCLUSION

A unique technique has been proposed in this paper using energy based feature set for automatic identification system. These sounds having two segments S1 & S2 belongs to first and second sounds respectively. Heart samples are collected through ten volunteers as ten data's (i.e. heart sounds) per individuals. As every segment of heart sound possess a redundant data in it, so special characteristics or features are extracted from the heart sounds by means of energies of the data collected from the cycle extraction. Then Classification is done, using BP-MLP-ANN where 69 % of total numbers of heart sound signal as Training and remaining 31 % numbers of heart sound signal as Testing are applied. The identification results show 63.3824 % of performance accuracy. It shows that the proposed method yields higher accuracy. The experimental result demonstrated that heart sound which is naturally made physiological parameter can be used in modern biometric systems.

4.2 FUTURE WORKS

The project has achieved some of the major objectives such as implementing a new energy feature set. It is giving suitable result. These are

1. If we use other classifiers like a support vector machine and Proximal support vector machine, Gaussian Mixture Models then they shows better accuracy results among all.

2. With the help of with other biometric systems i.e. fingerprint recognition, Face recognition, Iris recognition showing the benefits of biometric systems in future.

3. A better segmentation technique can be applied. Because of windowing the segmentation process is not accurate. But the problem is overcome through aligning process.

4. This technique can be used in college campus as attendance system.

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