BIOMETRIC IDENTIFICATION USING ANALYSIS OF CARDIAC SOUND

Thesis submitted in partial fulfilment for the

Award of the degree of

Master of Technology

in

Electronics and Instrumentation Engineering

by

Girish Gautam

(Roll no: 211EC3307)

Department of Electronics and Communication Engineering

National Institute of Technology, Rourkela-769008, India

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under the guidance of

Prof. Samit Ari

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2013

Declaration

I hereby declare that the work presented in the thesis entitled "*Biometric Identification using analysis of cardiac sound*" is a bona fide record of the research work done by me under the supervision of Prof. 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.

Girish Gautam

(211EC3307)

National Institute of Technology
Rourkela

CERTIFICATE

This is to certify that the thesis titled "**Biometric Identification using analysis of cardiac sound**" submitted by **Mr. Girish Gautam** 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 Engineering**" during the session 2011-2013 at **National Institute of Technology, Rourkela** is an authentic work by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been sub-mitted to any other university/ institute for the award of any Degree or Diploma.

Dr. Samit Ari
Assistant Professor
Dept. of Electronics & Comm. Engg.
National Institute of Technology
Rourkela- 769008

Abstract

Human Heart Sound is unique in nature. It helps to regulate the pumping blood to the rest of the organ system for proper function, so that that pumping blood abruptly passes through the heart chamber to create heart sounds which are sounds as *LUB* and *DUB* via closure of Bicuspid and Tricuspid valve. These sounds having two segments S1 belongs to first sound and S2 belongs to second sound. In my works, first we made data collection from our ten volunteer of the age group 20-40 during three months period using Digital Stethoscope. We are having 100 heart samples stored in database. Then feature extraction using LFBC (linear frequency band cepstral), feature extraction method includes STDFT for converting the time domain signal into frequency domain. Then magnitude was taken and rejecting the phase part which generally include noise interference. Next the filter bank is applied, which reject the unwanted high frequency components. After that Dimension compression technique was used. Using DCT (Discrete Cosine Transform) here logarithmic first 24 coefficient was taken. Then Spike removal is done for removing the artifacts of position of hand movement while taking heart sound. At last, cepstral means subtraction is done, which removes the artifacts, here position of stethoscope is not same at all the time, after this operation is done, cepstral coefficient as our feature vector. Then Classification is done, using BP-MLP-ANN where 50 numbers of heart sound signal as Training and 50 numbers of heart sound signal as Testing are applied. The identification results show 52 % of performance accuracy.

Acknowledgements

I would like to express my gratitude to my supervisor Prof. Samit Ari for his guidance, advice and constant support throughout my thesis work. I would like to thank him for being my advisor here at National Institute of Technology, Rourkela. Next, I want to express my gratitude to Prof. S. Meher, Prof. S.K. Patra, Prof. K. K. Mahapatra, Prof. S. K. Behera, Prof. Poonam Singh, Prof. T. K. Dan, Prof. U. C. Pati, Prof. A. K. Sahoo, Prof. D. P. Acharya, and Prof. S. K. Das for their teachings and extended help.I would like to thank all faculty members and staff of the Department of Electronics and Communication Engineering, N.I.T. Rourkela for their generous help which played a vital role in various ways for the successful completion of this thesis. I would also like to mention the names of Manab Das, Dipak Ghosh, Gautam, Deepesh, Pankaj, Avinash, Satya, Sonu, Rakesh, Bijay and Ramesh for their help and support during the heart sound data collection. I would like to thank all my friends and especially my classmates for all the thoughtful and motivating discussions we had, which encouraged me to think beyond the observable. I am especially grateful to my parents for their love and support and would like to thank my parents for raising me in a way to believe that I can achieve anything in life with hard work and dedication.

Girish Gautam

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Dedicated to

My parents, and my sisters

CHAPTER 1

INTRODUCTION

1. Introduction

1.1 *What is a Biometric System*

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 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 one duplicate it.[33][34]

Biometric identifiers are the distinctive and measurable characteristics used to label and describe individuals identity.[35] Biometric identifiers are often categorized as physiological versus behavioural characteristics. A physiologic biometric should be identify by iris scan, DNA or fingerprint.[1]

More traditional means of getting at control including the nominal-based identification systems, such as a driver's license or passport, and knowledge-based identification systems, such as a password or personal identification number[37][38]. Since biometric identifiers are unique to every individuals, they are more honest in verifying identity than token and knowledge-based methods, however, the collection of the biometric identifiers arouses secrecy concerns about the prime use of this information.[1]

Biometric authentication processes comprising of two phases. In first phase the database is made where the feature sets of Heart sound of each individual is stored. In second phase the extracted feature sets are compared with the feature templates stored in the database to find a match.[1][2].

1.2 *IDENTIFICATION*

Now a days, Crime is growing very fast in our world. To identity the suspect behind it.We have to identity through by our memory based picture. Or any other means of photograph, and through different person claiming for that. This type of system already present in police department for thief to identity. If we make the data base of all the previous visited thiefs with their every means of biometric identification i.e, Fingerprint, Face, iris, and DNA etc. The process of identification can be realized from how a crime defendent is known by a witness. Witness's job is to find out the criminal among the suspects on the basis of the physical assign that is stored in his memory. In biometric system the classifier is first trained with the features of the different classes. Feature extracted from the query sample is matched with the stored classes and finally a conclusion is made about which class of query sample going to match first.

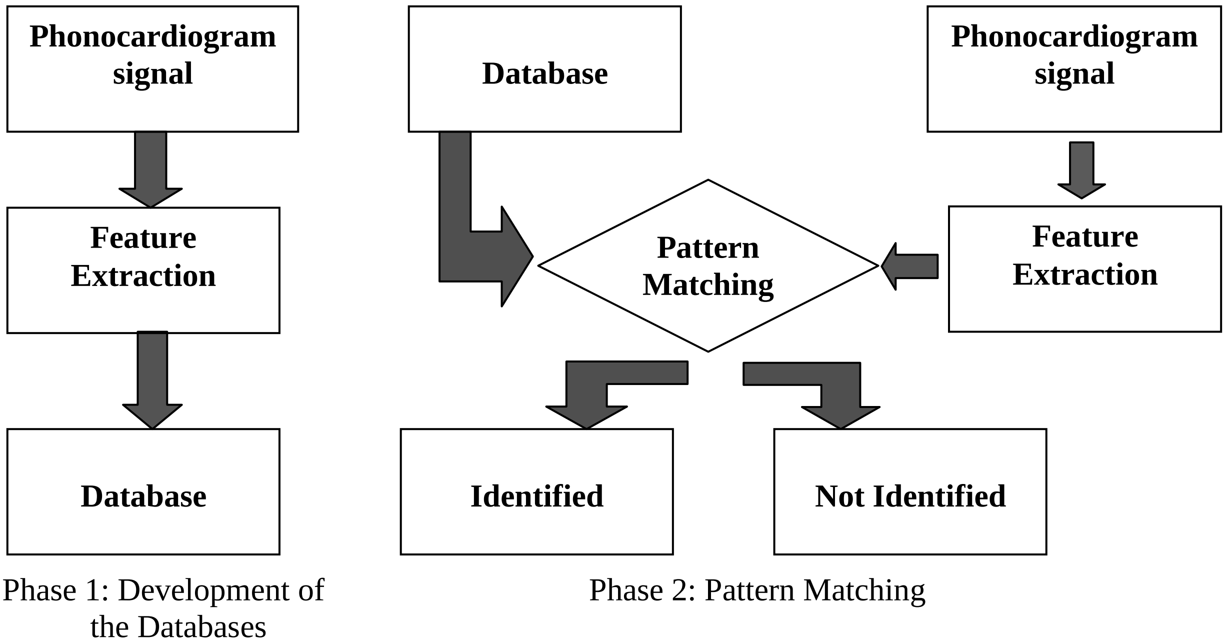

Figure 1.1 Two phases of Biometric Authentication System.[2]

1.3 *Salient Features of heart Sound as Biometric*

- *Distinctiveness*. Two persons should be different in terms of the characteristic property.
- *Permanence.* The characteristic should be sufficiently in-variant over a period of time.
- *Universality*. Each person should be having the unique characteristic.
- *Invariability* : The system performance should remain same over a long duration of time.
- *Uniqueness* : Every person's Heart Sound is unique in nature.
- *Easy accessibility*: The physiological trait should be easily accessible.
- *Collectibility*. The feature should be quantitatively measurable.[49]

There are many other types of trading points for a biometric system, like data storage requirements, cost, sensor quality etc.[28][29] One of the important counter is to consider is whether heart sound as phonocardiogram based biometric system will be a good option or not. For universality purpose, this biometric system is best for all privacy point of you. Although for accessing BANK locker, Password protected jewellery shop, Personal Computers etc.[3]

1.4 *PCG as a physiological trait for Biometric Systems*

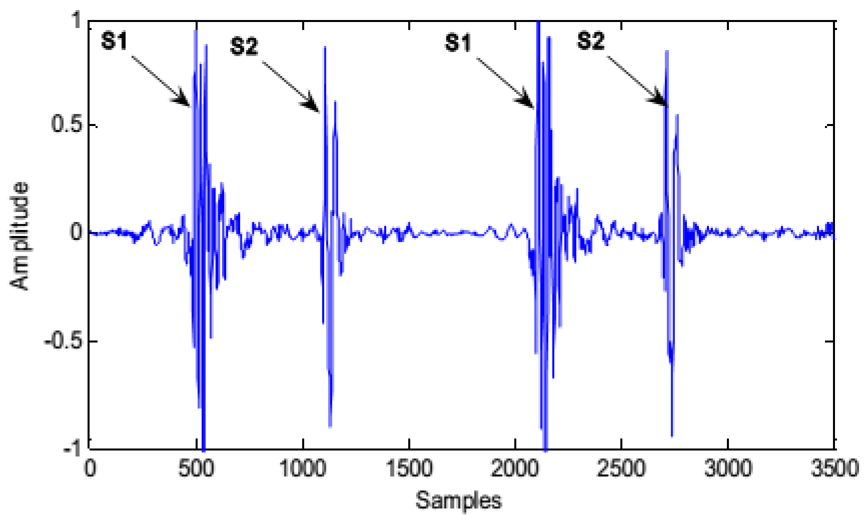

Figure-1.2 Typical waveform of S1 and S2 of PCG wave[4]

First and second heart sounds as S1 (LUBB) and S2 (DUBB) are produced by sudden closure of atrio-ventricular and semi lunar valves i.e, bicuspid and tricuspid valve present between the atria and ventricle with the flow of blood abruptly S1 and S2 segment contain information of activity of heart as working normal.[36] The frequency range is 20-150Hz. Every living human being has a universal heart sound and the sound can easily be accessed by holding stethoscope in the auscultation sites in the chest region.[30] By the advent of improved data acquisition systems these sounds can promote be stored in a computer using a digital stethoscope developed by HD fon. All these features create heart sounds suited for the use in Biometric system. Therefore the sound produced depends on the valves. As the valve's nature differs from person to person. Figure 1.3 shows the auscultation point present i.e, Aortic, Pulmonary, Mitral and LLSB[31][32]

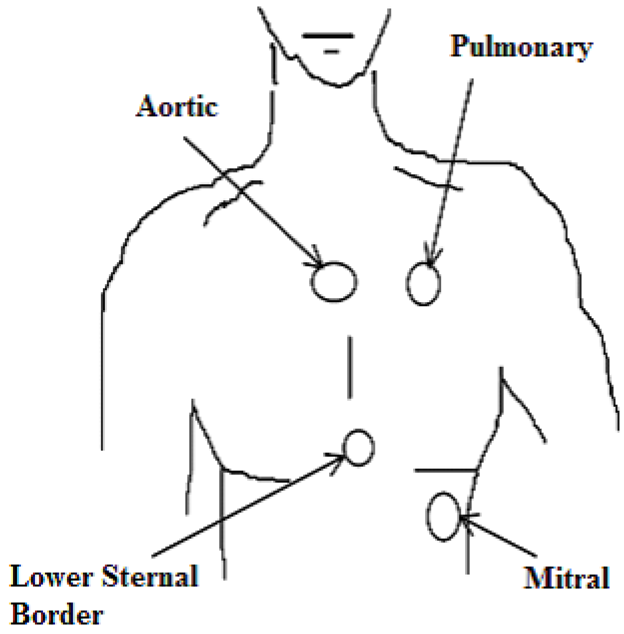

Figure 1.3 – Auscultation Point present in human chest [4]

1.5 *Heart Sound Production*

The human heart has four chambers, left and right Atrium, left and right Ventricles. Inside the heart, blood flows from Atrium to Ventricles and from Ventricles it is pumped out from the heart through Pulmonary Artery and Aorta.[4]. The process of pumping the blood occurs in two stages, Diastole and Systole which determine the Blood pressure. There are 2 types of Blood Pressure i.e., Low Blood Pressure and High Blood Pressure.[50]

Table 1.1: Different between Diastolic and Systolic [5]

	Diastolic	**Systolic**
Definition:	It's the pressure that is maintain on the walls of the various arteries around the body in between heart beats when the heart is relaxed.	It measures the amount of pressure that blood exerts on arteries and vessels while the heart is beating.
Normal Range:	60 – 80 mmHg (adults); 65 mmHg (infants); 65 mmHg (6 to 9 years)	90 – 120 mmHg (adults); 95 mmHg (infants); 100 mmHg (6 to 9 years)
Importance with ages:	Diastolic readings are particularly important in the monitoring blood pressure in younger individuals.	As a person's age increases, so too does the importance of their systolic blood pressure measurement.
Blood Pressure:	Diastolic represents the minimum pressure in the arteric	Systolic represents the maximum pressure exerted on the arteries.
Blood Pressure reading:	The lower number is diastolic pressure.	The higher number is the systolic pressure.
Ventricles of the Heart:	Fill with blood	Left ventricles contract
Etymology:	"Diastolic" comes from the Greek diastole meaning "a drawing apart."	"Systolic" comes from the Greek systole meaning "a drawing together or a contraction."
Blood Vessels:	Relaxed	Contracted

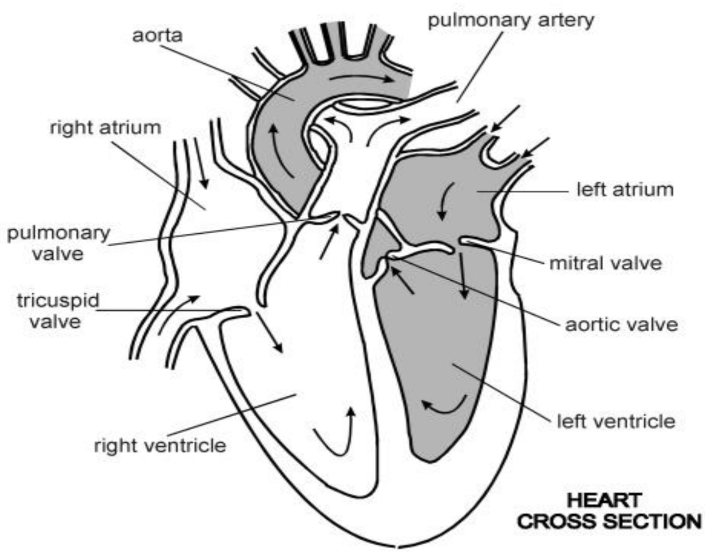

Figure 1.4: Cross section of a human heart [6]

Heart sound is in the range of 15-200 Hz. Two major heart sounds are the S1 or LUBB and S2 or DUBB. S1 sound is caused by the sudden blockage of reverse blood flow due to closure of the Atrio-ventricular valves, i.e. Tricuspid and Mitral (Bicuspid), at the beginning of ventricular contraction, or Systole. S2 sound is caused by the abrupt blockage of reversing blood flow due to closure of the Semilunar valves (the Aortic valve and Pulmonary valve) at the end of ventricular systole, i.e. beginning of ventricular diastole. [39]

1.6 *Data Collection*

Generally PCG signals are not freely available on a large scale for research purposes. So we have to create our own database of PCG signals. Here ten volunteers contributed to the building of the database of heart sounds. For the project it was required to store heart sounds for further processing. The digital Stethoscope manufactured by HDFono Doc has the USB connectivity and the heart sound can be stored in Personal Computer directly in .wav format

Figure 1.5: Data Collection using Digital Stethoscope [7]

Through the USB connectivity the instrument can directly store the heart sound into the PC in Waveform Audio File Format, also known as WAV format. The volunteers are in the age group 20-35. For a particular volunteer each sample (of 20 second duration) was collected with a minimum time gap of one hour. This process of data collection continued for three months. All the volunteers were having normal heart sounds [2].

1.7 *Advantages of PCG Signals*

There are various advantage of PCG signals some of them can be stated as follows:

1. It detects diseases.

2. It designate the failure of valves

3. It shows tachycardia and bradycardia.[42]

1.8 *Normal and Abnormal PCG Signals*

Normal heart sound contain normal heart sound segment S1 and S2, which gives information of functionality of heart sound.[40] Abnormal Heart sound contain irregularity in nature which give rise to 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.[41]

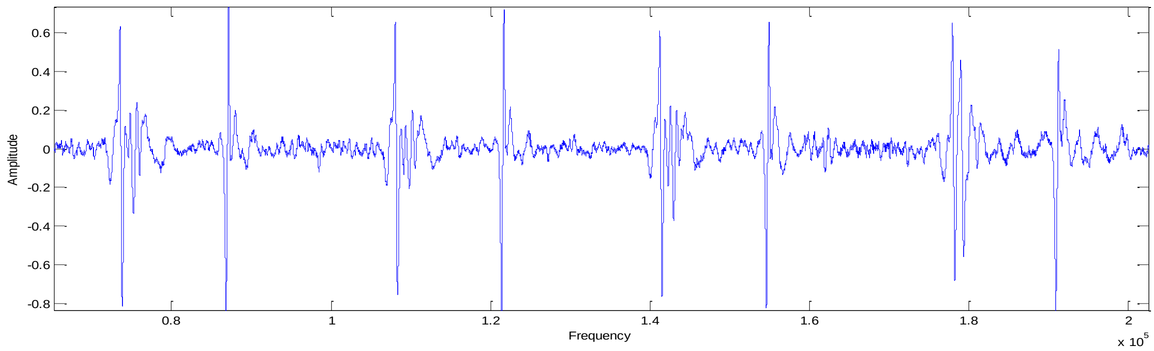

Figure 1.6-Recorded heart sound

1.9 *Motivation*

The heart sound collection is amazing using Digital stethoscope. Auscultations point be used to identify an individual is storming. The Phonocardiogram signals of any two individual cannot be same and cannot be rebuilt by artificial means, but if is made sound production mechanism fails. Its is biggest advantage as a biometric trait. The experiments carried in our laboratory indicates feature extraction using linear frequency band cepstral based processes lacked the some accuracy due to noisy interference in data. While ANN will take more time for registration of person but once it was enrolled and the network was created with different hidden nodes and weight values, Over all the fields of Biometric identification based on phonocardiogram are still an active and important field of research. The estimate to try a LFBC based feature set was motivating enough to go for the project.

1.10 *Thesis Outline*

The rest of the thesis is organized in the following manner.

- Chapter two describes the Extraction of Feature using LFBC. The feature extraction technique is composed of STDFT, Magnitude, Filter Bank, Dimension Compression, Spike Removal, Cepstral means Subtraction. The cepstral coefficient itself as Features containing 24 coefficients.
- Chapter three 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 50 samples used as a Training and remaining 50 samples as Testing. The Identification Results shows only 52 % efficiency.
- Chapter four 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 and Bibilography.

CHAPTER 2

FEATURE EXTRACTION

Introduction

Generally why we need feature extraction of any signal ? however any kind of signal contain some information in it. The characteristic of signal differ by a single second. To take out the information present in the signal. That process of extracting feature is called feature extraction.

Extraction of Feature using LFBC

Feature extraction is the process of extracting useful information from a signal. In this project we require features that can describe the individuality of a PCG signal of a particular person. For PCG signal frequency ranges from 20-200 Hz in frequency[33][43]

2.1 *Block diagram of LFBC based feature extraction*

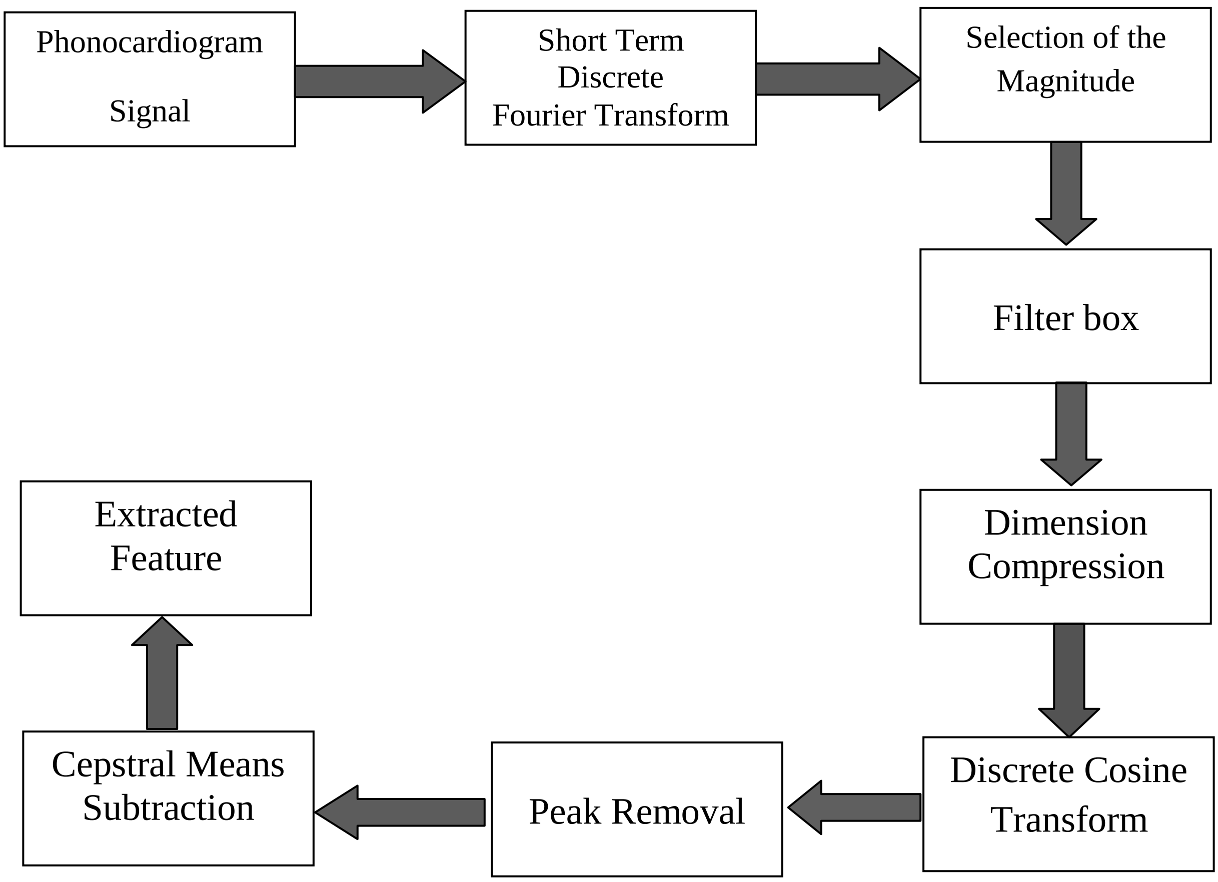

Figure 2.1: Block diagram of the LFBC feature extraction process[9]

2.1.1 *STDFT*

The process of feature extraction starts with the Short Time Discrete Fourier Transform (STDFT) of the stored PCG signals, which convert in the frequency domain.[9][4]. STDFT is a special class DFT technique where we use a shifting window. If x[n] is the discretize signal then DSTFT is given by:

$$DSTFT\{x[n]\} \equiv X(m,w) = \sum_{n=-\infty}^{\infty} x[n]w[n-m]\, e^{-iwn} \qquad 2.1$$

With the window w[n] and m is the shift. For heart sounds we apply a window of 0.5 Sec with a shift of 250 milliseconds.

2.1.2 *Magnitude*

After acting the transform only the magnitude part is selected as it contain less noisy portion and rejecting the phase part because it retain with heavy disturbance.

2.1.3 *Filter Bank*

Next the signal (Magnitude part) is band pass filtered 20-150 Hz. So that it will reject the high frequency components i.e., it contains noisy interference.

2.1.4 *Dimension Compression with DCT*

Next the logarithm of the coefficients is taken as it helps to compensate the effect of the air column channel of the Stethoscope. And then we perform Discrete Cosine Transform (DCT) as its an empirical formula of Principal Component Analysis which gets the desired Cepstral coefficients.[4]. The overall process can be represented mathematically as:

$$x_n(m,w) = \log[X(m,w)] \qquad 2.2$$

$$X_k = \sum_{n=0}^{N-1} x_n \cos[\frac{\pi}{N}(n+\frac{1}{2})k] \qquad 2.3$$

So, X_k is our desired cepstral coefficients. K denotes the total number of frequency bins present between 20 to 150 Hz. We reduce the dimension of feature vector to 24 by selecting only first 24 cepstral coefficients. It is done because the higher order cepstral contain very little information.

2.1.5 *Removal of spikes*

After the dimension compression the next step is the peak removal which is generally done to remove the artifacts due to hand movement and other activities etc. To perform this operation we will take the energy of each segment E[n], so that every window should removal artifacts, where n denotes the segment index. We take threshold value of 15dB.

$$10\lg E[n] - \min_n(10\lg E[n]) \geq \mu \qquad 2.4$$

Next, we are going to compensate to the effect of the channel into the signal. The dispute is a channel transfer function of stethoscope depends upon the region from where data is collected which cannot be kept exact same point at all the time. So it is impossible to neutralise the effect completely.

2.1.6 *Cepstral means Subtraction*

Now the mean over a range of data was taken and deducted the mean of the data. If the dimension of the data is k (Cepstral coefficient/window) total transfer function of the process can be assign as Z[n,k] and the process transfer function as X[n,k] and the average channel transfer function was given by Y[k]. So we can write this as follows:

$$Z(n,k) = X[n,k] \times Y[k] \tag{2.5}$$

As the log Cepstral coefficient is taken as 24 here, the process has become additive in logarithm

$$\log(\left|Z[n,k]\right|) = \log(\left|X[n,k]\right|) + \log(\left|Y[k])\right| \tag{2.6}$$

So the Cepstral coefficients C_Z[n: k] can be written as follows:

$$C_z(n,k) = C_x(n,k) + C_y(k) \tag{2.7}$$

Now after subtracting the mean $\left\langle C_{Z,k}[n] \right\rangle$ over n data, we can theoretically cancel the effect of the channel.

$$C_{z,k}[n] - \left\langle C_{z,k}[n] \right\rangle = C_{x,k}[n] - \left\langle C_{x,k}[n] \right\rangle \tag{2.8}$$

Atlast, from the one samples of one volunteer, having 24 cepstral coefficient as its feature

But in reality the effect is never fully deleted.

CHAPTER 3

CLASSIFICATION

Artificial Neural Network

The fundamental 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.[10]

3.1 *Structure of a single node*

In mathematical terms we can write:

$$v_k = \sum_{j=0}^{m} w_{kj} x_j \qquad 3.1$$

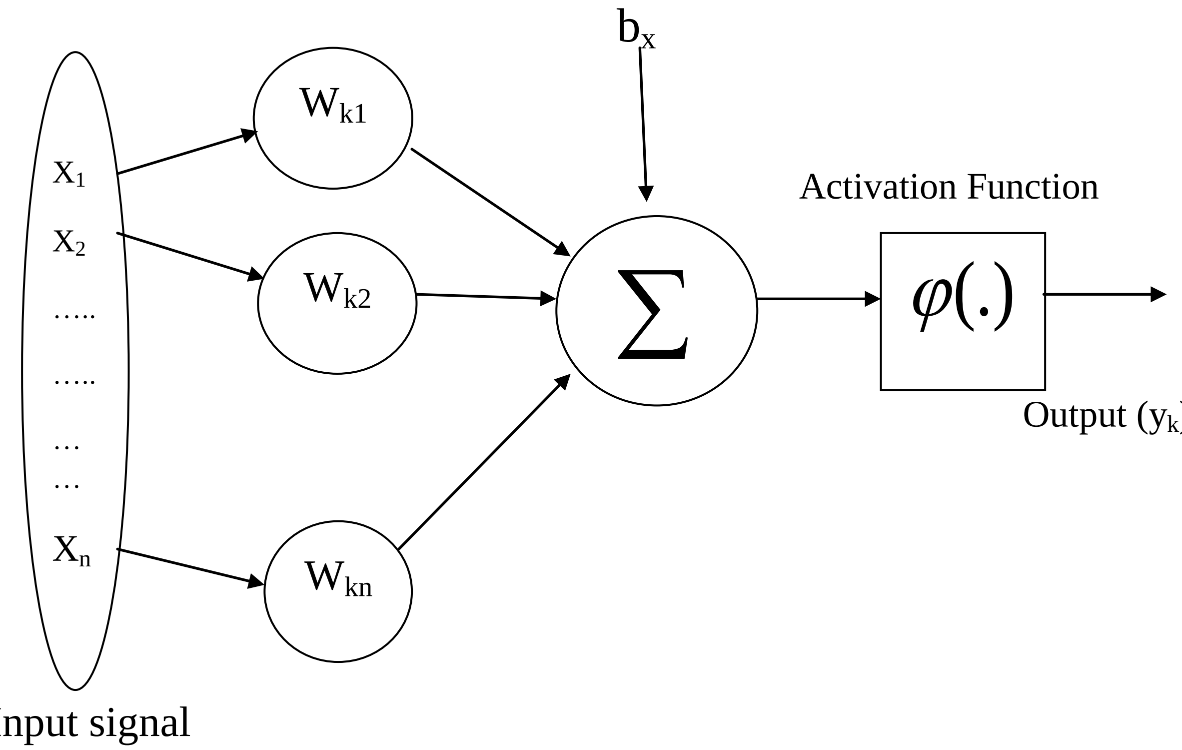

Figure 2.2: Structure of a single neuron

Here x_1 x_2 are the input signals and w_1, w_2 are the synaptic weights of the kth neuron. v_k is the activation potential of the neuron. Bias b_k is considered as $b_k = w_{0j}\ x_0$ Output of the neuron y_k can be represented as:

$$y_k = \varphi(v_k) \qquad 3.2$$

$\varphi()$ is called the activation function. Activation function can be settled or it can be the probabilistic. Most popular and commonly used activation function is sigmoid function

$$\varphi(v) = \frac{1}{1 + \exp(-av)} \qquad 3.3$$

3.2 *Multilayer Network*

Generally Neural Network are made up of multiple hidden layers of nodes or artificial neurons same as our neuron in brain. The overall function of this hidden layer is to make the network output follow the desired form. The network with the multiple layer can follow higher order statistics.

3.3 *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.

3.4 *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 $\varepsilon_{av}(n)$ is obtained by adding "(n) overall n and normalizing with respect to the set size N. $\varepsilon(n)$ 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.

$$\varepsilon_{av}(n) = \frac{1}{N}\sum_{n=1}^{N}\varepsilon(n) \qquad 3.4$$

The change in the synaptic weight is given by:

$$\Delta_{\omega_{ji}}(n) = -\eta\frac{\partial\varepsilon(n)}{\partial\omega_{ji}(n)} \qquad 3.5$$

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 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:

$$\frac{\partial\varepsilon(n)}{\partial\omega_{ji}(n)} = \partial_j(n).y_i(n) \qquad 3.6$$

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

$$\Delta\omega_{ji}(n) = \eta.\partial_j(n).y_i(n) \qquad 3.7$$

3.5 *Perceptron*

Suppose we have to a set of learning sampled consisting of an input vector x_j and a desired output y_k. For the classification job the y_k is usually +1 or -1 The perceptrons learning rule is very easy and robust can be submitted as follows [11]:

1. Start with the random weights for the connections in Neural Network.

2. Select an input vector x_j from the set of training samples of heart sound.

3. If $y_k = x_j$ the perceptron gives an wrong response, then modify all connections w_{kj} according to

$$\Delta\omega_{kj} = y_k . x_j \qquad 3.8$$

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].

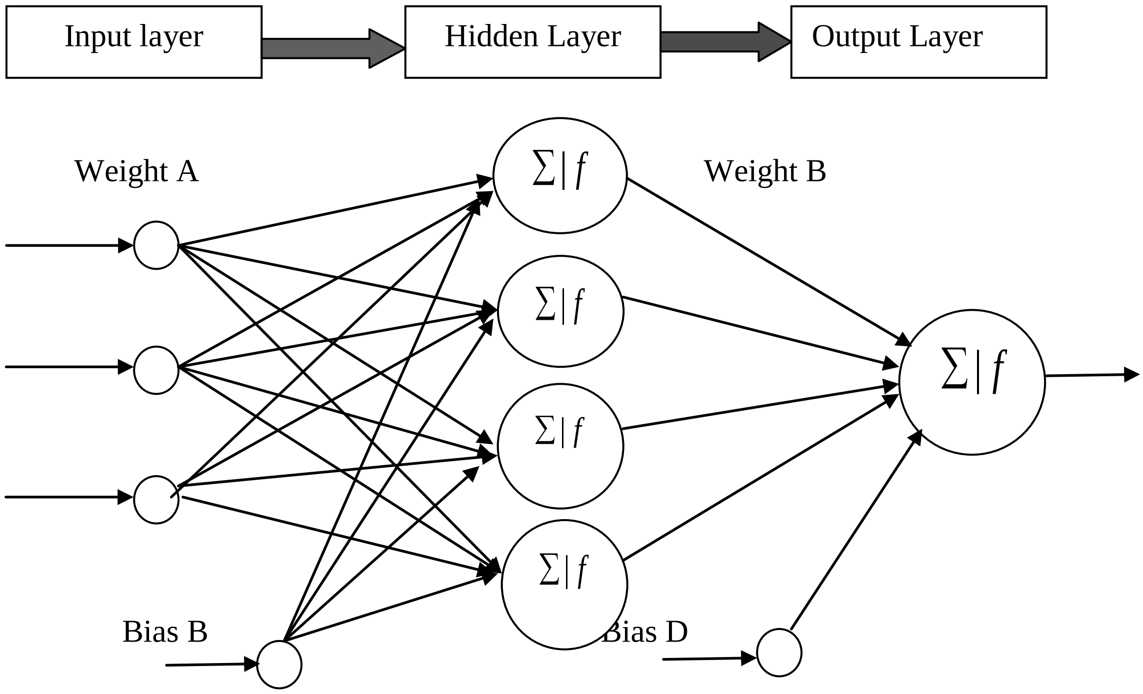

Figure 2.3: Structure of a Multi layer Back Propagation NN [20]

Back propagation 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] uses ANN for classification of heart murmurs and a classification accuracy of 52 % 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 is 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 W_{ij}. This process continues until the error E reaches a permissible optimal value $E_{T.}$ 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.

3.6 ***ANN Parameter***

```
% INITIALIZE NETWORK PARAMETERS
net = init(net);
net.trainParam.show = 25;
net.trainParam.lr = 0.5;
net.trainParam.mc = 0.9;
net.trainParam.lr_inc = 1.01;
net.trainParam.lr_dec = 0.9;
%%% CHANGEABLE VARIABLE %%%%
net.trainParam.epochs = 100000;
net.trainParam.goal = .000001;
%%%%%%%%%%%%%%%%%%%%%%%%%%%
net.trainParam.max_fail = 5;
net.trainParam.min_grad = 1e-007;
net.trainParam.max_perf_inc = 1.04;
net.trainParam.time = Inf;
```

CHAPTER 4

EXPERIMENTAL RESULTS

The Normalised feature vector from linear frequency band cepstral 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 49 hidden nodes. For first 24 Cepstral Coefficient as features. Identification results shows 52% 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.

4.1 *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. the query sample is compared with the database of stored heart samples to find a matching. MLP-ANN classifier was trained using 50 heart feature vector. After training the Identification system was tested using 50 heart samples. Each sample is 15 heart cycle long. Each sample goes through the process of feature extraction and then 24 feature vectors are created for each sample and made a feature vector of dimension 100x24. Although these 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 classes are match while 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 upto 52 % . i.e. which is very less as we expected.

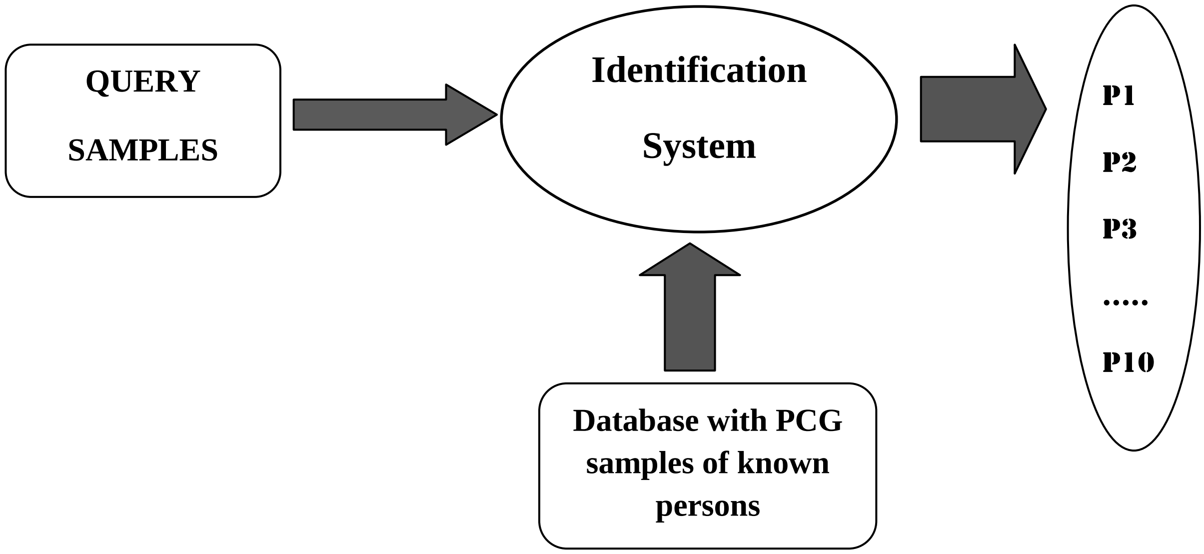

Figure 4.1: Block diagram of identification process.

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 upto 52 % 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 49 hidden nodes for that, Training plays important role to understanding the pattern of each classes and Testing is done according from the training data.

Table 4.1 Confusion Matrix for 24 feature vector

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
P1	5	0	0	0	0	0	0	0	0	0
P2	0	5	0	0	0	0	0	0	0	0
P3	0	0	5	0	0	0	0	0	0	0
P4	0	0	0	5	0	0	0	0	0	0
P5	0	1	0	1	0	0	1	1	0	1
P6	0	0	2	1	0	0	0	1	0	1
P7	1	0	1	1	0	0	1	0	1	0
P8	0	0	1	1	0	1	0	0	2	0
P9	0	0	0	1	0	0	1	0	1	2
P10	0	0	0	0	0	1	0	0	0	4
Total Sampled Tested -50 Correct Identification- 26										
Accuracy-52 %										

CHAPTER 5

CONCLUSIONS AND FUTURE WORK

Conclusions and Future Work

5.1 *Conclusion*

A novel technique has been used with linear frequency band cepstral based feature set for automatic identification system. The PCG signal is in time domain, so to convert in frequency domain from STDFT ,then the magnitude part is taken and rejecting the phase part, which contain noisy, Next the filter bank is applied to remove the high frequency component present in it, although filtering the signal between 20-150 Hz. Due the position of hand movement which affect the signal to store, For removing this artefact we use peak removal operation, At last but not least Cepstral means subtraction, Due to position of stethoscope is not fixed all the time, the relative transfer function of device is affected, we have to multiply the transfer function of device and with the signal. So that the remaining part left is cepstral coefficient as our feature vector. Which results showing accuracy of 52 %..

5.2 *Future works*

The project has achieved some of the major objectives such as implementing a new time frequency domain feature set. It is giving satisfactory 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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