International Journal of Emerging Research in Management &Technology
ISSN: 2278-9359 (Volume-4, Issue-5)
Research Article **May 2015**

A New Method for Biometric Application Using PCG Signals

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Abstract—

Phonocardiogram (PCG) signals as a biometric is a new and novel method for user identification. Use of PCG signals for user recognition is a highly reliable method because heart sounds are produced by internal organs and cannot be forged easily as compared to other recognition systems such as fingerprint, iris, DNA etc. A novel technique is described in this paper for the authentication of the person using Mel frequency cepstral coefficient (MFCC) and Vector quantization. Support vector machine is used as a classifier to classify the different types of PCG signals.

***Keywords**— Phonocardiogram, Biometric, MFCC, Vector quantization, Support vector machine.*

I. Introduction

Reliable authentication and identification is becoming mandatory in recent years in applications such as defense, finance, personnel security and other important fields, where information security is facing issues on illegal copying and sharing of digital media [18]. A biometric system aims at implementing security systems that recognizes a person immediately and certainly. Knowledge-based or possession based access control methods proved to be immortal. It is difficult to forge biometric traits and they seem to be more powerful. They constitute a strong and reasonably permanent link between a person and his identity [1]. So, it has become mandatory to use a reliable and robust authentication and identification system to identify a user. [17] Heart sound is distinctive in nature and it can also contribute a lot to recognize a person by their heart sound. In the past, study of heart sounds focus mainly on the heart rate variability. In the last 4 years, many researchers have investigated the possibility of using heart sounds as physiological traits for biometric recognition [2], [3], [4], [5], [6], [7], [8].

Recording of the sounds made by the heart during a cardiac cycle is known as phonocardiogram. The sounds are thought to result from vibrations created by closure of the heart valves. There are at least two: the first when the atrioventricular valves close at the beginning of systole and the second when the aortic valve and pulmonary valve close at the end of systole. PCG signal is invariable, unique, universal easy to accessible and unique in nature. PCG signal contain very useful information about the condition of heart.

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. The main drawbacks of heart-sounds biometry are probably the Low Performance and, its overall immaturity as a biometric trait. Of course, heart sounds biometry is a new technique, and as such many of its current drawbacks will probably be addressed and resolved in future research work.

II. Literature Review

In the last years, different research groups have been studying the possibility of using heart sounds for biometric recognition. In this section, we will briefly describe their methods [18].

Phua et.al proposed a Novel method based on Cepstral analysis of heart sounds for feature extraction, combined with the Gaussian Mixture modeling technique. Francisco Beritelli made a frequency analysis by z-chirp transform (CZT) algorithm. Euclidean distance was used to measure the signal spectra. Later he proposed a multi-band analysis approach to enhance the seperability between intrapersonal and interpersonal classes of values.

Gupta et.al segmented heart sounds using Homomorphic filtering and K-means clustering. They introduced a new neural network strategy, GAL and MLP-BP techniques for differentiating murmurs. Bendary et.al used Discrete Wavelet Transforms for analyzing signals which divided the signals into sub-bands. They were trained using MSE and KNN classifiers.

Tran et.al worked on the different feature extraction methods, exploring 7 set of features. All features were fed to a feature selection method called RFE-SVM to find the best set of features. Out of which, Gaussian models gave good results.

Fatemian et. al investigated both ECG and PCG for biometric recognition. The heart sounds were processed using Daubecchies 5 wavelets and used two energy (low & high) thresholds to select the coefficients for further stages. The frames were processed by STFT, Mel-frequency filter banks and LDA for dimensionality reduction.

Sumeth et.al segmented cardiac cycles by envelope detection and calculated the length of the signals using auto-correlation of envelope signal. He classified by neural network bagging predictors.

Gill et.al presented a model which detected and identified using Homomorphic envelogram and HMM for feature vectors.

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Jasper and Othman computed various energy parameters like Shannon entropy, Shannon energy of different sub-bands taken through DWT.

Olmez et.al segmented PCG signals using multi-band wavelet energy (WTE). It gave better performance in comparison with Shannon energy and Homomorphic filtering methods.

III. FEATURE EXTRACTION: MFCC

Feature extraction is related to dimensionality reduction. That is, feature extraction transforms the data in the high-dimensional space to a space of fewer dimensions. The best and popular choice for feature extraction of acoustic signals is the Mel Frequency Cepstral Coefficients (MFCC) which maps the signal onto a Mel-Scale which is non-linear and mimics the human hearing. The idea of using Mel Frequency Cepstral Coefficients (MFCC) as the feature set for a PCG biometric system comes from the success of MFCC for speaker identification [19] and because PCG and speech are both acoustic signals. MFCC is based on human hearing perceptions which cannot perceive frequencies over 1Khz. MFCC has two types of filter which are spaced linearly at low frequency below 1000 Hz and logarithmic spacing above 1000Hz. Mel-frequency cepstrum coefficients (MFCC), which are the result of a cosine transform of the real logarithm of the short-term MFCCs are more efficient. The overall process of the MFCC [10] [11] is shown in Fig.1.

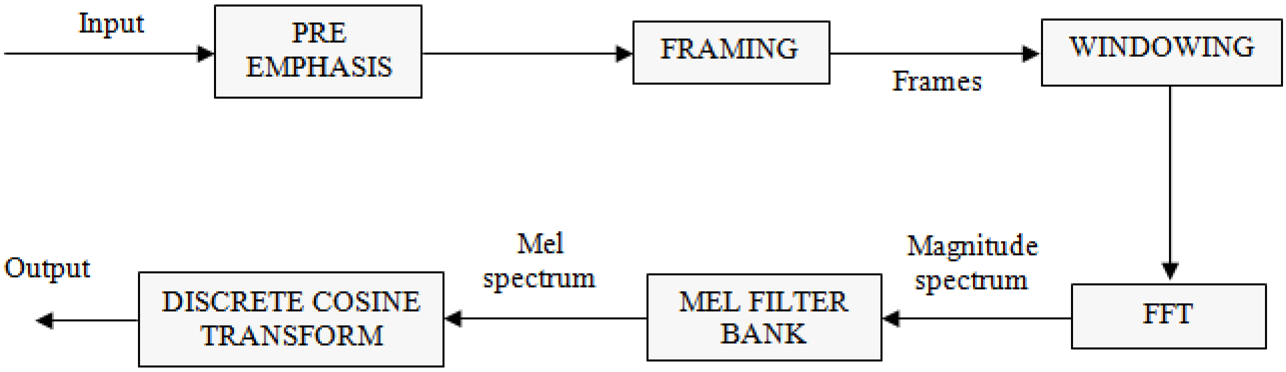

Fig.1 MFCC Block Diagram

As shown in Fig.1, MFCC consists of six computational steps and each step has its function and mathematical approaches as discussed briefly in the following: [17]

Step 1: PRE–EMPHASIS

This step of pre-emphasis process the signal through a filter and compensates the high frequency part that was suppressed during the sound production mechanism of humans. The speech signal s (n) is sent to a high-pass filter which at higher frequency increases the energy of signal:

$$So\ (n) = s\ (n) - a*s\ (n-1)$$

Here, so (n) is the output signal and the value of a usually lies between 0.9 and 1.0. The z-transform of the filter is:

$$H\ (z) = 1 - a*z^{-1}$$

Step 2: FRAMING

The heart sound signal is quasi-stationary (slowly varying over time) that is when the signal is examined over a short period of time, the signal is fairly stationary. Therefore signals are often analyzed in short time segments.

In this step the continuous speech signal is blocked into frames of N samples, with adjacent frames being separated by M ($M < N$). The first frame consists of the first N samples. The second frame begins M samples after the first frame, and overlaps it by N - M samples and so on. This process continues until all the speech is accounted for within one or more frames. Typical values for N and M are N = 256 and M = 100.

Step 3: WINDOWING

The next step in the processing is to window each individual frame so as to minimize the signal discontinuities at the beginning and end of each frame. The concept here is to minimize the spectral distortion by using the window to taper the signal to zero at the beginning and end of each frame. If we define the window as w(n), $0 \le n \le N-1$, where N is the number of samples in each frame, then the result of windowing is the signal

$$y(n) = x(n)w(n), \quad 0 \le n \le N-1$$

Typically the Hamming window is used, which has the form

$$w(n) = 0.54 - 0.46\cos\left(\frac{2\pi n}{N-1}\right), 0 \le n \le N-1$$

Step 4: FAST FOURIER TRANSFORM (FFT)

The next processing step is the Fast Fourier Transform, which converts each frame of N samples from the time domain into the frequency domain. The FFT is a fast algorithm to implement the Discrete Fourier Transform (DFT), which is defined on the set of N samples as follows

$$Y\ (k) = \sum_{n=1}^{N} x(n)h(n)e^{-j2\pi kn/N} \quad 1 \le k \le K$$

Where h (n) is N sample long analysis window (e.g. hamming window), and K is the length of the DFT.

Step 5: MEL-FILTER BANK PROCESSING

In this step, the above calculated spectrums are mapped on Mel scale to know the approximation about the existing energy at each spot with the help of Triangular overlapping window also known as triangular filter bank. These filter bank is a set of bandpass filters having spacing along with bandwidth decided by steady Mel frequency scale. Thus, Mel scale helps how to space the given filter and to calculate how much wider it should be because, as the frequency gets higher these filters are also get wider. For Mel-scaling mapping is need to done among the given real frequency scales (Hz) and the perceived frequency scale (Mels). During the mapping, when a given frequency value is up to 1000Hz the Mel-frequency scaling is linear frequency spacing, but after 1000Hz the spacing is logarithmic as shown in Figure 3 The formula to convert frequency fhertz into Mel mf is given by

$$M(f) = 1125 \ln (1+f/700)$$

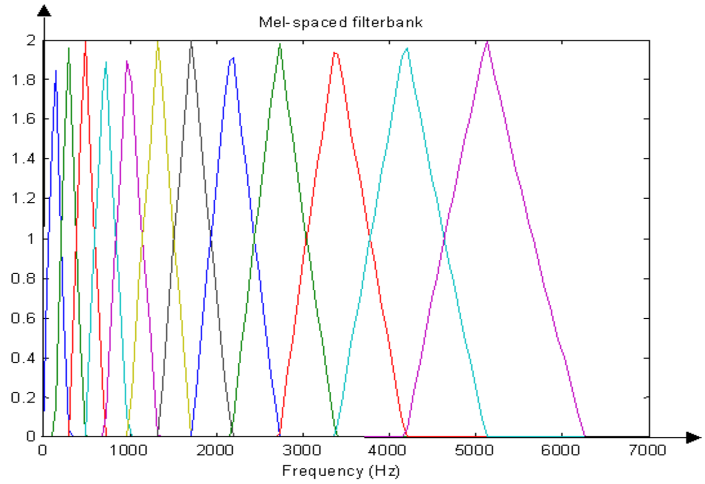

Fig.2 Mel scale filter bank

Step 6: DISCRETE COSINE TRANSFORM

The mel spectrum coefficients are real numbers (and so are their logarithms), this process convert the log Mel spectrum into time domain using Discrete Cosine Transform (DCT). The MFCC parameters are computed as

$$Cj = \sum_{i=1}^{M} X_i.\cos (j.(i - 1/2).\pi/M), \text{ with } j = 1, 2\ldots J$$

Where M is the number of filters in the filter bank, J is the number of cepstral coefficients which are computed and Xi is formulated as the "log-energy output of the ith filter".

IV. CLASSIFICATION: SVM

Support vector machine (SVM) is an effective approach for pattern recognition. The main aim of an SVM classifier is obtaining a function f(x), which determines the decision boundary or hyperplane. SVM is used to construct the optimal hyperplane with largest margin for separating data between two groups. The main objective of Support Vector Machine is maximizing the margin width in order to reduce the misclassification error.

SVM works equally well for both linearly separable data as well as nonlinearly separable data.Here we use linear SVM. In the case of support vector machine, an object is viewed as a n-dimensional vector and we want to separate such objects with a n-1 dimensional hyperplane. This is called a linear classifier. The goal of SVM is try to address the nearest distance between a point in one class and a point in the other class being maximized and draw a hyperplane to classify two categories as clearly as possible.[16]

Linearly Separable classification separates the high dimensional data into two groups, yi={+1,-1} without any overlapping or misclassification. SVM produces number of decision margins where the best margin is identified. There are many hyperplanes that might classify the data, we also interested in finding out whether we can get the maximum margin between the two data sets [9].

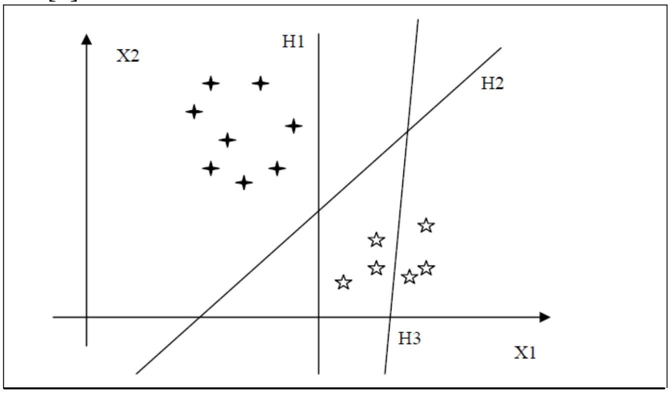

Fig.3 Example for SVM

The above figure shows 3 hyper planes in 2-Dimentional space. H3 does not separate the two classes; H1 does, with a small margin and H2 with the maximum margin. The goal of SVM is trying to find H2.

For implementing SVM, we are given a certain number p of training data, each data has two parts: the n-dimensional vector of signal features and the corresponding labels of data (either 1 or - 1).

$$S = \{(x_i, y_i) \mid x_i \in \Re^n, y_i \in \{-1,1\}\}_{i=1}^{p}$$

Each x_i is an n-dimensional vector. SVM want to give out the maximum-margin hyper plane dividing the objects with label (i*y)* = 1 from those with label = -1.

V. VECTOR QUANTISATION

Vector quantization (VQ) [19] is a lossy data compression method based on the principle of block coding [11]. It is a fixed-to-fixed length algorithm. In the earlier days, the design of a vector quantizer (VQ) is considered to be a challenging problem due to the need for multi-dimensional integration. In 1980, Linde, Buzo, and Gray (LBG) proposed a VQ design algorithm [11] based on a training sequence. The use of a training sequence bypasses the need for multi-dimensional integration. A VQ that is designed using this algorithm are referred to in the literature as an LBG-VQ.

A. LBG Design Algorithm

The LBG VQ design algorithm [5], [9] is an iterative algorithm which alternatively solves the above two optimality criteria. The algorithm requires an initial codebook $C^{(0)}$. This initial codebook is obtained by the splitting method. In this method, an initial codevector is set as the average of the entire training sequence. This codevector is then split into two. The iterative algorithm is run with these two vectors as the initial codebook. The final two codevectors are splitted into four and the process is repeated until the desired number of code vectors is obtained [9].

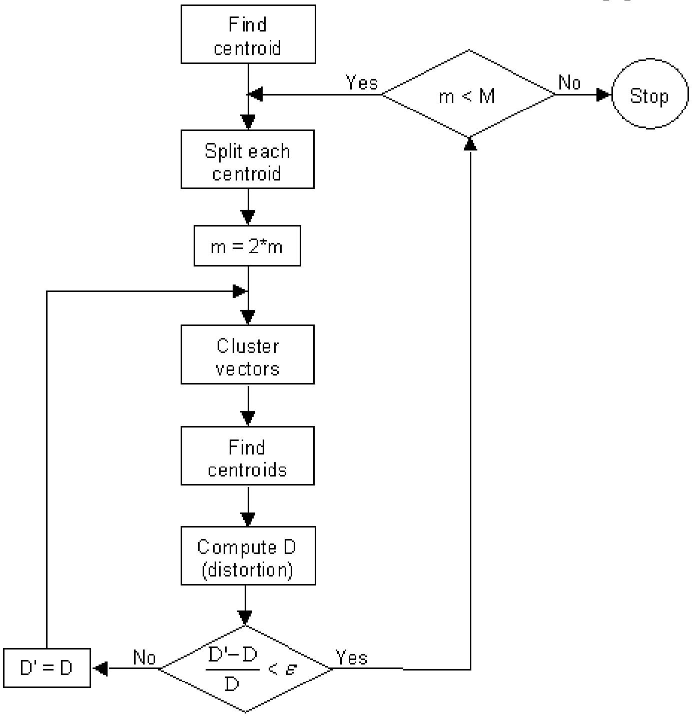

Fig. 4 Flowchart of LBG algorithm

VI. RESULT AND DISCUSSION

Authentication is done using vector quantization where 30 number of heart sound signal as training and 30 number of heart sound signal as testing are applied. The authentication results show 86.66% of performance accuracy.

A classification is done using SVM where 10 numbers of heart sound signal as Training and 20 numbers of heart sound signal as testing are applied. The classification results show 70% of performance accuracy for normal PCG signal and 95% of performance accuracy for murmur PCG signals.

The experimental results of the proposed human identification system are achieved by using 30 speakers selected from the database [21].All of the heart sound signals are sampled at 44100 Hz. Each heart sound in database is approximately of 4 seconds. These heart sounds are analyzed using MATLAB. The overall performance of the proposed recognition system is summarized in table below:

TABLE I NO. OF PERSONS VS. VARIOUS IDENTIFICATION RATIO'S

Number of persons	TPR	TNR	FPR	FNR
N=10	0.8	0.9	0.1	0.2
N=15	0.8	0.933	0.066	0.2
N=20	0.7	0.95	0.05	0.3

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Table I show the variation of identification ratio's with no. of persons, where TPR is true positive rate, TNR is true negative rate, FPR is false positive rate and FNR is false negative rate.

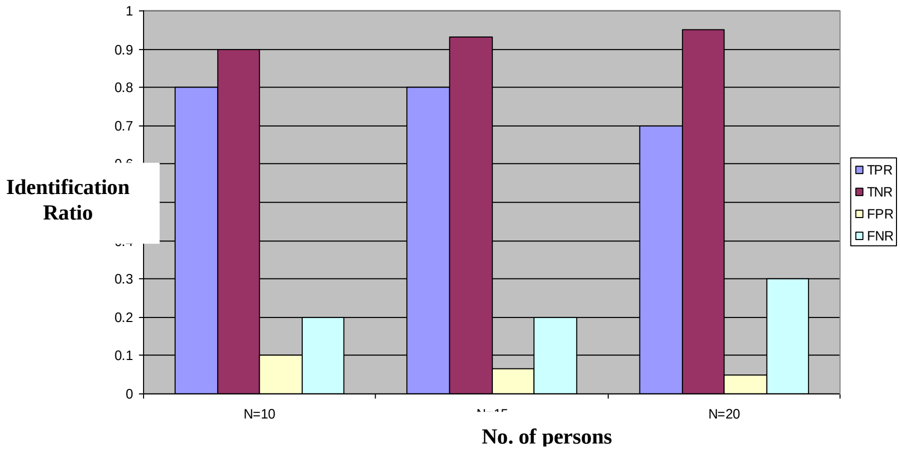

Fig.5 No. Of persons vs. Various Identification Ratio's

Fig.5 shows the graph of number of persons v/s various identification ratio's. The True-positive Rate (TPR) describes the proportion of true positive and false negative. False-negative Rate (FNR) describes the proportion of false negative to the true positive and false negative. True negative rate (TNR) describes the proportion of true negative to the false positive and true negative. False-positive Rate (FPR) describes the proportion of false negative to the true positive and false negative.

VII. CONCLUSION

In this paper, the possibility of using the heart sound signal for human identity verification is investigated, and proposes a study on the use of MFCC, SVM and VQ. After the initial study of heart signals in time domain and frequency domain we got the motivation to use PCG signals for user identification. Hence, we can conclude that heart sounds can be used as a biometric, and are reliable as compared to other biometric identification systems as it cannot be easily simulated or copied. Heart sound can be itself used for identification or we can use it with other available identification system to make the overall system easy and reliable to implement. PCG signals are easy to capture and enables real time identification system design.

VIII. FUTURE WORK

Other algorithms can be implemented for feature extraction and classification. The main objective could be to find the best algorithm suitable for heart sound processing. By increasing the number of samples in training phase we can increase the efficiency of the system. Further, this work can be extended to make a real time system for user identification and verification. The new dimension of the work could be to use the heart sounds to find the heart diseases and other pathological cases. With the help of the other biometric systems i.e., Fingerprint recognition, Face recognition and Iris recognition showing the benefits of biometric systems in future.

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