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Cardiac Biometrics: Human Identity Verification using PCG signals by Binary Decision Tree based SVM

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***Abstract* – Automatic Identity verification through Cardiac Biometrics is a profound area of Research where Heart sounds are analyzed, aiming in enhancing accuracy, thus reducing falsification. This paper examines the applicability of Biometric features of Heart sounds by analyzing the Phonocardiogram signals. Binary decision tree based Support Vector Machine Method is a new approach in the research. DWT results with different frequency bands that are smoothed by Multi-pass Moving Average Filters. Peaks are detected by Averaging Neighbors. Spectral features are extracted and clustered by HSOM. Rough Sets Theory (RST) selects the best features for classification. Binary Decision tree based SVM is used as a classifier for recognition and Identification.**

Keywords – DWT, Phonocardiogram, Rough sets, Threshold, SVM.

I. INTRODUCTION

Accurate Identity verification is becoming increasing important in our day to day life in all domains especially finance, healthcare, defense and other fields, where information security is facing issues. Traditional identity recognition methods like PIN, Passwords, tokens, etc now gets ease of access from the unauthorized third parties. A Biometric system should aim at implementing a system that recognizes a person immediately and certainly. Biometric recognition was introduced as a means of more security as they are characteristics of an individual which are unique. They cannot be easily forged. They are Physiological – fingerprint, iris, palm print, etc. or behavioral – keystroke dynamics, voice, etc. Still, they lack in the accuracy when the features are affected by psychological or environmental changes. No two readings of the biometric feature are identical. Medical Biometrics has great advancements in the last few years which uses internal characteristics such as vein pattern, heart sounds, etc that takes signals used in clinical diagnostics. Examples include Electrocardiogram (ECG), Electroencephalogram (EEG), Phonocardiogram (PCG), Blood pressure Volume and others [1]. Acquisition of the signals was quite a complicated process, a decade ago. Advancements in the technology which developed sensors that could be used by non-trained employees, medical biometrics started flourishing.

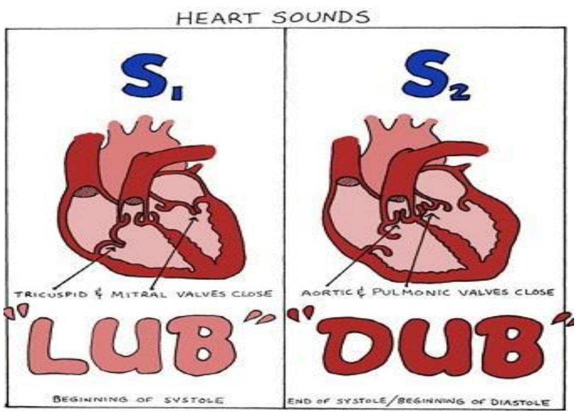

Figure 1. Working of S1 and S2 heart sounds

Cardiac Biometrics uses ECG, EEG, PCG signals for Identity recognition. Many researches are made with the Heart sounds as samples are fresh and new at every point of time. Electrocardiogram (ECG) reveals the electrical activity of the heart and uses ultrasound waves to create the image of the working of the heart for assessing the conditions of the heart. It needs a setup for recording and is longer. Cardiac Auscultation is the primary step in the

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analysis of heart sounds. Thus PCG signals are obtained when microphone is attached to the stethoscope. PCGs cannot be visually analyzed and are complex signals; hence there can be no replication.

Heart Sounds are discrete bursts of auditory vibrations of varying Intensity, frequency, quality and duration [7]. S1 and S2 are two normal sounds when heart contracts and pumps blood. The first Heart sound S1 is produced by the closing of the Mitral and the tricuspid valve leaflets. The Working is shown in Figure 1.

The Second sound S2 is produced by the closing of the aortic and pulmonary valve leaflets[1] . The first sound has slightly greater intensity than the second heart sound.S1 has duration of about 0.15s and frequency ranges from 25-45Hz. S2 lengths about 0.12s and frequency ranges from 50-200Hz.

II. Literature Review

Due to the popularity of the ECG, there was a gradual decline in the PCG research but it does not confirm all valvular diseases. PCG is an excellent tool for auscultation training and helps in understanding the hemodynamic of the heart[1]. In recent years, different research teams study the possibility of using heart sounds for biometric recognition.

Francisco Beritelli proposed the z-chirp transform algorithm for the frequency analysis and used Euclidean distance to measure the signal spectrum. Later he proposed a multi-band analysis approach to enhance the seperability between interpersonal and intrapersonal classes of values. Phua et.al proposed a novel method based on the cepstral analysis combining the Gaussian Mixture Modeling technique.

Gupta et.al segmented heart sounds using Homomorphic filtering and K-means clustering. They employed a Neural Network strategy called GAL and MLP-BP techniques for differentiating murmurs. Bendary et.al used DWT for analyzing signals and used MSE and KNN classifiers.

Foteini et.al made a research of the ECG biometrics and its challenges. It also compared the different methodologies in other approaches. Tran et.al worked on the different feature extraction methods exploring 7 set of features and fed into the Recursive FE-SVM to choose the best set. Out of which, Gaussian models gave better results.

Fatemian et.al considered both ECG and PCG signals for recognition. The heart sounds were processed using Daubecchies 5 wavelets and used two energy thresholds to select the coefficients for further stages. Short time Fourier transform analyzes the signals and are filtered by Mel frequency filter banks.LDA was used for dimensionality reduction. Gill et.al presented a model which detected and identified using Homomorphic envelogram and Hidden Markov Model for further processing of feature vectors.

Sumeth et.al segmented cardiac cycles by envelope detection and used auto correlation for calculating the length of the signals. Jasper and Othman computed various energy parameters of different sub-bands taken through DWT. Olmez et.al segmented PCG signals using Multiband wavelet energy. It gave better performance when compared to Shannon energy and Homomorphic filtering techniques.

III. Methodology

A. Segmentation of S1 and S2

The authentication process manipulates the signal which involves the capturing of the signal, amplification and remove noise, transforming the signal to emphasize certain characteristics, training and matching. Phonocardiogram signals are easily obtained by placing the electronic stethoscope with recording device attached, against the chest. The signals are recorded as WAV files. The raw signal is decomposed into frames of length N. Rectangular windowing function returns frames such that each frame contains one and half cardiac cycles of 20ms of frame length and 5ms of overlapping time. They are then normalized to remove offsets. As PCG signals are non-stationary, non-linear and are not smooth wave signals, Fourier transform fails. Since the initial condition does not exist, Laplace transform also loses its importance. Wavelet decomposition suits well as PCG signals can be analyzed with frequency dependent or time dependent factors.

Discrete Wavelet transform (DWT) decomposes the signals to different sub-bands of different resolutions according to Nyquist's rule. Daubecchies 5^{th} order wavelet is taken for the transform. S1 and S2 fall within the range of frequencies 30-250Hz. The detailed coefficients of the 3^{rd}, 4^{th} & 5^{th} level are taken for amplification of the signal. Murmurs have frequencies higher than 600Hz. obviously they are removed during this transform. This is highly advantageous and this is the reason for using DWT. The outputs are then up-sampled and summed for emphasizing the difference between S1 and S2 sounds.

The Heart sound signal still has very complicated patterns with numerous spikes that has little impact on the diagnosis but may influence the location of S1 and S2 [8]. Hence the signal is smoothed. Moving Average Filters

1 www.easyauscultation.com

operate by taking the average of the number of points from the Input signal to produce each point in the output signal, given by the equation

$$y[i] = \frac{1}{M}\sum_{j=0}^{M-1} x[i+j] \tag{1}$$

Where M is the number of points in the average. The input signal is passed through MAF two or more times which is equivalent to a 'triangular smoothing'. The peaks of the smoothed signal are then detected by averaging the neighbors. Let $X=[x_1, x_2, .., x_i, .. x_N]$ be the uniformly sampled signal of length N. The search exists till the length of the signal from left to right. Let L and R be the set of k samples of highest amplitude, to the left and right of the i^{th} point of x_i in X respectively. Then the peak is defined as the average of the maximum of L and R

$$F = \frac{max\,(L) + max\,(R)}{2} \tag{2}$$

If the computed peaks function F is greater than or equal to the threshold then it is considered as a peak. The automatically computed threshold h obtained by Ma, ven, Genderen and Beukelman (2005) [3] is given by

$$h = \frac{\max\ + abs\_avg}{2 + k\ \times abs\_dev} \tag{3}$$

The peak distance is calculated by the distance between the current and the previous peak position, if the number of peaks is more than one.

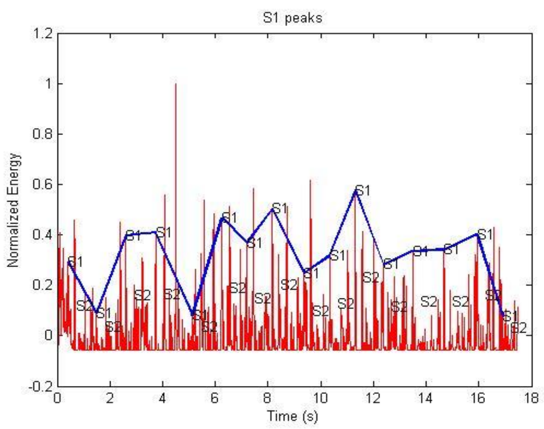

Figure 2. S1 and S2 peaks are detected

If the peak distance between the 1^{st} and the 2^{nd} is greater than that of 2^{nd} and 3^{rd}, then the peaks will be as S2-S1-S, else S1-S2-S1. The detected peaks are shown in figure 2.

B. Feature Extraction and Selection

The segmented signals are now ready for feature extraction, which simplifies the amount of resources required to describe a large set of data accurately. Dimensions are reduced in the feature set and are called feature vectors. Often it requires a large amount of memory and computation power or a classification algorithm which over fits the training sample. Feature extraction may be temporal or spectral. This study considers the spectral representation of the signal for further analysis. Spectral analysis is a frequency domain analysis that quantifies various parameters (amplitude, power, intensity, etc) Vs frequency. It can be performed on the entire signal or on frames. The peak detected signal when represented as amplitude varies with time will produce a corresponding frequency spectrum. Spectral features such as Spectral Rolloff, spectral centroid, spectral entropy and spectral flux of the signal are obtained.

Spectral Rolloff measures the spectral shape of the bins in the power spectrum where 85% of the power is at lower frequencies. Spectral Centroid measures the centre of gravity of the spectrum. Higher the centroid, the textures become brighter. Spectral flux is the squared difference of the current value of the each magnitude of the spectrum bin in the current position and the previous window. Spectral entropy measures the energy level. The S1-sound and S2 sound spectral coefficients, extracted with the spectral features are used to characterize sound and provide scaling of the frequency spectrum similar to the human ear's response.

The dimensionality of the data is reduced by the use of Discrete Cosine Transform. The spectral features are extracted for each sound and then the remaining noise channels are removed. The K-means clustering is executed to extract two groups (S1 and S2) of the heart sound components as in figure 3. The clustering data is first partitioned to three groups: 1) a finite set of objects, 2) set of attributes (S1 and S2 features) and 3) Domain of the attribute (positive or negative). For each group in the dataset, decision system is constructed. Each group splits into two parts: the training dataset and the testing dataset. The training set uses the corresponding S1, S2 features and fall into two classes: normal (+1) and abnormal (-1). Figure 3 shows the cluster of S1 and S2 sounds. They are then fed into Hierarchical Self-organizing Maps for further reduction. As SOM has the capability of detecting small differences between objects, it is an efficient tool for finding multivariate data outliers [2, 4, 5].

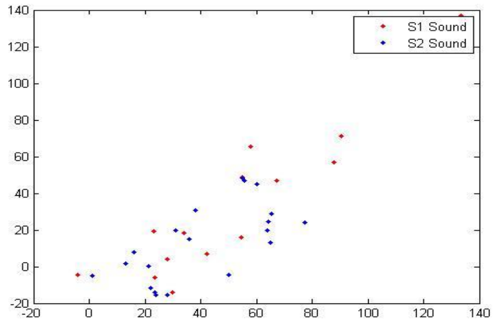

Figure 3. K-means clustering of S1 and S2

A Hierarchical self-organizing map (HSOM) is a type of ANN. It is an unsupervised learning method to produce a low-dimensional discretized representation of the input of the training set, called maps. They operate in two modes: training and mapping. Training builds the map by the inputs and mapping classifies a new input vector. It uses a hierarchical structure of the multiple layers where each layer has a number of SOMs. One SOM is used at the first level of hierarchy and the process is repeated with the third and any further layers of the HSOM. The training data set is spatially clustered to remove all outliers as in figure 4.

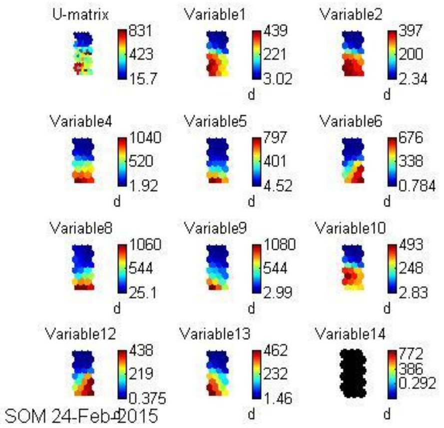

Figure 4. Spatial clustering by HSOM

The Features are then selected by a process called Rough sets which selects a subset of S1 and S2 features. It is based on the concept of Upper and Lower approximation of a set as in figure 5.

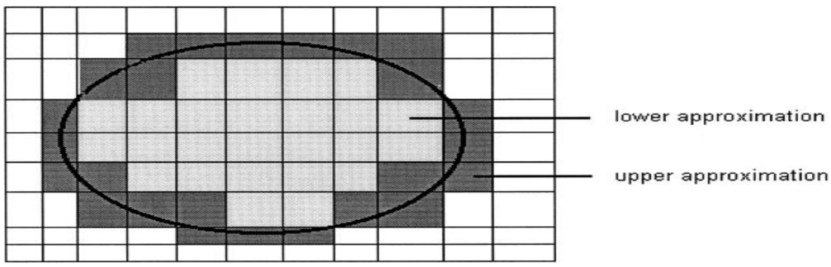

Figure 5. Rough set approximations

The straightforward feature selection procedures are based on the evaluation of the predictive power of the individual features, followed by ranking and the choice of first best m features. A single feature alone have a low predictive power but when all put together it may have a significant predictive power [6]. In rough sets, there will be a decision function and have a relation function on finite set of objects. The information system is represented by S= (U, A, V, f), where U is the universe, a non empty set of finite objects, A is the finite set of attributes, V is the domain of the attributes such that U: A→V is the decision function such that f(x, a) $\in Va$ for every $a\in A$, $x\in U$.

C. Classification

The SVM – Binary Logical Decision tree method that is proposed is based on recursively dividing the spectral features in two disjoint groups in every node of the decision tree (true or false) and training a SVM that will decide in which of the groups the incoming unknown sample should be assigned. The feature classes from the first k-means clustering group are assigned to the left sub-tree, while the classes of the second clustering group are assigned to the right sub-tree. This method uses multiple SVMs arranged in a Logical Decision binary tree structure as shown in Figure 7. A Binary SVM in each node of the tree is trained feature using two of the classes. The verification algorithm employs probabilistic outputs to measure the similarity between the remaining samples and the two classes used for training. All training samples in the node are assigned to the two sub-nodes derived from the previously selected classes by similarity. This step repeats at every node until each node contains only samples from one class. The main problem here is the training time.

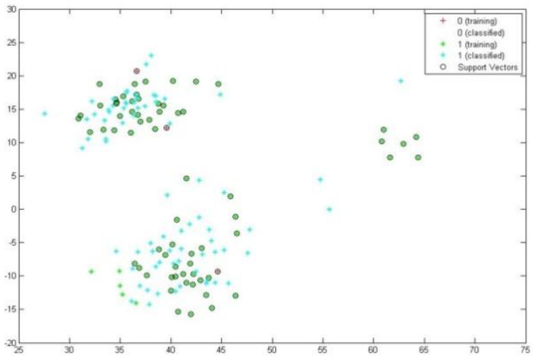

Figure 6. Classified Support Vectors

The testing (identification) approach can be multiclass binary SVM by OAO (One Against One) or OAA (One Against All).

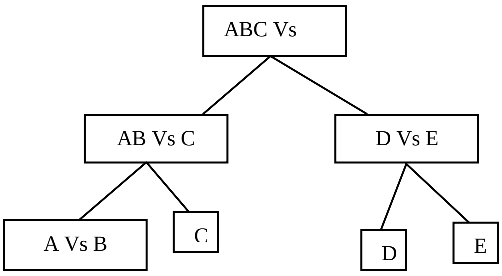

Figure 7. SVM- Binary Decision Tree

The decision is based on the automatic thresholding by OTSU method. In this method, it exhaustively searches for the threshold that minimizes the intra-class variance defined as the weighted sum of the two classes. Distances D_i are the probabilities of the two classes separated by a threshold t and σ^{2i} variances of these classes. Otsu shows that minimizing the intra-class variance is the same as maximizing the inter-class variance. The Output is shown in Figure 6 and the tree is depicted in figure 8.

$$\sigma^2_{between}\ (t)=D_1(t)D_2(t)[\mu_1(t)-\mu_2(t)] \tag{4}$$

IV. EXPERIMENTAL EVALUATION

A Database of 20 PCG sequences comprising of heart sounds of different pathologies from 20 people, both male and female patients are taken with digital stethoscope. Each sound is a .WAV file of 70ms of length. The proposed algorithm gave higher accuracies of 95% of S1 and 93% of S2 segmentations. Multiple passes in the MAF will be slower, but still very quick when compared to other filters. The HSOM divides the input data space into several subspaces according to different themes. Each of these data spaces is used to train a SOM, and its output will be used to train a final merging SOM. This has the advantage of setting equal weight for each frame.

So is well suited for spatial analysis. The proposed method, during recognition found to be more accurate and had a very low False Acceptance Rate as shown in Figure 9.

The SVM Classification accuracy is found to be 95.9%. Though it is little time consuming because of the multi-pass MAF, Hierarchical and decision trees, accuracy matters in case of identity recognition. Ignoring minor time consumptions, this method proves to be very accurate during recognition.

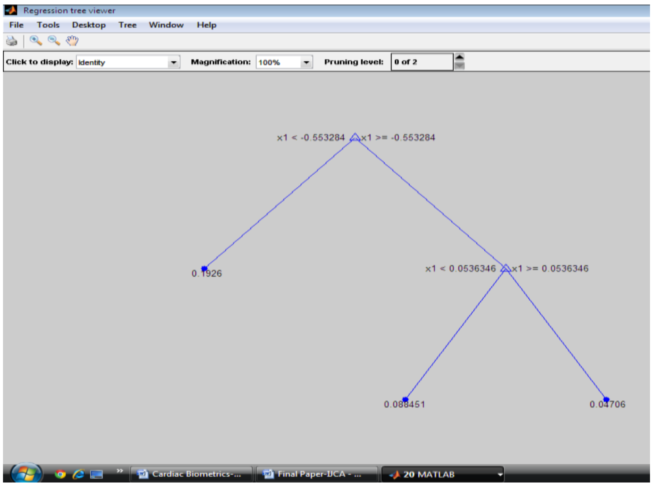

Figure 8. Regression tree view of the Matching process

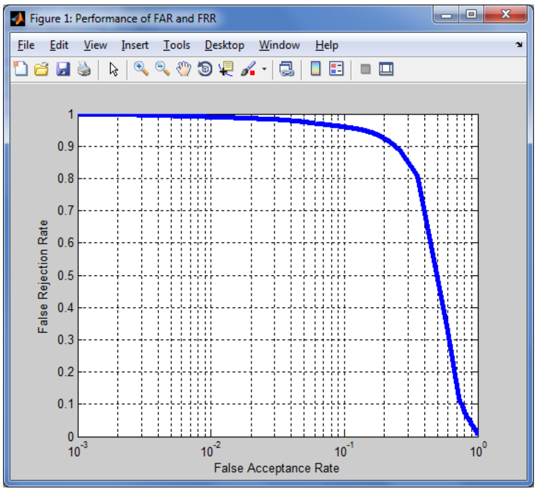

Figure 9. False Acceptance Rate

V. Conclusion

In this paper, a Novel method for the human identity verification is discussed. The system is tested for identification with various Heart sounds containing arrhythmias like Mitral regurgitation, Mitral stenosis, aortic regurgitation and stenosis. It showed better results. Further research can be contributed in the direction of reducing time consumption, parallel to the accuracy. Authentication in spite of arrhythmias is of more importance. Enhancements can be made to the research in the direction considering the age and the changes to the heart sounds that may happen years later.

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