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Feature Extraction of PCG Signal using MFCC

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Abstract:
In this paper, we use heart sound as a biometric for human identification. The most significant contribution of using heart sound as a biometric is that it cannot be easily simulated or replicated as compared to other conventional biometrics. Our approach consists of a robust feature extraction scheme which is based on cepstral analysis with a specified configuration, combined with Gaussian mixture modelling. Various experiments have been conducted to determine the relationship between various parameters in our proposed scheme. The results suggest that parameter values appropriate for heart sounds should be significantly different for equivalent parameters used in conventional cepstral analysis for speech processing. The performance of traditional biometric identification systems is, as yet, unsatisfactory in certain applications. For this reason, other physiological or behavioural characteristics have recently been considered, using new electrical or physical signals linked to a person's vital signs. This paper examines the biometric characteristics of PhonoCardioGram (PCG) signals from cardiac auscultation. The idea is that PCG signals have specific individual characteristics that can be taken into consideration as a physiological sign used in a biometric system. More specifically, the paper proposes a preliminary study related to the identification of individuals via cardiac sounds.

I. INTRODUCTION

Since the last decade, reliable human authentication and identification systems have been used in many applications, such as personnel security, military, finance, airport, hospital, digital rights management systems, etc. [1]. Conventional biometric systems using behavioural and/or physiological characteristics to allow recognition of an individual, e.g. fingerprint, iris, face and voice, are becoming more popular [1,4]. However, a common weakness of these systems is their vulnerability to the possibility to falsify these features. [2,4,5] Studies into new paradigms in multi-modal biometrics are currently a very active research topic. New biometrics using features such as hand vascular pattern, vein, gait, human tissue, knuckle, ear canal and even evoked brain signals have been proposed [6,7]. Another new and prospective candidate for biometric is the electrocardiogram (ECG) [8,9] which yields a relative high result for human identification tasks [8,9]. 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. PCG signals have been recorded using an electronic stethoscope. Database of heart sound is made using the electronic stethoscope. In the beginning, heart sounds for different classes is observed in time as well as frequency for their uniqueness for each class. The first step performed is to extract features from the recorded heart signals. We have implemented MFCC algorithm as a feature extraction algorithm to get the cepstral component of heart sound. The next objective is to classify these feature vectors to recognize a person.. However, we note that PCG for identification is generally cumbersome due to the many (at least three) electrodes required [9]. In this work, we investigate the possibility of using human heart sounds – an acoustic signal as a reliable biometric for human identification. Human heart sounds are very natural signals, which have been applied in the doctor's auscultation for health monitoring and diagnosis for thousands of years. In the past, study of heart sounds focus mainly on the heart rate variability [10]. However, we conjecture that since the heart sounds also contain information about an individual's physiology, such signals have the potential to provide a unique identity for each person. Like ECG, these signals are difficult to disguise and therefore reduces falsification. Moreover, heart sounds are relatively easy to obtain, by placing a conventional stethoscope on the chest, for example.

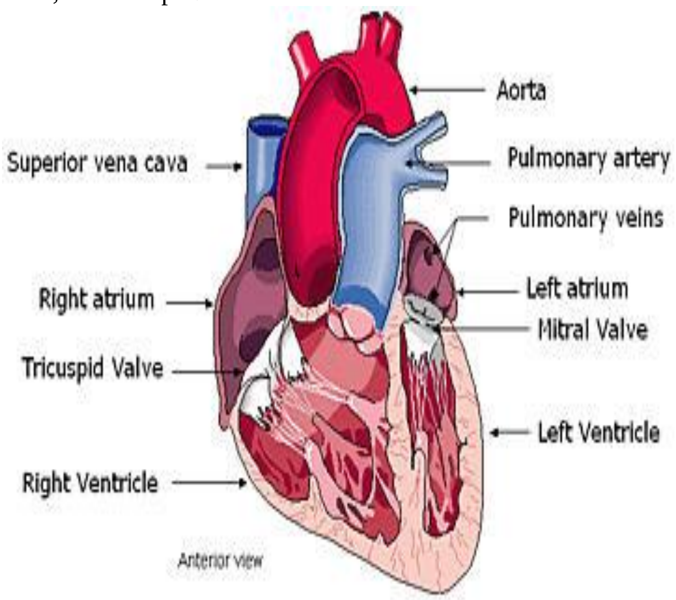

Figure.1. Cross-section of a typical human heart.

II. BIOMETRIC IDENTIFICATION

Biometric technologies are based on the use of individual characteristics for the recognition or identification of an individual [7].

They are divided into two areas:

1) Physiological characteristics (unique and unvarying), which include the geometry of the hand and the palm print, fingerprints, retina, or iris image, and the (geometrical) features of the face;

2) Behavioural characteristics (unique but varying), which include signature, way of walking, voice (the latter also belongs to the previous group), and keyboard typing style.

A feature common to all biometric technologies is the capability of human recognition from biometric data. This consists of a series of basic processes:

1) Acquisition and storage of reference biometric data acquired by means of sensors (optical, ultrasonic, thermal, etc.);

2) Acquisition of new biometric data at the start of a recognition process, for comparison with the reference data;

3) Determination of the correspondence of the newly acquired data to the stored reference to determine whether they both could have been generated by the same person.

Drawbacks of various biometric systems.

Identification trait	**weaknesses**
1]DNA	Easy to steal a piece of DNA.
2]Speech	Speech can be recorded and played.
3]Signature	Can be reproduced easily.
4]Fingerprint	Can be recreated in latex using an object touched by the person.
5]Face and iris	Can be recorded by a camera.

Human heart sounds are natural signals, which have been applied in the doctor's auscultation for health monitoring and diagnosis for thousands of years. In the past, study of heart sounds focus mainly on the heart rate variability [5]. However, we conjecture that since the heart sounds also contain information about an individual's physiology, such signals have the potential to provide a unique identity for each person. Like ECG, these signals are difficult to disguise and therefore reduces falsification. Moreover, heart sounds are relatively easy to obtain, by placing a conventional stethoscope on the chest.

Mechanism for heart sound production

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. It is biggest advantage as a biometric trait. The experiments carried in our laboratory indicates feature extraction using mail frequency cepstral coefficients 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 human heart has four chambers, two upper chambers called the atria and two lower chambers called ventricles, as shown in Fig.1. There are valves located between the atria and ventricles, and between the ventricles and the major arteries from the heart [6]. These valves close and open periodically to permit blood flow in only one direction. The electronic stethoscope used for recording PCG signals is HD Fono /HD FonoDoc manufactured by HD Medical Services (India) Private Limited. This device allows us to adjust audio volume. It also has a visual display for observing heart sounds that represent valvular functions of the heart in real time, called Phonocardiogram (PCG). The stethoscope head is put on the user’s chest for recording. It also has a USB interface with the computer for data download, review and storage. This device allows us the storage of 10 seconds signals that can be downloaded to PC/Laptop.

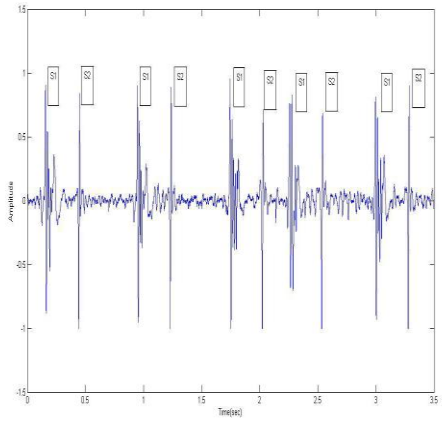

Figure.2.waveform of first heart sound S1 and second heart sound S2.

Two sounds are normally produced as blood flows through the heart valves during each cardiac cycle as shown in Fig.2. The first heart sound S1, is a low, slightly prolonged “lubb”, caused by vibrations set up by the sudden closure of the mitral and tricuspid valves as the ventricles contract and pump blood into the aorta and pulmonary artery at the start of the ventricular systole. The second sound S2 is a shorter, high-pitched “dupp”, caused when the ventricles stop ejecting, relax and allow the aortic and pulmonary valves to close just after the end of the ventricular systole. They are the “lubb-dupp” sounds that are thought of as the heartbeat. S1 has duration of about 0.15 s and a frequency of 25–45 Hz. On the other hand, S2 lasts about 0.12 s, with a frequency of 50 Hz. The PCG signals stored in the PC are processed using sound editing software AUDACITY and MATLAB. Programming for the feature extraction and classification is done in MATLAB software. 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 [14].

Normal and Abnormal PCG Signals

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III. FEATURE EXTRACTION: MFCC

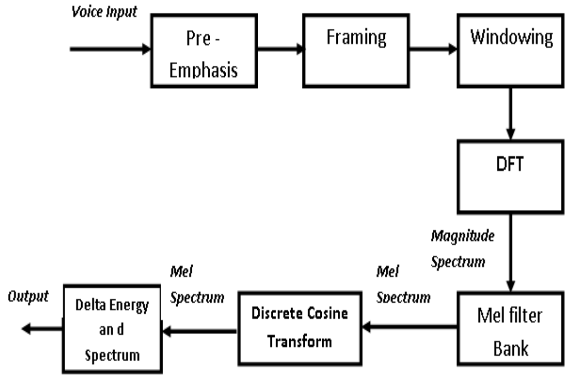

Figure.3. MFCC Block Diagram [8, 9]

Feature extraction is a special form of dimension reduction, which transforms the input data into the set features. Heart sound is an acoustic signal and many techniques used nowadays for human recognition tasks borrow speech recognition techniques. 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. MFCC system is still superior to Cepstral Coefficients despite linear filter-banks in the lower frequency range. 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 [10] and because PCG and speech are both acoustic signals. MFCC is based on human hearing perceptions which cannot perceive frequencies over 1Khz. In other words, in MFCC is based on known variation of the human ear's critical bandwidth with frequency [3, 10].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 provide more efficient. It includes Mel-frequency wrap-ping and Cepstrum calculation. The overall process of the MFCC [8, 9] is shown in Figure 1. As shown in figure 1, MFCC consists of seven computational steps and each step has its function and mathematical approaches as discussed briefly in the following:

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 which practically means that the signal is blocked in frames of typically 20-30 msec. with optional overlap of 1/3~1/2 of the frame size, this is done in order not to lose any information due to the windowing. The signal is divided into frames of N samples and adjacent frames are being separated by M (M<N).

Step 3: HAMMING WINDOWING: After the signal has been framed, each frame is multiplied with a window function $W(n)$. Windowing is done to avoid problems due to truncation of the signal and helps in the smoothing of the signal. Typically the Hamming window is used. If the window is defined as W (n), 0 ≤ n ≤ N-1 then the result of windowing signal is shown below:

Y (n) = X (n) × W (n)

Where, N = number of samples in each frame; Y (n) = Output signal; X (n) = Input signal.

If the signal in a frame is denoted by s (n), n = 0…N-1, then the signal after Hamming windowing is s (n)*w(n), where W(n) is the Hamming window defined by:

W (n) = (0.54 - 0.46 cos(2Πn/(N-1))， 0≦n≦N-1

Step 4: FAST FOURIER TRANSFORM: This mathematical method is used for transforming a function of time into a function of frequency. The Fourier transform convert the convolution of the glottal pulse U[n] and the vocal tract impulse response H[n] in the time domain. The given equation supports the above statement:

Y (w) = FFT [h (w) * X (w)] = H (w) * X (w)

If X (w), H (w) and Y (w) are the Fourier Transform of X (t), H (t) and Y (t) respectively.

Step 5: MEL FILTER BANK PROCESSING: In this step, the powers of the spectrum obtained above are mapped onto the mel scale, using windows. A set of triangular filters are used to compute a weighted sum of filter spectral components so that the output of process approximates to a Mel scale. The magnitude frequency response of each filter is triangular in shape and equal to unity at the centre frequency and decrease linearly to zero at centre frequency of two adjacent filters. Then, output of each filter is the sum of its filtered spectral components. After that the following equation is used to compute the Mel for given frequency f in Hz:

F (Mel) = [2095 * Log10 (1 + *f) 700*)]

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:

$Cj = XiCj = \sum_{i=1}^{M} Xi \cdot \cos(j.\ (i - 1/2).\ \pi/M)$,

With j = 1,2,…..,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 *i*- th filter".

Step 7: DELTA ENERGY AND DELTA SPECTRUM: The voice signal and the frames changes, such as the slope of a formant at its transitions. Therefore, there is a need to add features related to the change in cepstral features over time. The energy in a frame for a signal x in a window from time sample t1 to time sample t2, is represented at the equation below:

Energy = $\sum x^2\ t$

IV. 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. The performance of the technique has been measured by various parameters. 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.

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