Phonocardiogram Heartbeat Segmentation and Autoregressive Modeling for Person Identification

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***Abstract*—With the rapid advancement of biosensors and increasing demand of more secured biometric authentication system, cardiac signals are getting special attention. Because of its very simple acquisition technique, phonocardiogram (PCG) signal is getting popularity in this field. This paper presents an automatic person identification scheme based on autoregressive modeling of PCG beats. On a given PCG recording first preprocesing and then wavelet denoising are applied. In order to perform beat by beat operation, a segmentation scheme is proposed using the Hilbert envelope which extracts the PCG beat containing the first and second heart sounds. Next reflection coefficients are extracted by employing the AR Burg modeling of the PCG beat. Finally the AR Burg reflection coefficients are used in ensemble bag trees classifier to identify a person. Performance of the proposed method is being tested on PCG signals of 50 different person taken from a publicly available PCG dataset and very satisfactory identification performance is achieved.**

***Index Terms*—Phonocardiogram (PCG), Autoregresive (AR) Model, Biometric, Burg's Method, Hilbert-Huang Transform, Classification, Person Identification.**

I. Introduction

Security has become a major issue in our modern society. Today's security systems are dominated by various biometrics, such as face, fingerprint and voice. Traditional biometric systems can be manipulated by using synthesized signal. Phonocardiogram (PCG) signal captures the heart sound and can serve as a unique biometric trait for person identification. Employment of the PCG signal has many advantages over other biometrics [1] [2]. It is intrinsic in nature and cannot be reproduced and manipulated easily. Moreover, to reproduce a specific person's heart sound, an anatomy of the heart and its surroundings needs to be considered. The state of an individual's health, age and physical structure of the heart affects generation of heart sound. Even heart sounds of two different persons suffering from same heart disease vary. The PCG can be easily recorded by using an electronic stethoscope. It is produced due to closure of valves during pumping of blood through the arteries. The PCG signal is very commonly used by the physicians for determining heart rate and pathologies [3]. Normal heart sound consists of two major parts known as first heart sound Lub and second heart sound Dub for each heartbeat. The PCG beat of a healthy person exhibits distinctive spectral behavior [1]. The ideal waveform of the PCG signal is shown in Fig. 1 In [1], a biometric identification system is proposed based on frequency analysis of cardiac sound. Here, a database of 20 individuals is analyzed and Euclidean distance based algorithm is used for classification. Cepstrum based features, such as Mel frequency cepstral coefficients (MFCC) and its various modifications are used for identification purpose [2] [4] [3] [5]. In [2], identification system is proposed on a database containing heart sound of 10 subjects. Wavelet and MFCC based identification system to recognize individuals is developed in [4]. In [6], a new process of biometric identification system is implemented using marginal Hilbert spectrum analysis over 40 persons. Two new features are proposed based on modifying MFCC features in [3] and [5]. The first one uses modified Mel-frequency equation to increase the nonlinearity of the triangular filters in the frequency range of PCG signal. The second one utilizes non-linear wavelet packet filter banks. The MFCCs are alos extracted from the first (S1) and second (S2) heart sounds for biometric identification in [7] [8].

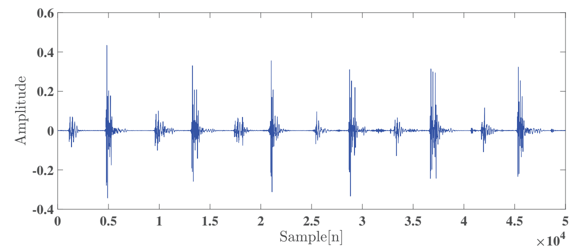

Fig. 1. Phonocardiogram signal waveform.

In this paper, PCG signal analysis is carried out beat by beat basis. From a given PCG signal the effect of noise is first removed by using the wavelet denoising. A segmentation scheme is proposed using the Hilbert envelope to extract the PCG beat. Considering autoregressive (AR) modeling of the PCG beat, AR Burg reflection coefficients are extracted as features. An ensemble bag decision tree classifier is employed for person classification. Identification performance is tested on publicly available PCG dataset.

II. Proposed PCG Beat Segmentation Method

In general, the heart sound exhibits major energy concentration in lower frequency regions, mainly below 300 Hz [1]. From extensive experimentation, it is observed that the presence of major spectral energy in a heart beat is dictated by the voiced portion of the heart sounds "lub" and "dub".

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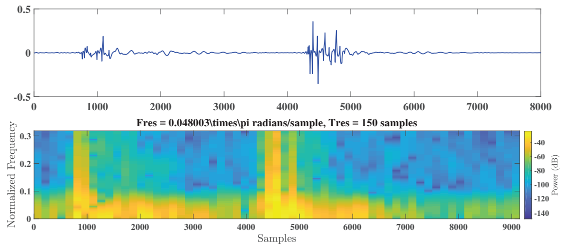

Fig. 2. (a) Heartbeat (b) Spectrogram of a heartbeat.

For better understanding, a sample beat of PCG signal and corresponding spectrogram are shown in Fig.2. The PCG data used here are acquired at a sampling frequency of 11025 Hz. The PCG signal analysis is performed on a beat by beat basis, where a beat contains "lub" and "dub" corresponding to the first heart sound with a duration S1 and the second heart sound with a duration S2, respectively. By definition a heartbeat is defined as the starting instance of S1 to the beginning of next S1, which includes both S1 and S2. It is to be noted that the recorded PCG signal may also be corrupted due to the presence of various types of external noises and internal irregularities. As a result, the first challenge here is to develop an efficient heart beat segmentation algorithm for analyzing PCG signal.

In order to avoid high frequency noises, first the PCG signal is downsampled by a factor D. Moreover to restrict the PCG signal analysis up to a certain frequency F_c, a lowpass filter is used with a cutoff frequency at F_c. As mentioned before, due to energy concentration in the low frequency region, it is sufficient to consider $F_c = 300$ Hz. The proposed heart beat segmentation algorithm is manifested in Algorithm-01.

Algorithm 1 Proposed PCG Signal Segmentation Algorithm

1: Input: PCG Signal, $s[n]$
2: Output: Heart Beats, $beat[n]$
3: Wavelet Denoising: $x[n]$ = Operates on DWT($s[n]$)
4: Compute: $y[n] = | x[n] |$
5: Envelope Extraction: $envelope[n]$ = HHT($y[n]$) ; Hilbert-Huang Transform (HHT)
6: Peak Detection: Local maxima of $envelope[n]$
7: Verification: Compute power spectrum of windows containing peaks
8: Decision Making: Power spectrum compared with threshold to detect false peak

Considering the presence of noise in recorded PCG signal, first the Wavelet denoising technique is applied on the given band-limited PCG data. Next, the Hilbert-Huang Transform (HHT) is computed on the absolute value of the denoised signal. A local maxima search is performed on the resulting Hilbert envelope to find the location and amplitudes of the local maxima. In order to eliminate the false peak locations, a narrow band power spectrum encompassing a local peak is computed and each of these power spectra is then compared with a threshold level (T_P). The value of this threshold is chosen based on the power spectrum values in S1 and S2 regions.

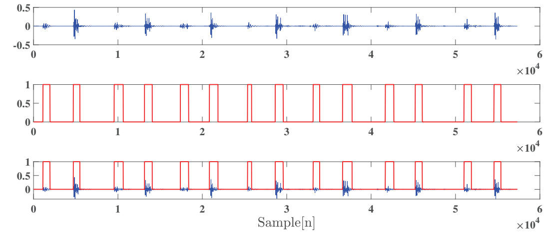

Fig. 3. Performance of the proposed segmentation scheme. Top: A sample PCG signal, Middle: Selected S1 and S2 regions are marked by rectangles, Bottom: Selected regions (red rectangles) are superimposed on the original PCG signal for better visualization of segmentation accuracy.

In order to demonstrate the performance of the proposed segmentation scheme, in Fig.3, a sample ECG signal and extracted segmentation markings are shown. From the bottom portion of Fig.3, it is clearly observed that the extracted segmentation marking accurately corresponds to the S1 and S2 regions. Hence, one can easily obtain the the beats from these identified S1 and S2 regions.

III. Proposed AR Burg Modeling of PCG Signal

Considering the cardiac system as a linear time invariant (LTI) system, PCG signal can be modeled as the output of such a system. Like most of the biosignals, here also the characteristics of the system input are unknown. Autoregressive (AR) modeling of the cardiac system is widely used for the analysis of ECG signal. For the purpose of modeling the PCG signal, in this paper, the cardiac system is assumed to be an LTI autoregressive system with additive white Gaussian noise input. It is expected that each human being possesses unique cardiac system and it differs from person to person. As a result, the characteristics of cardiac system can be used as potential biometric. Given the output of the autoregressive cardiac system, one can utilize parametric blind system identification methods to estimate the AR system parameters. Basically they correspond to various poles of the system. However, the values of the AR parameters can vary in a wide range. As an alternate we propose to utilize the reflection coefficients that can be found directly in the Burg method of AR system identification. Extracted reflections coefficients are proposed as unique features of for the identification of individual person.

In the Burg method each output sample is predicted based on the linear combination of previous samples. The output signal $y(n)$ can be represented as a linear combination of preceding values of the same signal plus a white noise input in an autoregressive model of order P [9] [10] [11].

$$y(n) = \sum_{j=1}^{P} \alpha_j y(n-j) + x(n); \tag{1}$$

The forward and backward linear predictions are

$$\hat{y}(n) = -\sum_{k=1}^{m} \alpha_m y(n-k) \tag{2}$$

$$\hat{y}(n-m) = -\sum_{k=1}^{m} \alpha_m y(n-m+k) \tag{3}$$

Forward and backward predictors are respectively expressed as

$$f_m(n) = y(n) - \hat{y}(n) = \sum_{k=0}^{m} \alpha_m(k) y(n-k) \tag{4}$$

$$b_m(n) = y(n-m) - \hat{y}(n-m) = \sum_{k=0}^{m} \beta_m(k) y(n-m+k) \tag{5}$$

Here α_m and β_m represents the forward and backward prediction residuals. It should be noted that $\alpha_m(0) = 1$ $\beta_m(0) = 1$ by the definition. The FIR prediction error filter or the lattice filter is given by the set of recursive equations: [9]

$$f_m(n) = f_{m-1}(n) + k_m b_{m-1}(n-1) \tag{6}$$

$$b_m(n) = k_m f_{m-1}(n-1) \tag{7}$$

Where the initial values of the residuals are $f_0(n) = b_0(n) = f(n)$ and k_m are the reflection coefficients of the m_{th} recursion step

$$k_m = \frac{-2\sum_{n=p+1}^{N}[f_{m-1}(n) + k_m b_{m-1}(n-1)]}{\sum_{n=p+1}^{N}[(f_{m-1}(n))^2 + b_{m-1}(n)^2]} \tag{8}$$

$$\alpha_m(k) = \alpha_{m-1}(k) + k_m \alpha_{m-1}(k-m) \tag{9}$$

where $\alpha_0 = 1, \alpha_m = k_m$ where $m = 1$ to p and $k = 1$ to m. All-pole prediction coefficients method excel in comparison to the autocorrelation method as they decrease the total prediction errors and the data sequence is not subjected to any window function. The advantage of the Burg AR method is that it is computationally efficient, stable and has satisfactory frequency resolution [9].

In Figs. 4 and 5, estimated poles of cardiac system of person 1 are shown for two different samples of heartbeats obtained by AR Burg method. The PCG signal used here is band limited and AR model order is set at $P = 12$. It is clearly observed from the figure that two different heartbeats of a same person demonstrate quite similar pole positions.

In a similar way, in Figs.6 and 7 the estimated poles of cardiac system of person 2 for two different heartbeats are shown. Here also we can see the similarity among the two cases corresponding to a same person. However, if the pole locations obtained for person-1 and person-2 are compared, one can easily observe significant differences. For more better understanding, in Figs. 8 and 9, the frequency responses of several heartbeats corresponding to person 1 and person 2 are presented, respectively. Here we have used Burg AR spectrum, a parametric approach for obtaining the spectral representation instead of using non-parametric approaches. It can clearly be visualized that there exists high similarity within the same class and significant dissimilarity between two classes.

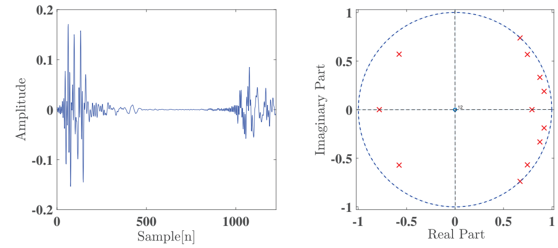

Fig. 4. A sample of heart beat of Person 1 and corresponding poles obtained using AR Burg algorithm.

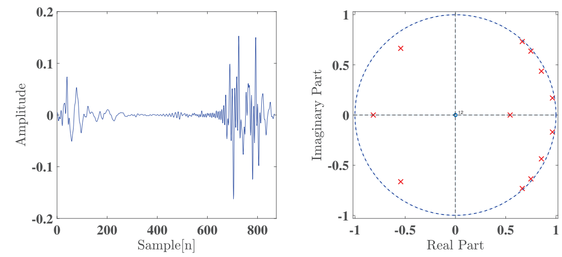

Fig. 5. Another sample of heart beat of Person 1 and corresponding poles obtained using AR Burg algorithm.

It is to be mentioned that the use of AR Burg method directly provides AR reflection coefficients those were utilized as the desired features. The Burg method performs very well in comparison to the autocorrelation method, since it reduces the overall prediction errors [12] [10] [13]. It is observed that maneuver of reflection coefficients as features provides better performance in comparison with the AR parameters. As mentioned before, the AR parameters does not have any certain limit on their values. A feature without a specific boundary may create problem in feature based classification. On the contrary, the values of reflection coefficients are bounded for stable AR system $(0$ to $1)$ and they offer better noise immunity [13].

The selection of order of the Burg AR model is of prime concern. For larger order, spurious peaks are observed while lower order results in a smoothed approximation. Akaike Information Criterion (AIC) is one of the most prominent techniques that have been applied to estimate the required order of AR model [14] [13].

IV. Classification

From the given PCG signal of a person, first heartbeats are segmented and then AR Burg reflection coefficients are estimated for each beat considering a particular model order in each case. Finally the average of the extracted reflections coefficients are used as the feature of a person. Hence the feature dimension is equal to the AR Burg system order. For the purpose of identification, ensemble of bagged decision trees classifier is employed. In this case, different classifiers

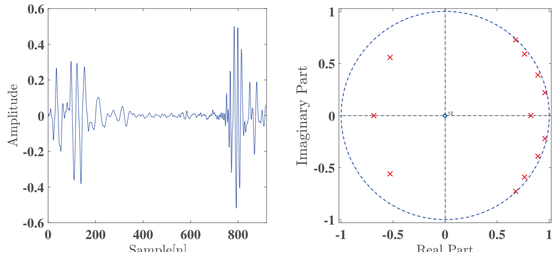

Fig. 6. A sample of heart beat of of Person 2 and corresponding poles obtained using AR Burg algorithm.

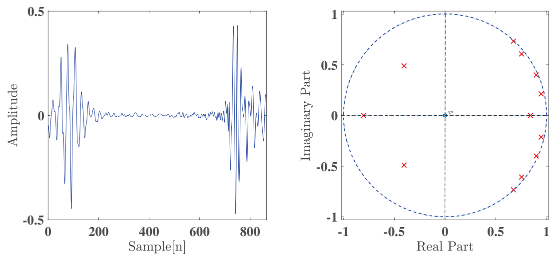

Fig. 7. Another sample of heart beat of Person 2 and corresponding poles obtained using AR Burg algorithm.

are used to build a predictive model and thus the classification bias and variance are significantly reduced [15].

V. Results

In this section the performance of the proposed method is evaluated under various conditions using a publicly available PCG dataset namely Heart Sounds Catania 2011 Database (HSCT-11) [7]. The dataset contains heart sound recordings from both male and female [7] [5]. ThinkLabs Rhythm Digital Electronic Stethoscope is used for the data acquisition. Each person has two recordings and the average length of the recordings is 45 seconds and the minimum length is 25 seconds and maximum length is 70 seconds. The data acquisition was performed using a sampling frequency of 11025 Hz and 16 bits per sample [7]. Acquired PCG signals are stored in .wav format. The results presented in this section are obtained by considering PCG signals of 50 persons from that dataset (both male and female). In order to build a test-train platform, half of duration of PCG signal of each person is kept as training and the remaining half is used for testing purpose.

TABLE I
Comparison among the AR models for various preprocessing methods.

Method / Preprocessing	Cov	MCov	YW	Burg
Segmented Raw Data	79.2	80.8	81.3	82.9
Moving Average Filtering	80.5	81.44	82.1	84.2
Wavelet Denoising	85.1	83.6	81.23	86.7
Savitzky-Golay Filtering	84.3	84.7	82.1	85.6

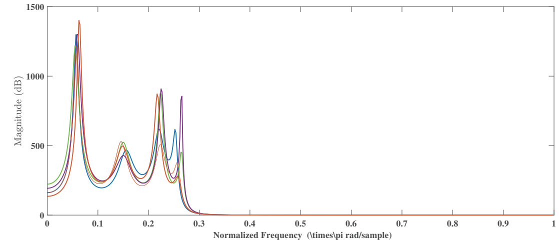

Fig. 8. Frequency response of cardiac system of Person 1.

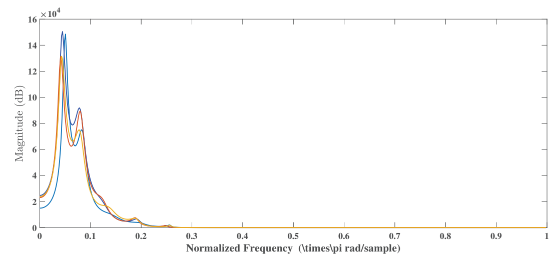

Fig. 9. Frequency response of cardiac system of Person 2.

In view of comparing the performance of the Burg AR system identification scheme with other state-of-the-art methods, Yule-Walker's (YW) method, covariance (Cov) method and modified covariance method (Mcov) are taken into consideration. In each case AR model order of 12 is chosen. Another important step in the proposed method is to use of wavelet denoising to reduce the effect of unwanted noises. Performance of the proposed scheme with and without using the wavelet denoising is investigated. Moreover, the performance of wavelet based denoising techniqie is also compared with some other conventional noise reductions schemes, such as moving average filtering and Savitzky-Golay filtering. In Table I, a comparative performance evaluation is shown for four different AR system identifications schemes, namely covariance (Cov) method, modified covariance method (Mcov), Yule-Walker's (YW) method, and Burg method. Moreover, in each case, the performance with and without the wavelet denoising technique and the performances with the moving average filtering and Savitzky-Golay filtering are also reported. It is clearly observed that the best performance is achieved when AR Burg algorithm and wavelet denoising scheme are employed.

Next the performance of the proposed AR Burg reflection coefficient feature based scheme is compared with some other feature based methods utilizing Mel frequency cepstral coefficients (MFCC), modified MFCC [[3]] and marginal Hilbert spectrum MHS [[6]]. For a fair comparison in all these feature based schemes, similar pre-processing (segmentation) and denoising are used. Moreover, performance of the ensemble of bagged decision trees classifier is compared with various state of the art classifiers like support vector machine (SVM) and K nearest neighbor (KNN) classifier. In Table II, performance of the proposed AR Burg feature based scheme is compared

TABLE II
COMPARISON AMONG FEATURES EXTRACTED FROM PCG SIGNAL

Classifier / Feature	Q-SVM	F-KNN	EB-Trees
MFCC	77.6	79.7	80.1
M-MFCC [[16]]	79.3	80.5	82.2
MHS [[6]]	80.5	77.2	81.9
Proposed	86.1	82	86.7

with other feature based methods utilizing MFCC, modified MFCC [[3]] and MHS [[6]]. In each case, results are reported considering the ensemble of bagged decision trees (EB-Trees) classifier, quadratic SVM (Q-SVM)and fine KNN (F-KNN) classifiers. It is found that the proposed method, utilizing the AR Burg reflection coefficient feature with EB-Trees classifier, offers the best identification performance.

VI. CONCLUSION

One major contribution of the proposed method is to analyze the PCG signal beat by beat for human identification. The PCG signal corresponding to a heartbeat is modeled as an AR system and AR Burg reflections coefficients are extracted as unique features. In view of obtaining the heartbeat, an efficient PCG beat segmentation scheme is proposed that operates in Hilbert space and utilizes wavelet denoising. It is shown that the PCG beats of a same person exhibits similar AR Burg spectral representation, while it differes significantly for two different persons. Hence the proposed scheme offers very satisfactory identification performance in comparison to that obtained by some existing methods.

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