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Classification of Homomorphic Segmented Phonocardiogram Signals Using Grow and Learn Network

[1]Cota Navin Gupta, [2]Ramaswamy Palaniappan, [1]Sundaram Swaminathan

Abstract—**A segmentation algorithm, which detects a single cardiac cycle (S_1-Systole-S_2-Diastole) of Phonocardiogram (PCG) signals using Homomorphic filtering and K-means clustering and a three way classification of heart sounds into Normal (N), Systolic murmur (S) and Diastolic murmur (D) using Grow and Learn (GAL) neural network, are presented. Homomorphic filtering converts a non-linear combination of signals (multiplied in time domain) into a linear combination by applying logarithmic transformation. It involves the retrieval of the envelope, *a(n)* of the PCG signal by attenuating the contribution of fast varying component, *f(n)* using an appropriate low pass filter. K-means clustering is a non-hierarchical partitioning method, which helps to indicate single cardiac cycle in the PCG signal. Segmentation performance of 90.45% was achieved using the proposed algorithm. Feature vectors were formed after segmentation by using Daubechies-2 wavelet detail coefficients at the second decomposition level. Grow and Learn network was used for classification of the segmented PCG signals and a classification accuracy of 97.02% was achieved. It is concluded that Homomorphic filtering and GAL network could be used for segmentation and classification of PCG signals without using a reference signal.**

I. Introduction

PHONOCARDIOGRAPHY is the recording of sonic vibrations of heart and blood circulation [1] and it provides valuable information concerning the function of heart valves and the hemodynamics of the heart. It has a high potential for detecting various heart diseases [2]. Many pathological conditions that cause murmurs and aberrations of heart sounds (HSs) manifest much earlier in phonocardiography than which are reflected by symptoms. With proper interpretation of the phonocardiogram (PCG) signal, corrective measures can be taken. The heart sound signal or PCG signal of normal heart is comprised of two distinct activities namely the first heart sound S_1 and the second heart sound S_2. These correspond to the normal heart sounds of lup and dup. In the case of abnormal heart, there could be several other signal activities between first and second sounds. The extraneous signal activities between S_1 and S_2 are considered as abnormal sound signals (S_3, S_4, murmurs, clicks, snaps) and help in detecting heart diseases.

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Cota Navin Gupta is with the Biomedical Engineering Research Center, Nanyang Technological University, Singapore-639815 (phone: 65-91496723 ; fax: 65-67920415; e-mail: cnavin_gupta@ pmail.ntu.edu.sg).

Dr.Ramaswamy Palaniappan, is with Department of Computer Science, University of Essex, Colchester, UK. (e-mail: rpalan@essex.ac.uk).

Dr.Sundaram Swaminathan is with the School of Electrical and Electronic Engineering and Biomedical Engineering Research Center, Nanyang Technological University, Singapore-639815 (e-mail: esswamin@ntu.edu.sg).

In this study our aim is to detect a single cycle of PCG signal, extract features and classify the features. Most segmentation methods use ECG signal or/and carotid pulse, as reference [3]. Correlation techniques have been used in absence of ECG [4] but this method may not perform well when the duration and the spectra of sound signal components show huge variations and this technique cannot be automated. Segmentation was also achieved using wavelet decomposition and reconstruction into four parts (S_1, S_2, systolic period, diastolic period) [5]. In this method, on selected detailed and approximate coefficients a segmentation process was carried out based on the envelope calculated using Shannon energy. In a previous study [6], each component of S_2 was modeled by a narrow-band non-linear chirp signal having a fast decreasing instantaneous frequency (IF) with time. The two components of S_2 (A_2 and P_2) were defined by a pair of functions and it described the signal envelope and instantaneous phase. The study highlighted the fact that S_2 is a modulated signal. This observation is exploited in the proposed novel methodology. Homomorphic filtering which was used to extract the voiced components of the speech [7] were applied to heart sound signals to find the envelope in time domain, which helps in finding the locations of S_1 and S_2.

Wavelets have been used to extract features from the segmented PCG signals. Feature extraction algorithm based on wavelet decomposition and reconstruction was proposed in [8] and adopted here. Daubechies-2 wavelet was used to obtain the wavelet coefficients [9]. Classification of PCG signals has been reported previously [9, 10]. Two-dimensional self-organizing map (SOM) were trained using time frequency features of HSs but satisfactory performance was not reported [10]. Incremental networks like Grow and Learn (GAL) network, have also been used for classification of PCG signals [9]. GAL network is an incremental, competitive learning network and is trained by a supervised learning scheme. In this study, GAL network was used as simple structured classifier in order to carry out HSs classification.

II. Signal Pre-processing

The recorded PCG signal is first preprocessed before performing segmentation. PCG signal is downsampled to 4000 Hz and normalized according to (1).

$$x_{norm}(t) = \frac{x_{4000}(t)}{max(|\, x_{4000}(t)\,|)}, \qquad (1)$$

where $x_{4000}(t)$ is the downsampled signal. Normal and abnormal HSs have a frequency range of 50 to 700 Hz.

Higher frequencies are not of clinical significance for analysis and diagnosis; hence a low pass Chebyshev type I filter with cutoff frequency at 750 Hz was designed. After filtering in the forward direction, the filtered sequence is then reversed and run back through the filter to obtain zero phase distortion.

III. SEGMENTATION OF HEART SOUNDS

The automatic segmentation algorithm is based on Homomorphic filtering and uses K-means clustering to indicate single detected cycle. Homomorphic filtering technique results in smooth envelope enabling easy peak detection. Peak conditioning was performed to remove peaks, which do not correspond to S_1 and S_2. K-means clustering of the time intervals between peaks was used to indicate the occurrence of single cardiac cycles and also to point to missed cycles.

A . Homomorphic Peak Detection

The similarity in structure of HSs to modulated components is exploited in this methodology. Heart sound signal activities (S_1, S_2) are similar to amplitude modulated waveform while heart murmurs are found to be similar to amplitude and frequency modulated waveform. Homomorphic filtering technique involves a logarithmic transformation, which converts a non-linear combination of signals (multiplied in time domain) into a linear combination. Thus the resulting spectrum can be viewed as a combination of slowly varying and fast varying parts wherein the high frequency content is removed using a low-pass filter. The used equations are as follows:

- Let *v(n)* represent PCG signal and *x(n)* the energy of PCG signal, then we can express the energy of PCG signal by:

$$x(n) = a(n) f(n) \ , \tag{2}$$

  where *a(n)* – slow varying part and *f(n)* – fast varying part. S_1 and S_2 contribute predominantly to *a (n),* while murmur contributes to *f(n)*.
- Multiplication operation is converted to addition by taking a simple logarithmic transformation:

$$z(n) = \log x(n) . \tag{3}$$

- This results in

$$z(n) = \log a(n) + \log f(n) . \tag{4}$$

The logarithms of the two signals are now combined in an additive manner. The high frequency component is characterized by rapid variations in time. We apply an appropriate linear low-pass filter L to filter the *f(n)* components:

$$z_1(n) = L[z(n)] . \tag{5}$$

Assuming the logarithmic transformation has not affected the separability of the Fourier components of *a (n)*, *f(n)* and also since *L* is linear, we have:

$$z_l(n) = L[\log a(n)] + L[\log f(n)] \approx \log a(n) \tag{6}$$

.

By exponentiation we arrive at:

$$\exp[z_l(n)] \approx \exp[\log a(n)] = a(n) . \tag{7}$$

With some preliminary experimentation, low pass Chebychev filter (*L*) with transition bandwidth from 10 Hz to 20 Hz was used. The exponentiation operation enables us to obtain a smooth envelope of the signal. Maximum value of the envelope was found and all points greater than 0.35 of maximum value were considered as peaks.

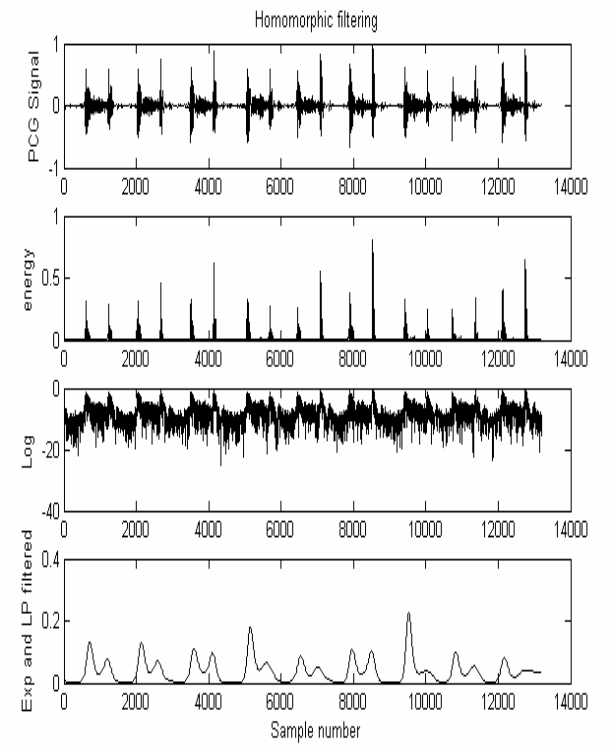

Fig.1. Peak detection (HSs with Systolic murmur).

Observations from the envelope after homomorphic filtering were:

- Normal heart sound had both slow varying and fast varying part. S_1 comprised of a low frequency range and a high frequency range [11] with the dominant frequency being between 100-200 Hz.
- The slow varying parts were from S_1 and S_2 while the fast varying parts were due to the higher frequency component of S_1 (M_1) or S_2 (A_2). Noise also contributed to the envelope in the systolic and diastolic regions but was reduced in amplitude.
- In heart sounds with murmur, the fast varying parts in the systolic region (Systolic murmur) and diastolic region (Diastolic murmur) were due to the murmurs.

B. Peak Conditioning

Peak conditioning was performed for the peaks obtained using homomorphic filtering, which enables cycle detection process. Peaks, which do not correspond to the first and second HSs, were rejected. Parameters of the peak like peak width, peak start point, peak end point and distance between peaks were found.

- The mean width of detected peaks was calculated and all peaks less than 0.5 of mean peak width were

considered as peaks, which do not correspond to S_1 and S_2 and were rejected.

- The distance between two detected peaks, which correspond to distance between S1 and S2, cannot be less than 80 ms. During inspiration the two components of S_2 (A_2 and P_2) can be separated from each other by 30-80ms [12]. If it is less than 80 ms then it corresponds to a split S_2. The split peaks of S_2 were combined into a single peak.
- The range of possible width of S_1 and S_2 is 80-120 ms. Greater peak widths do not correspond to S_1 and S_2 and might result from above step two. These combined peaks might correspond to S_2 sound and diastolic murmur like in the case of Aortic Regurgitation (AR). These peaks were limited to 120 ms and peak conditioning was achieved.

C. Cycle Detection

This stage involves extraction of single cardiac cycle of PCG signal after the peak detection and peak conditioning stages. K-means clustering helps indicate single cardiac cycles and is a non-hierarchical partitioning method that partitions the observations in the data into K mutually exclusive clusters, using an iterative algorithm that minimizes the sum of distances from each object to its cluster centroid, over all clusters.

The systolic (S_1-S_2) and the diastolic (S_2-S_1) time intervals excluding the S_1 and S_2 sounds were calculated after the peak conditioning process. The calculated time intervals were clustered into two clusters. The occurrence of cluster 1 and cluster 2 consecutively indicates a single cardiac cycle. The smaller time interval was then identified as systole while the other interval was identified as diastole. Consecutive occurrence of cluster 1 and cluster 1 (or) cluster 2 and cluster 2 might be due to loss of peak, extra peak or due to equal systolic and diastolic intervals. It was observed that K-means clustering showed better performance than hierarchical clustering methods in indicating single detected cycle. Single cycle of PCG signal was then extracted using the clusters as shown in Fig. 2 (HSs with Systolic murmur).

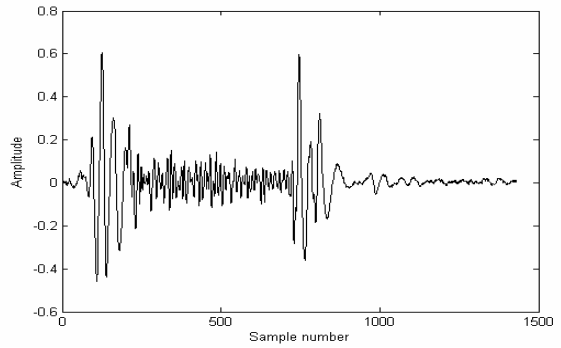

Fig.2. Single cycle (HSs with Systolic murmur).

D. Results of segmentation algorithm

The proposed segmentation algorithm was tested on three classes of HSs (Normal, Systolic murmur and Diastolic murmur) and the results are as tabulated in Table 1.

TABLE I
PCG SEGMENTATION RESULTS

	Correct	Incorrect	Total	%
Normal	109	1	110	99.09
Systolic murmur	106	18	124	85.48
Diastolic murmur	92	14	106	86.79
Total cycles			340	90.45

High intensity murmurs and high background noise could cause the segmentation algorithm to fail. Appreciable S_1 and S_2 amplitude when compared to murmurs enhances the performance of the proposed algorithm. The incorrectly segmented cycles were hand segmented to enable feature extraction and classification.

IV. Wavelet Based Feature Extraction

The spectrum of HSs was divided into sub-bands to extract the discriminating information from normal and abnormal HSs. Wavelet coefficients were determined by using Daubechies-2 wavelet for the cycles of segmented PCG signals (340 cycles). These coefficients were obtained for a single cycle of PCG signal and wavelet detail coefficients at second decomposition level were seen to have the distinguishing features as reported in [9] for three cases of PCG signals. The signal formed by the wavelet detail coefficients at the second decomposition level was split into 32 sub windows with each window containing 128 discrete data values. The power of the signal within these sub-windows formed the elements of the feature vectors. The computed 32-wavelet features were used as input for the GAL network.

V. GAL Classification of PCG Signals

Classification of the segmented PCG signal features was achieved using GAL. The 32-wavelet features form the input vector for classification. GAL allows learning at one iteration since it is incremental and uses local representation. The structure of the GAL network [9] is shown in Fig.3. The procedure for GAL network learning and forgetting was implemented as in [9].

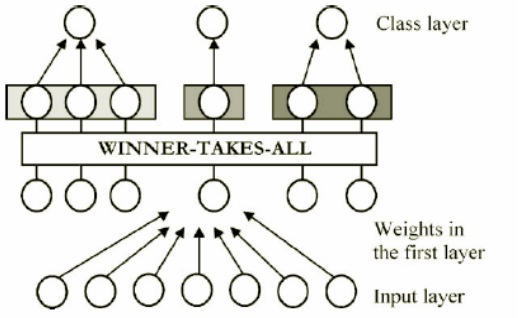

Fig.3. Grow and Learn Network.

The segmented heart sounds dataset (340 patterns) was divided into three datasets each with 112 patterns. 45 patterns (15N, 15S, 15D) were used for used for training and

67 patterns (21N, 26S, 20D) were used for testing. Three patterns (1N, 1S, 1D) were used as initial class pattern for the GAL network. The entire GAL network was implemented in Matlab (Mathworks, Inc.). Table 2 shows the classification performance using GAL network.

TABLE II
CLASSIFICATION RESULTS OF GAL NETWORK

Performance	Dataset 1	Dataset 2	Dataset 3
Classification of Normal(N)	21/21	21/21	21/21
Classification of Systolic murmur(S)	24/26	25/26	24/26
Classification of Diastolic murmur(D)	20/20	20/20	19/20
Classification Percentage	97.01%	98.50%	95.55%

V. CONCLUSION

It is vital to identify a single cardiac cycle to obtain information about the health of heart valves and also to detect certain heart diseases. Current techniques use a reference signal like ECG to obtain a single cardiac cycle or to identify the fundamental activities of the PCG signal. We proposed a novel method to segment PCG signal into single cycle using Homomorphic filtering and K-means clustering if the heart rate is uniform for the entire sequence of PCG signal recording. The algorithm has shown 90.45% of success. Wavelet features of the segmented heart sounds were obtained and classification was achieved using Grow and Learn Network (GAL). A classification performance of 97.02% was achieved. It is concluded that segmentation and classification of PCG signals is achievable without the aid of any reference signal.

VI. DATABASE

With the co-operation of Singapore General Hospital (SGH), 41 volunteers participated in the recording of HSs. The sounds were recorded with 16-bit accuracy and 8000 Hz sampling frequency. The various types of PCG signals obtained were Normal, Systolic murmurs(SM) and Diastolic murmurs (DM), which were used to test the algorithms.

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