SEGMENTATION AND CLASSIFICATION OF HEART SOUNDS

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Abstract

An algorithm for segmentation of heart sounds (HSs) into a single cardiac cycle (S_1-Systole-S_2-Diastole) 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), based on neural networks is developed. This algorithm does not require additional reference signal such as ECG signal. Feature vectors are formed after segmentation by using Daubechies-2 wavelet detail coefficients at the second decomposition level. Redundant features are removed using principal component analysis (PCA). Multilayer perceptron- Backpropagation neural network (MLP-BP) is used for classification of three different HSs. A classification accuracy of 94.5% and a segmentation accuracy (or performance) of 90.45% was achieved; thus, demonstrating that segmentation and classification of heart sounds without the aid of reference signal is achievable.

Keywords: Classification of murmurs; Heart Sounds; Homomorphic Segmentation;Phonocardiogram Signals; Prinicipal Component Analysis; Wavelet transform;

1. Introduction

The heart sound signal or Phonocardiogram (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. In abnormal heart sound signals, murmurs manifest in addition to S_1 and S_2 signals, due to certain pathological conditions. These murmurs are generally present between S_1 and S_2 signals. In most cases, the activities in the PCG signal relating to a given disease are contained in a single interval of cardiac cycle. Hence it is important to segment the heart signals into single cardiac cycle. Murmurs present in the signal may at times obscure S_1 and S_2, thus making proper interpretation of auscultation a very difficult task. However, utilizing the advances in signal processing, it is possible to aid the doctors in efficiently analyzing and interpreting the heart signals. By efficiently using such diagnostic tools, frequent referrals to alternate expensive tests such as echocardiography may be reduced.

In this paper our aim is to detect a single cycle of PCG signal, extract wavelet features, remove redundant features using PCA and classify the reduced features using MLP-BP. Most segmentation methods use ECG signal or/and carotid pulse, as reference [1]. This requires simultaneous recording and synchronous processing of ECG and PCG signals. This imposes hardware and computational burden. In a previous study [2], 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 which described the signal envelope and instantaneous phase. The study highlighted the fact that S_2 is a modulated signal. The methodology used in this paper, exploits this observation. This observation was also used in [3] but a time-frequency approach based on Morlet wavelets was used to obtain cardiac information. In this paper, we propose a methodology using time domain followed by a time-frequency domain approach to obtain cardiac information.

Feature vectors are usually obtained from the segmented HSs for classification. Coifman fourth order wavelet was used in [4] to characterize five different cases. Feature extraction algorithm based on wavelet decomposition and reconstruction was proposed in [5] and adopted here. The feature vector included 95 elements obtained from the original signal and three selected sub-band signals ([3]rd, [4]th and [5]th level details). Daubechies wavelet of sixth order was used to decompose the signal into five levels. Principal Component Analysis was used to achieve feature reduction. PCA identifies patterns in data of high dimension in such a way so as to highlight their similarities and differences which enables reduction of redundant features for classification.

Classification of the PCA reduced PCG wavelet features was achieved using MLP-BP network. MLP-BP is frequently used in biomedical signal processing applications [6]. In [7], backpropagation (BP) neural network (NN) was used to identify individuals using visual evoked potential (VEP) signals. In the proposed method, the MLP-BP was used instead of parametric classifiers or other types of NN architecture. When compared with parametric classifiers most NN architectures have good generalisation ability but they are also difficult to train and are time consuming. However MLP-BP was used in this study because of its good classification accuracy with PCA.

2. PCG 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(N), Systolic murmurs(S) and Diastolic murmurs (D). The recorded signal was first preprocessed before performing segmentation. PCG signals were then down sampled to 4000 Hz and normalized according to (1).

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

where $x_{4000}(t)$ is the down sampled 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 was then reversed and run back through the filter to obtain zero phase distortion.

3. Segmentation of PCG signals

The automatic segmentation algorithm is based on homomorphic filtering and uses k-means clustering to indicate the presence of single detected cycle.

3.1. Peak detection using homomorphic filtering

The approach makes use of the similarity in structure of HSs to modulated components. 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 waveforms. 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 equations for these are given below:

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

$$x(n) = a(n)f(n) \quad (2)$$

  $a(n)$ – slow varying part
  $f(n)$ – 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.

$$z(n) = \log x(n) \quad (3)$$

- We have

$$z(n) = \log a(n) + \log f(n) \quad (4)$$

  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.

$$z_l(n) = L[z(n)] \quad (5)$$

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:

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

By exponentiation we arrive at

$$\exp[z_l(n)] \approx \exp[\log a(n)] = a(n) \quad (7)$$

After some preliminary experimentation, low pass Chebychev filter (L) with transition bandwidth from 10Hz to 20Hz was used. The exponentiation operation enables us to obtain a smooth envelope of the signal as in Fig.1. Maximum value of the envelope is found and all points greater than 0.35 of maximum value were considered as peaks.
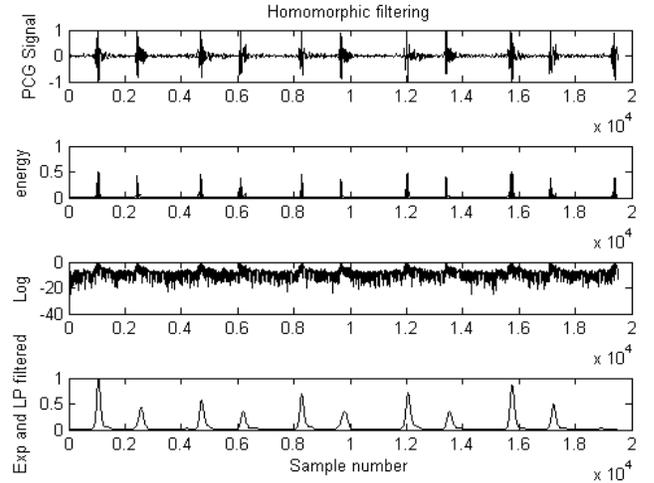

Fig.1: Peak detection (Normal HSs)

3.2. Peak conditioning and cycle detection

This stage involves extraction of single cardiac cycle of PCG signal after peak conditioning. Peak conditioning is performed for the peaks obtained using homomorphic filtering, which enables cycle detection process. Peaks which do not correspond to the first and second HSs are rejected. Parameters of the peak like peak width, peak start point, peak end point and distance between peaks are found.

- The mean width of detected peaks was calculated and all peaks less than 0.5 of mean peak width were considered as peaks that do not correspond to S_1 and S_2 and were rejected.
- The distance between two detected peaks which correspond to distance between S_1 and S_2 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 [9]. If 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 step one. These peaks were limited to 120 ms and peak conditioning is achieved.

K-means clustering is a non-hierarchical partitioning method and helps indicate single cardiac cycles. 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. Single cycle of PCG signal was extracted using the clusters as shown in Fig. 2 (Normal HSs).
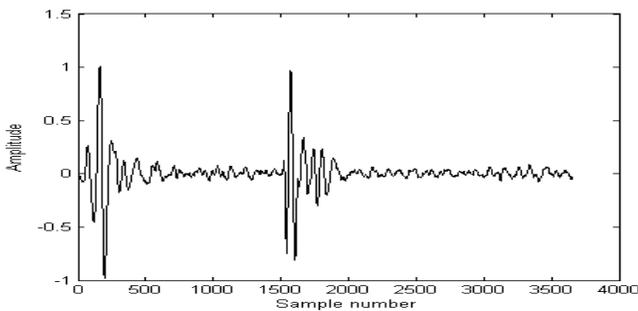

Fig.2: Segmented HSs (Normal)

3.3 Segmentation results

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

Table.1: Results from segmentation algorithm

	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. The incorrectly segmented cycles were hand segmented to enable feature extraction and classification. Appreciable S_1 and S_2 amplitude when compared to murmurs enhances the performance of this algorithm.

4. Feature extraction of PCG signals

The spectrum of HSs was divided into sub-bands to extract the discriminating information from normal and abnormal cases.

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 elements of the feature vectors were then formed by computing the powers of the signal within these sub-windows. Principal component analysis was used to reduce these 32 element feature vector of each segmented cycle as follows.

Step 1: Each of the segmented PCG signal was combined into a matrix, y after removing the mean.

Step 2: Covariance computation. The covariance of matrix y was computed using:

$$\mathbf{R} = E(yy^T) - E(y)E(y^T). \qquad (8)$$

Step 3: Next, matrices $\mathbf{E}$ and $\mathbf{D}$, are computed where $\mathbf{E}$ is the orthogonal matrix of eigenvectors of $\mathbf{R}$ and $\mathbf{D}$ is the diagonal matrix of its eigenvalues, $\mathbf{D} = diag(d_1,.....d_n)$. It is shown that the first few principal components (PCs) account for a large proportion of the features while the rest represent less important features [10]. In our work, residual power method was used to select the number of PCs to be used. Using this method, PCs which account for 95% of the variance in the data were retained.

Step 4: The reduced feature set was computed using

$$\mathbf{P} = \mathbf{\hat{E}}^T \mathbf{y}^T. \qquad (9)$$

where $\mathbf{\hat{E}}$ is matrix representing the eigenvectors corresponding to the chosen first few PCs. PCA reduces the 32 element feature vector into 12 element feature vector. The 12 element feature vector was then normalized to a range of 0 to 1 and was used as the input for the MLP-BP classifier.

5. Classification of PCG signals

MLP neural network trained by the BP algorithm was used to classify the computed features into either Normal (N), Systolic murmur(SM) or Diastolic murmur (DM). The input layer consisted of 12 nodes because the number of input features was 12, while the output layer was set to 3 nodes for the three classes of heart sounds. With some preliminary simulations, we found that 12 hidden nodes gave the best performance. This is also in line with the rule of thumb [11] that says the number of hidden nodes should be set equal to the number of input nodes which was 12 in our case. The target output for the trained pattern was set to 1.0, while for the rest of the classes, it was set to 0. Training was conducted until the average error falls below 0.01 or the maximum iteration limit of 1000 was reached. Fig.3 shows the architecture of the network.
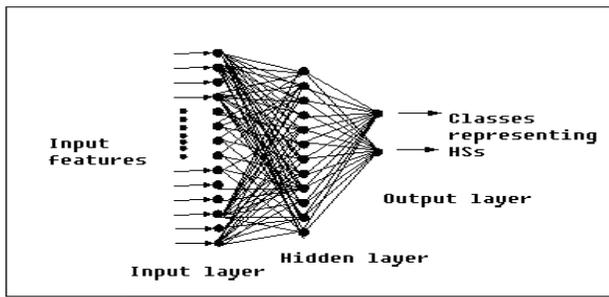
Fig.3: MLP-BP network used in the study

The segmented heart sounds dataset (i.e. totaling 340 patterns) was divided into two sets. Set 1 consisted of 135 patterns (45N, 45S, 45D) and was used for training the MLP-BP network. Set 2 was used for testing and consisted of 205 patterns (65N, 79S, 61D). Table 2 shows the classification performance of MLP-BP network.

Table 2: Testing Classification using MLP-BP network

	Correct	Incorrect	Total	%
Normal	64	1	65	98.46
Systolic murmur	75	4	79	94.93
Diastolic murmur	55	6	61	90.16
Total cycles(3cases)			205	94.51

6. Conclusions

Information about the health of heart valves is contained in a single cycle of PCG signal. Hence it is very important to identify single cycle for analysis of defects. Current state of art techniques uses a reference signal like ECG or Carotid pulse, to obtain a single cycle or to identify the fundamental activities of the PCG signal. We have 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 segmentation algorithm has shown 90.45% of success. The 32 wavelet features of each segmented cycle were reduced to 12 using PCA. These reduced feature sets were classified by the MLP-BP into 3 classes. Classification performance of 94.51% was obtained. It is concluded that classification of segmented PCG signals obtained without using a reference signal can be achieved.

Acknowledgements

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