Heart Sounds Clustering using a Combination of Temporal, Spectral and Geometric Features

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Abstract

Heart murmurs are the first sign of heart valve disorders. Several studies have been conducted in recent years to automatically differentiate normal heart sounds from heart sounds with murmurs using various types of audio features. In this study, the feasibility of using a combination of temporal, spectral and geometric features in clustering five types of physiological and pathological heart sounds is shown. Thirty six heart sound recordings comprising normal and abnormal heart sounds were collected from training CDs and online resources. The proposed combination of features exhibits a promising discriminatory power in phonocardiographic signals clustering.

1. Introduction

Cardiovascular disease remains the leading cause of death worldwide (1). Heart valve disorders or so called heart murmurs receive a substantial amount of attention from health-care providers, because murmurs are the earliest sign of heart valve diseases. A large body of recent researches has been dedicated to detect murmurs (2-4) from phonocardiographic (PCG) signals.

Fundamentally, during each cardiac cycle, four sounds can be heard; S1, S2 (high-frequency and strong sounds) and S3, S4 (low-frequency and weak components. A heart murmur is an abnormal, extra sound that usually results from turbulence in blood flow through narrow cardiac valves or reflow through the atrioventricular valves due to congenital or acquired defects. In this study for automated classification, four categories of heart murmurs are used; aortic stenosis (AS), aortic regurgitation (AR), mitral stenosis (MS), and mitral regurgitation (MR).

In recent years, numerous signal processing techniques have been developed for automatic analysis of the heart sounds. In general, heart sound analysis involves various processes such as feature extraction, segmentation and classification. However, feature extraction has a key role in the whole analysis. Localized features are important for reliable segmentation whereby heart sounds are well separated into S1 and S2. Discriminative features are also crucial for obtaining high classification accuracy which is the focus of this study.

Many types of features have been previously introduced. Temporal and spectral features were the common types of audio features that were widely proposed and evaluated for heart sound analysis. Spectral flux, spectral roll-off, spectral centroid and spectral energy are some examples of spectral features were used before for segmentation and classification of heart sounds (4, 5). One example is the work by Kumar et al. (6) that proposed a set of temporal and spectral features for detecting noise during heart sound recording. Another example is utilization of combination of temporal and spectral features of the heart sound as a biometric measure (7).

Geometric features also have been successfully extracted for delineation and segmentation of heart sounds. Homaeinezhad et al (8) described a robust unified framework for segmentation of the PCG signals based on the false-alarm probability bounded segmentation. Area Curve Length on DWT of the heart sound signals was the new geometric feature proposed to be used as the segmentation decision statistics. In another work by Homaeinezhad et al (9), six geometric feature were proposed and exploited for heart sound segmentation. Gupta et al. (5) introduced a segmentation method using homomorphic filtering and K-means clustering to separate different parts of a cardiac cycles.

Discriminatory power of the extracted features can be evaluated through classification. Clustering is an unsupervised classification that was considered in this paper for evaluating features. Recently, an adaptive clustering method using Hilbert-Huang Transform was proposed to detect the presence of S3 and S4 in PCG signals (10). A visual simplicity based fuzzy clustering also introduced by Nigam et al. (11) to extract murmurs from the phonocardiogram. A density based dynamic clustering technique was proposed by Tang et al. (12) for heart sound segmentation. Several heart sound analysis framework also were designed including clustering step (1, 13).

In this study, the feasibility of adding geometric features to the previously proposed combination of temporal and spectral features (6, 7) was examined and the discriminatory power of proposed feature set was evaluated through three different clustering algorithms. The rest of this paper is organized as follows: Section 2 provides details about the features and experimental setup. Results are presented in section 3, and concluding remarks are given in section 4.

2. Materials and methods

2.1. Feature generation

Features should have high inter-class variance with low-intra class variance to be useful in the following steps of detecting abnormalities in heart sounds. In this paper, three types of features, temporal, spectral and geometric features, were generated from each heart sound. These features where combined to construct a feature vector. The combination of temporal and spectral features has been shown to be successful in detecting noise in heart sound recording and utilization of heart sound as a biometric measure (6, 7). In this study the addition of geometric features to this combination is proposed. Geometric features were employed successfully for heart sound segmentation in the study by Homaeinezhad et al. (9). For each PCG signal a vector combining temporal, spectral and geometric features was constructed and stored in a comma separated value (.CSV format) file to be fed into the clustering algorithms.

For temporal feature, the Zero Crossing Rate (ZCR) was used. ZCR, a commonly used temporal feature, are obtained from direct characterization of the signal as a time series of sampled amplitude values. For the spectral and geometric features used, brief definitions of these features are as follows.

Spectral features. Spectral feature were extracted from fast Fourier transform (FFT) of the signals.

- **Spectral flux (SF):** SF is a measure which characterizes the change in the shape of the signal's spectrum. SF can be calculated as the Euclidean norm of the delta spectrum magnitude as follows:

$$SF = \frac{1}{M}\sqrt{\sum_{k=1}^{M}(X_i(k) - X_{i-1}(k))^2} \tag{1}$$

where M is the total number of frequency bins, i is the frame index, k is the frequency bin index. X_i and X_{i-1} are the spectrum magnitude vectors of frames i and $i-1$, respectively.

- **Spectral roll-off (SR):** SR measures the skewness of the signal's frequency spectrum. It is the value of the frequency under which usually 95% (c=0.95) of the signal's power resides. SR can be obtained as:

$$SR = c\sum_{k=1}^{M} X(k) \tag{2}$$

- **Spectral centroid (SC):** SC defines the centre of a signal's spectrum power distribution. Like spectral roll-off, spectral centroid is also a measure of spectral shape. SC can be computed as follows:

$$sc = \frac{\sum_{k=1}^{M} k.X(k)}{\sum_{k=1}^{M} X(k)} \tag{3}$$

- **Spectral energy entropy (SE):** SE is the measure of information content. It is the summation of the products of the probability of outcome multiplied by the log of the inverse of the outcome probability as follows:

$$SE = \sum_{i=1}^{k} p(i)log_2\frac{1}{p(i)} \tag{4}$$

Geometric features. In this paper geometric features were defined based on the DWT of the signals. In the following definition of features, $x(t)$ is the PCG signal, F_s is the sampling frequency, W_L is the length of the window sliding on the signal and k is the slide number.

- **Summation of the absolute first-order derivative (M_{dfI}):** The activity of the high-frequency components of the original signal can be detected through M_{dfI} as follows:

$$M_{dfI}\ (k) = F_s \sum_{t=k}^{k+W_L-1} [|x(t+1) - x(t)|] \tag{5}$$

- **Summation of the absolute second-order derivative (M_{dfII}):** M_{dfII} indicates the ascend/descend rate of the signal *x(t)* which are the probable edges of the signal in the analysis window. M_{dfII} can be computed as:

$$M_{dfII}\ (k) = F_s^2 \sum_{t=k}^{k+W_L-2} [|x(t+2) - 2x(t+1) + x(t)|] \tag{6}$$

- **Curve length (*MCL*):** The curve length is a suitable quantity to measure the duration of the signal *x(t)* events (such as S1, S2). MCL can be calculated as follows:

$$MCL(k) \approx \frac{1}{F_s}\sum_{t=k}^{k+WL-1}\sqrt{1 + [(x(t+1) - x(t))Fs]2} \tag{7}$$

- **Area under curve (M_{AR}):** M_{AR} is the approximation of the area under the curve of *x(t)* that can be formulated as:

$$M_{AR}(k) \approx \frac{1}{Fs}\sum_{t=k}^{k+WL} |x(t)| \tag{8}$$

- **Centralized mean square value (M_{MS}):** M_{MS} shows the variance of the samples around the mean value and can be computed as follows:

$$M_{MS}(k) = \frac{1}{WL}\sum_{t=k}^{k+WL}\left[x(t) - \mu_k\right]^2 \quad (9)$$

where μ_k is the sample mean of the signal *x(t)* in the analysis window and can be obtained from the following:

$$\mu_k = \frac{1}{W_L}\sum_{t=k}^{k+WL} x(t) \quad (10)$$

2.2. Experimental setup

Preprocessing: A data set of 36 heart sounds comprising of 8 normal and 28 murmurs was collected from online resources and teaching materials. Four types of murmurs were analyzed; aortic stenosis, aortic regurgitation, mitral stenosis, and mitral regurgitation. Preprocessing was performed in several steps. The heterogeneity of PCG signals in the dataset was eliminated through frequency re-sampling. As for removing noise, a digital band-pass finite impulse response (FIR) filter with Kasier minimum order window was applied on all samples. lastly, segmentation was done using the approach proposed by Homaeinezhad et al. (9) and ten cycles of each heart sound were randomly chosen.

Feature sets: Temporal, spectral and geometric features, listed in section 2.1, were then extracted. These features were organized as two feature sets. Feature set1 (FS1) includes temporal and spectral features, while feature set 2 (FS2) comprised of all temporal, spectral and geometric features.

Clustering: FS1 and FS2 were clustered using three clustering algorithms; K-means, hierarchical and expectation maximization (EM) clustering. These three clustering algorithms were selected from differing clustering categories. EM has not been used for heart sound clustering. The clustering experiment was performed using Weka version 3.7.5[1] which includes the implementation of various clustering algorithms.

Evaluation: Accuracy degree and the entropy measure, which are two commonly used criteria, were used for evaluating clustering performance.

As discussed in the study by Olszewski (14) accuracy degree determines the number of correctly assigned objects divided by the total number of the objects. Therefore, for the *i*th cluster, the accuracy degree is determined as follows:

$$q_i = \frac{m_i}{n_i} \quad (11)$$

where m_i, $i = 1, \ldots, k$ is the number of objects correctly assigned to the *i*th cluster, n_i, $i = 1, \ldots, k$ is the number of objects in the *i*th cluster, and k is the number of clusters. For the entire data set, the total accuracy degree is determined as follows:

$$q_{total} = \frac{m}{n} \quad (12)$$

where m is the total number of correctly assigned objects, and n is the total number of objects in the entire data set. The total accuracy degree q_{total} assume values in the interval [0, 1], and naturally, greater values are preferred.

Entropy measure is an evaluation criterion which measures the uncertainty for the clustering of objects that belong to the same cluster. The entropy measure was determined as follows:

$$I = \frac{\mu}{n} \quad (13)$$

where μ is the number of overlapping objects. The entropy measure assumes values in the interval [0, 1], and smaller values are desired.

3. Results

Tables 1 and 2 present the accuracy degrees for the clustering of FS1 and FS2.

Table1. Accuracy degree for FS1.

Heart Sound	K-means	Hierarchical	EM
Normal	70/80=0.87	71/80=0.87	80/80=1.00
AS	90/110=0.82	90/110=0.82	92/110=0.84
MR	43/50=0.86	36/50=0.72	44/50=0.88
MS	43/50=0.86	40/50=0.80	44/50=0.88
AR	60/70=0.86	61/70=0.87	61/70=0.87
q_{total}	306/360=**0.85**	298/360=**0.83**	321/360=**0.89**

Table2. Accuracy degree for FS2.

Heart Sound	K-means	Hierarchical	EM
Normal	72/80=0.90	72/80=0.90	80/80=1.00
AS	95/110=0.86	93/110=0.84	100/110=0.90
MR	43/50=0.86	44/50=0.88	45/50=0.90
MS	45/50=0.90	43/50=0.86	44/50=0.88
AR	61/70=0.87	61/70=0.87	61/70=0.87
q_{total}	316/360=**0.88**	313/360=**0.87**	330/360=**0.91**

The comparison between q_{total} in Table1 and Table2 shows a significant improvement of accuracy degree using FS2. This improvement indicates that contribution of geometric features to the overall clustering accuracy was acceptable; 3%, 4%, 2%, for K-means, hierarchical and EM clustering, respectively.

[1] http://www.cs.waikato.ac.nz/ml/weka/

Table3. Entropy measure for FS1 and FS2.

	K-means	Hierarchical	EM
FS1	84/360=0.233	85/360=0.236	78/360=0.216
FS2	71/360=0.197	77/360=0.213	69/360=0.191

Table3 shows that entropy was decreased in clustering of FS2, which confirms the effectiveness of adding geometric feature to FS1. Moreover, EM clustering algorithm outperformed K-means and hierarchical clustering through providing the higher clustering accuracy (91%) and lower clustering uncertainty (0.191).

4. Conclusion

In this paper, feasibility of combining three types of features to distinguish five types of heart sounds including normal and four types of murmurs was examined. Experimental results demonstrate that the result of clustering based on the combination of all features was improved. Future work includes the refinement of the geometric features in order to achieve better clustering accuracy. The heart sound categories would also be expanded to include more type of murmurs.

References

[1] Syed Z, Leeds D, Curtis D, Nesta F, Levine RA, Guttag J. A framework for the analysis of acoustical cardiac signals. Biomedical Engineering, IEEE Transactions on. 2007;54(4):651-62.

[2] Chen Y, Wang S, Shen C-H, Choy F. Intelligent Identification of Childhood Musical Murmurs. Journal of Healthcare Engineering. 2012;3(1):125-40.

[3] Cherif LH, Debbal SM, Bereksi-Reguig F. Choice of the wavelet analyzing in the phonocardiogram signal analysis using the discrete and the packet wavelet transform. Expert Systems with Applications. 2010;37(2):913-8.

[4] Choi S, Shin Y, Park HK. Selection of wavelet packet measures for insufficiency murmur identification. Expert Systems with Applications. 2011;38(4):4264-71.

[5] Gupta CN, Palaniappan R, Swaminathan S, Krishnan SM. Neural network classification of homomorphic segmented heart sounds. Applied Soft Computing. 2007;7(1):286-97.

[6] Kumar D, Carvalho P, Antunes M, Paiva RP, Henriques J. Noise detection during heart sound recording using periodicity signatures. Physiological Measurement. 2011;32(5):599-618.

[7] Tran DH, Leng YR, Li H, editors. Feature integration for heart sound biometrics. IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP). 2010;1714-7.

[8] Homaeinezhad MR, Atyabi SA, Daneshvar E, Ghaffari A, Tahmasebi M. Discrete wavelet-aided delineation of PCG signal events via analysis of an area curve length-based decision statistic. Cardiovascular Engineering. 2010;10(4):218-34.

[9] Homaeinezhad MR, Atyabi SA, Deneshvar E, Ghaffari A, Tahmasebi M. Optimal delineation of PCG sounds via false-alarm bounded segmentation of a wavelet-based principal components analyzed metric. International Journal for Numerical Methods in Biomedical Engineering. 2011;27(11):1711-39.

[10] Tseng YL, Ko PY, Jaw FS. Detection of the Third and Fourth Heart Sounds Using Hilbert-Huang Transform. BioMedical Engineering OnLine. 2012;11(1).

[11] Nigam V, Priemer R. A simplicity-based fuzzy clustering approach for detection and extraction of murmurs from the phonocardiogram. Physiological Measurement. 2008;29(1):33-48.

[12] Tang H, Li T, Qiu T, Park Y. Segmentation of heart sounds based on dynamic clustering. Biomedical Signal Processing and Control. 2012;7(5):509-16.

[13] Amit G, Gavriely N, Intrator N. Cluster analysis and classification of heart sounds. Biomedical Signal Processing and Control. 2009;4(1):26-36.

[14] Olszewski D. k-Means clustering of asymmetric data. Hybrid Artificial Intelligent Systems. 2012;1:243-54.

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