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A novel hybrid energy fraction and entropy-based approach for systolic heart murmurs identification

Yineng Zheng, Xingming Guo *, Xiaorong Ding

College of Bioengineering, Chongqing University, Key Laboratory of Biorheology Science and Technology, Ministry of Education, Chongqing 400044, PR China

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ABSTRACT

This paper presents a set of novel features of heart sound for the detection of the abnormality of heart sounds and classification of heart murmurs. The features include energy fraction of the first and the second heart sounds (*S1–S2EF*), energy fraction of heart murmur (*HMEF*), the maximum energy fraction of heart sound frequency sub-band (*HSEFmax*), sample entropy of the first and the second heart sounds component (*S1–S2sampen*) and sample entropy of heart murmur component (*HMsampen*). Firstly, the heart sound signals were de-noised and normalized, then decomposed by wavelet packet. The features, such as energy fraction and sample entropy were calculated from the reconstructed selective frequency components of heart sound signals. The support vector machine (SVM) was employed as a classifier to detect the abnormality of heart sound and discriminate heart murmurs. A dataset consisting of 80 normal heart sounds and 167 systolic heart murmurs samples, segmented from 40 healthy volunteers and 67 patients, were used to test and validate the proposed method. The performance of our proposed method was assessed in terms of sensitivity, specificity and accuracy. The result showed that our proposed method exhibited a satisfactory performance with a high accuracy of 97.17%, a specificity of over 98.55% and a sensitivity of over 93.48%. This suggests that the presented method can be used as an effective assistance for cardiac auscultation.

1. Introduction

Abnormal heart sounds may indicate a function or structure malfunction of the heart such as insufficiency or stenosis of heart valves. Heart sound auscultation technology is a rapid, non-invasive and convenient approach for cardiac function evaluation and cardiovascular disease diagnosis (Finley et al., 1998; PASegal & Likoff, 1966). Cardiac auscultation can clue the diagnosis of many cardiac abnormalities, and it also is a traditional way to distinguish heart murmurs from heart sounds. However, cardiac auscultation mainly depends on subjective experience and skills of the clinician. The clinicians require amount of training and experience to be capable to master cardiac auscultation technology and make a correct diagnosis. Especially some primary clinician cannot master the heart auscultation skills expertly and make an accurate diagnosis, because of lacking of enough experience. As a consequence, it is necessary and beneficial to exploit an intelligent diagnosis system to assist clinicians in clinical diagnosis of cardiovascular disease.

There are several studies reported on heart sound feature extraction and classification. Andrisevic et al. (2005) developed an intelligent diagnosis system to differentiate normal and abnormal heart sounds through the use of wavelet analysis and ANN. Ahlstrom et al. (2006) applied various feature extraction methods such as wavelet transform (WT), Shannon energy, fractal dimension (FD), recurrence quantification analysis (RQA), and artificial neural network (ANN) to classify systolic murmurs. Comak, Arslan, and Turkoglu (2007) proposed a diagnosis system to distinguish normal from abnormal doppler signals of the heart valve. Noponen, Lukkarinen, Angerla, and Sepponen (2007) used visual and numerical phono-spectrographic analysis to distinguish innocent systolic murmurs from pathological murmurs in children. Sengur and Turkoglu (2008) used hybrid artificial intelligence methods to classify normal and abnormal heart sounds for the heart valve diseases diagnosis. Chauhan, Wang, Sing Lim, and Anantharaman (2008) designed a computer auscultation system for distinguishing normal from abnormal heart sounds. Avci (2009) developed an intelligent classification system based on genetic-SVM to classify the heart mitral and aortic valve sound signals to two classes (normal or abnormal). Maglogiannis, Loukis, Zafiropoulos, and Stasis (2009) utilized heart sound peaks extraction and boundary detection to obtain recognition features, and

* Corresponding author. Tel.: +86 23 65112676; fax: +86 23 65102507.
E-mail addresses: zhengyn@cqu.edu.cn (Y. Zheng), guoxm@cqu.edu.cn (X. Guo), dingxiaorong86@126.com (X. Ding).

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identified heart valve diseases. Babaei and Geranmayeh (2009) proposed an algorithm combining WT with ANN for the classification of heart valve disorders. Choi and Jiang (2010) proposed autoregressive power spectral analysis method with multi-SVM technique to classify six types of heart valvular disorders. Saraçoğlu (2012) developed a Hidden Markov model (HMM)-based intelligent biomedical system to classify two types of heart valve murmurs. Chen, Wang, Shen, and Choy (2012) used matrix decomposition to extract feature and discriminated innocent murmurs from organic murmurs through the combination of multiple algorithms. Safara, Doraisamy, Azman, Jantan, and Abdullah Ramaiah (2013) classified four types of heart sounds using the multi-level basis selection of wavelet packet decomposition (WPD). Gharehbaghi, Dutoit, Ask, and Sornmo (2014) calculated the spectral power of adjacent frequency bands and employed time growing neural network to detect the systolic ejection sound in children. In conclusion, time–frequency and nonlinear analysis both are the effective feature extraction methods. On this basis, we proposed a novel hybrid energy fraction and entropy-based method, which combines the advantage of time–frequency analysis with nonlinear analysis. This is described below.

Time–frequency analysis is a widely used method in biomedical signal processing. WT is an efficient time–frequency analysis tool for feature extraction. Debbal and Bereksi-Reguig (2007) applied four common time–frequency analysis means such as short-time Fourier transform (STFT), fast Fourier transform (FFT), Wigner distribution (WD) and WT to the component analysis of the first (S1) and the second (S2) heart sounds. Dokur and Ölmez (2008) presented two feature extraction methods for the analysis of fourteen different heart sounds based on discrete WT. The signal decomposition through WT contains information similar to that of the STFT, but with additional special properties of the wavelet, which employs wide windows at low frequency space and narrow windows at high frequency space instead of a single analysis window used in STFT. Although WT has multi-scale analysis function and ability to characterize local features in both time domain and frequency domain, the signal only can be decomposed in the low frequency space, and the important information of certain high frequency space is omitted. Wavelet packet transformation (WPT) developed by Coifman and Wickerhauser (1992) can offer better resolution than WT. It decompose not only the low frequency part of signals but also the high frequency part of those so that the different time–frequency pieces decomposed from the whole time frequency plane can be obtained. As a result of the higher time–frequency resolution of WPT, it can overcome the shortcoming of WT. Choi (2008) extracted time–frequency features of the valvular heart disorder caused by aortic insufficiency (AI), aortic stenosis (AS), mitral insufficiency (MI) and mitral stenosis (MS) based on WPT. And they (Choi, Shin, & Park, 2011) applied WPT for the feature extraction and identification of insufficiency murmurs including AI and MI. Turkoglu, Arslan, and Ilkay (2002) (Turkoglu, Arslan, & Ilkay, 2003) developed a system to diagnose the heart valve diseases based on the feature extraction algorithm of WP and artificial neural network classifier. Cherif, Debbal, and Bereksi-Reguig (2010) studied the features extraction of heart sounds in time–frequency domain for their classification through a comparison between WT and WPT with the different mother wavelets.

Nonlinear analysis methods have been used in analyzing the complexity of various biological systems. Sample entropy is a widely used nonlinear index, which could be applied to the measurement and assessment of the complexity in time series. Previous studies showed the complexity of heart sounds, which could reflect the changes of hemodynamic flow characteristics caused by aortic valve stenosis in a dog model (Ahlstrom, Hoglund, & Hult, 2008) and the coronary artery disease model (Schmidt, Hansen, Hansen, Toft, & Struijk, 2010). On the other hand, sample entropy also has been employed for the complexity measurement of other physiological signals, such as EEG, ECG, etc (Richman & Moorman, 2000).

According to the occurrence phase of heart murmurs in cardiac cycle, it is not difficult to distinguish between systolic murmurs and diastolic murmurs. However, the murmurs caused by which heart valve insufficiency and/or stenosis are hard to be diagnosed by auscultation for inexperienced clinicians. Hence, we proposed a novel feature extraction approach for the classification of all systolic murmurs. It also provided a theoretical basis for the noninvasive diagnosis of heart valve disorders, and thus for assisting computer-aided diagnosis. In this paper, the energy information and the entropy information of systole murmurs and normal heart sounds were extracted to form the hybrid feature vector for classification. To obtain the remarkable and representative feature descriptions of heart sounds, the feature extraction method was based on the combination of WP with sample entropy. The SVM was used as a classifier and different kernel functions with the corresponding parameters were examined to determine the optimal choice for the classification scheme. The purpose of our study is to explore a new effective approach to classify and identify heart sounds, which can be used as a complementary method for cardiac auscultation. The rest of this paper is organized as follows: Section 2 will describe the experimental data. Section 3 will present the methodology including feature extraction method. Section 4 will illustrate and discuss the experimental results. Section 5 will conclude the paper.

2. Experimental data description

A normal heart sound from healthy volunteers has been represented in Fig. 2(a). It is comprised of four basic components such as the first, the second, the third and the fourth heart sound (S1, S2, S3 and S4). S1 and S2 are outstanding sounds and are easily observed in phonocardiogram. S1 is generated at the isovolumetric contraction phase of cardiac cycle, relating to the closure of the mitral and tricuspid valves. S2 is generated at the isovolumetric relaxation phase of cardiac cycle, relating to the closure of the aortic and pulmonary valves. S3 and S4 are weak sounds and hardly can be heard in cardiac auscultation, appearing at both small amplitudes and low frequency components (Safara et al., 2013). An abnormal heart sound from patients has been represented in Fig. 2(b). Besides the four basic components, it has additional components, such as murmurs in the systole or/and the diastole. A cardiac cycle includes the systole and the diastole. The aortic valve and pulmonary valve should be opened and mitral valve and tricuspid valve should be closed during systolic phase, and therefore systolic murmurs caused by valve abnormality includes MI, tricuspid insufficiency (TI), AS and pulmonary stenosis (PS).

A dataset presented in Table 1 with 247 heart sounds consisting of 80 normal, 44 MI, 46 TI, 39 AS and 38 PS samples was prepared for this study, which were acquired from 42 healthy volunteers and 38 patients. The normal heart sounds were acquired from healthy volunteers (college students and teachers) using an

Table 1
The dataset and subjects of this study.

Subjects	Total		Age	Types	N
Healthy volunteers	42		Aged 18–60 (mean age, 35.64 ± 7.52 years)	Normal	80
Patients (only one heart valve disorders and no other disease history)	38	10	Aged 38–70 (mean age, 61.56 ± 9.73 years)	MI	44
		12		TI	46
		8		AS	39
		8		PS	38