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Noninvasive detection of mechanical prosthetic heart valve disorder

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ABSTRACT

Auscultation is a widely used efficient technique by cardiologists for detecting the heart conditions. Since the mechanical prosthetic heart valves are widely used today, it is important to develop a simple and efficient method to detect abnormal mechanical valves. In this paper, the mechanical prosthetic heart valve sounds are analyzed by using different power spectral density (PSD) estimation techniques. To improve the classification accuracy of heart sounds, we propose two different feature extraction schemes, i.e., a modified local discriminant bases (LDB) scheme and a Hilbert–Huang Transform (HHT)-based scheme. A database of 150 heart sounds is used in this study and an average classification accuracy of 97.3% is achieved for both the two feature extraction schemes, when a generic linear discriminant analysis (LDA) classifier is used in the classification stage.

1. Introduction

Auscultation is the process of interpreting the sounds produced by the heart. Different mechanisms of heart diseases are known to produce distinct blood flow disturbances varying in velocity, Reynolds number and timing [1]. These distinguishing aspects are expressed in the corresponding acoustic findings of frequency content, loudness and timing; and provide the rationale for auscultatory analysis. In potentially deadly heart diseases, such as natural heart valve dysfunction or even heart failure, heart sound auscultation is one of the most reliable, cheap and successful techniques, some study showed that it exhibits 92% sensitivity over echophonocardiography and cinefluroscopy [7]. However, the acoustic signals from the heart contain information that cannot be easily perceived and analyzed by most physicians for a variety of reasons: the human ear hears changes in frequency better than changes in intensity and changes in frequency may be interpreted as changes in intensity; the sounds indicating cardiac disorders are typically much quieter than other heart sounds; and there is considerable beat-to-beat variation. So for traditional auscultation, to detect relevant symptoms and form a correct judgment is a difficult task that depends largely on the physicians' experience and the sensitivity of their ears. Signal processing and pattern recognition techniques thus could be introduced to tackle these problems.

For diagnosing heart sounds with native valves, numerous systems have been developed and some of them give promising results. Gupta et al. [2] extracted features by using wavelet transform (WT) and divided heart sounds into three categories by neural network. Barschdorff et al. [4], de Vos and Blanckenberg [5] also used neural network to classify heart sounds. Ari et al. [21] extracted features by WT and divided heart sounds into normal/abnormal two categories by least square support vector machine (SVM). Dokur and Ölmez [6] proposed a wavelet-based feature extraction method to classify fourteen different heart sounds. Uguz et al. [3] extracted features using both WT and short-time Fourier transform (STFT) and classified heart sounds into normal/abnormal two categories by a hidden Markov model. To improve the recognition rates of classifying 44 types of heart sounds, Kao and Wei [18] proposed to use binary SVMs and run an adaptive feature selection scheme to select only the most discriminant features from various feature sets for each SVM. Samjin Choi et al. [23] used wavelet packet based features to detect aortic and mitral insufficiency murmurs.

However, to a large degree, the heart sounds generated by artificial valves have not been addressed adequately so far. There are two kinds of artificial heart valves frequently used today: bioprosthetic and mechanical prosthetic heart valves. For the bioprosthetic valves, the first spectral study was conducted in 1981 [8], which revealed the frequency components of the first heart sound. Akay et al. [9] systematically studied the spectral differences between normal and abnormal bioprosthetic valves. Bentley et al. [10] tried to classify bioprosthetic valves into normal and abnormal two categories using both spectral and

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wavelet features, but they got recognition rates only around 60%–70%. As to the mechanical prosthetic valves, Koymen et al. [11] proposed a model to explain the heart sounds with implanted mechanical valve. Sava and McDonnell [12] investigated the overall spectral composition before and after mechanical valve implantation. Hiroshi Sugiki et al. [13] used continuous WT to analyze the acoustic properties of bileaflet mechanical valve sounds. Altunkaya et al. [22] compared the spectral features of S1 and S2 components of the normal mechanical heart valve sounds obtained after aortic valve and mitral valve replacement. Di Zhang et al. [14] studied the spectral components of heart sounds with normal and abnormal mechanical valves and tried to classify the heart sounds into normal/abnormal two categories. To our knowledge, by far little work has been reported in the literature to address the problem of classifying different kinds of mechanical prosthetic heart valve malfunction only via heart sounds.

In China today, the most frequently used artificial heart valve is the mechanical valve and it is necessary to investigate the possibility of classifying different kinds of mechanical heart valve malfunction via heart sound, which may provide a cheap and reliable technique for the detection of mechanical valve malfunction in clinical diagnoses. This paper focuses on the PSD estimation and feature extraction of heart sounds generated by normal and four different kinds of abnormal mechanical valves. With the proposed feature extraction schemes, we get promising classification results.

2. Data

Heart sound data collection was done in a three-year researching project. All the patients provided written informed consent and their heart sounds were collected after mechanical heart valve implantation had been done for at least 3 months. All the heart sounds were recorded while the patient held his or her emotion, using a chest contact heart sound sensor. A sampling frequency of 8000 Hz and a 16-bit resolution were used. Each recording was validated by the specialist performing or assisting the recording procedure. Pathological cases were confirmed with echocardiography assessment.

In this paper, five different heart sounds produced by mechanical valves are studied, i.e., normal (NOR), perivalvular leakage (PL), valve obstruction (VO), valve stenosis (VS), valve stenosis and perivalvular leakage (VSPL). The heart sound database contains 100 normal sounds and 50 pathological sounds (13 patients with PL, 9 patients with VO, 16 patients with VS, 12 patients with VSPL).

3. Methodology

The procedure used in this paper is shown in Fig. 1 and the discussion for each operation is listed as follows in the illustrated order.

3.1. Preprocessing

As detailed elsewhere, the heart sound is high-pass filtered to remove low-frequency noise and then filtered with a cutoff frequency of 1000 Hz low-pass filter. In this paper, we chose a fourth-order Butterworth high-pass IIR filter and a tenth-order Butterworth low-pass IIR filter, respectively. The de-noising operation contains three steps [15]: Eq. (1) calculate the wavelet packet decomposition of the heart sound to level 8 using the Daubechies wavelet of order 5; Eq. (2) apply thresholding to the coefficients of each level; and Eq. (3) compute wavelet packet reconstruction.

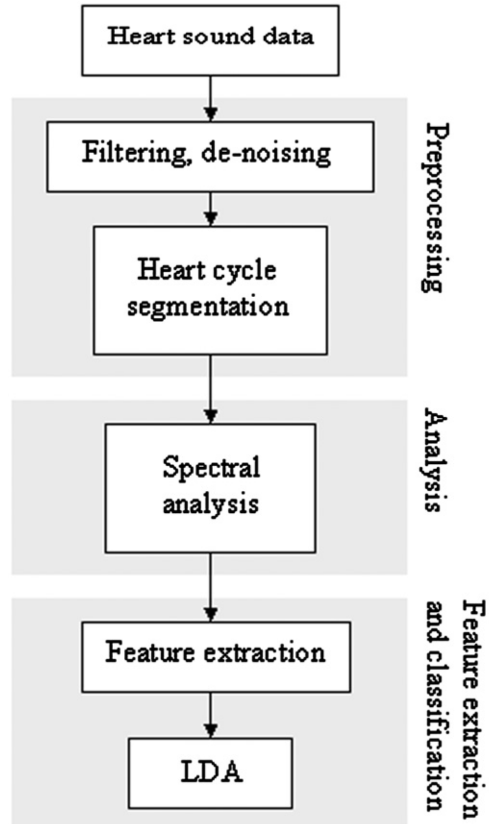

Fig. 1. Methodology layout.

Since the purpose of this paper is to analyze and classify heart sounds associated with mechanical prosthetic heart valves, we simply used the method described in [6] to segment heart sounds into separate heart cycles. Fig. 2 shows the segmentation results of 5 different heart sounds.

3.2. Spectral analysis

To compare the effectiveness of different PSD estimation techniques in analyzing acoustic signals associated with mechanical prosthetic heart valves, 4 methods, i.e., the fast Fourier Transform (FFT), the autoregressive (AR) method, the Eigenvector method, and the marginal spectrum of HHT are studied.

The AR method is the most widely used modeling method to estimate the PSD function associated with some biological signals. In the AR model, each sample of a signal can be expressed as a linear combination of previous samples and an error signal $e(n)$:

$$y(n) = -\sum_{p=1}^{m} a_p y(n-p) + e(n) \tag{1}$$

where $y(n)$ is the signal, a_p represents the coefficients of the AR model at the pth stage, and m represents the AR model order.

The Eigenvector method produces unbiased spectral estimates when the signal-to-noise (SNR) ratio is very low. In the Eigenvector method, the heart sound signal $y(n)$ may be represented as a number of sinusoids along with background noise:

$$y(n) = -\sum_{p=1}^{L} c_p e^{jw_p} + e(n) \tag{2}$$