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Identification of the normal and abnormal heart sounds using wavelet-time entropy features based on OMS-WPD

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HIGHLIGHTS

- A novel method for automatic identification of the normal and abnormal heart sounds.
- Combined the OMS-WPD and the wavelet-time entropy to extract the features of the heart sounds.
- The comparison experiments show that the proposed method has convincing identification results.

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ABSTRACT

In this paper, a novel method was put forward for automatic identification of the normal and abnormal heart sounds. After the original heart sound signal was pre-processed, it was analyzed by the optimum multi-scale wavelet packet decomposition (OMS-WPD), and then the wavelet-time entropy was applied to extract features from the decomposition components. The extracted features were then applied to a support vector machine (SVM) for identification of the normal and five types of abnormal heart sounds. To show the robustness of the proposed method, its performance was compared with four other popular heart sound processing methods. Extensive experimental results showed that the feature extraction method proposed in this paper has convincing identification results, which could be used as a basis for further analysis of heart sound.

1. Introduction

Along with the improvement of living standards in modern society, the survey reflects an upward trend in the percentage of the cardiovascular disease in recent years [1]. Since the mortality rate caused by heart diseases is increasingly high, it becomes one of the biggest threats to human health [2]. The heart sound reflects the mechanical action of the heart and the cardiovascular system, including the physiology and the pathology information of various parts of the heart. Heart auscultation, which is the interpretation of heart sounds by a physician, is a fundamental component of cardiac diagnosis. This interpretation includes evaluable information of the acoustic properties of the heart sounds, such as its intensity, frequency, duration and quality [3]. Therefore, it is capable of detecting various heart disorders. However, the traditional heart auscultation is over-dependent on the ear sensitivity and the subjective experience of the physician, which cannot meet the high accuracy requirement under clinical conditions [4]. In recent years, as a promising research field in modern artificial intelligence, the hybrid intelligence is becoming increasingly popular due to its capabilities in dealing with many real world complex problems [5], concerning vagueness, imprecision and uncertainty. Recently, with the development of digital signal processing technology [6,7], considerable research of the hybrid intelligence has been conducted for the automatic analysis of heart sound signals [8].

In healthy adults, heart sound consists of mainly two events: the first heart sound (S1) and the second sound (S2), which are together referred to as Fundamental Heart Sound (FHS). The cardiac cycle consists of two periods, systole and diastole respectively. The interval between the ends of S1 and the commencement of the same cycle's S2 is called systole. Diastole is defined as the interval between the ends of S2 and the commencement of the next cycle's S1 [9]. S1 contains a series of low-frequency vibrations,

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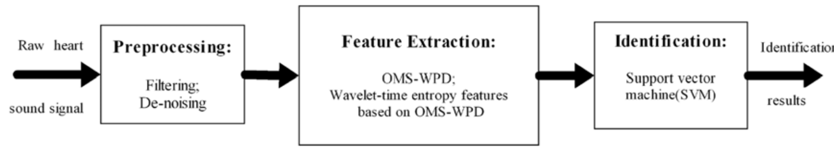

Fig. 1. Structure diagram of heart sound identification process.

and are usually the longest and loudest component of the heart sound signal. It lasts for an average period of 0.1–0.16 s and its frequency components lie in the range of 20–60 Hz. It is usually a single component, but may be prominently split with some pathologies [10]. On the other hand, S2 is heard at the end of the ventricular systole, during the closure of the semilunar valves. It lasts for about 0.08–0.12 s and its frequency components lie in the range of 60–100 Hz. Apart from S1 and S2, there can be a triple rhythm in diastole called a gallop, resulting in the presence of third heart sound (S3), fourth heart sound (S4) or both.

For decades, numerous papers have been published using computational methods based on the heart sounds to detect heart diseases [11–14], and some commercial software packages have been developed to screen with varying degrees of success. However, heart sound diagnostics based on computational methods is still not a straightforward task, with a number of challenges to overcome. The first challenge is the noise reduction [15]. Raw heart sound contains a variety of artifacts and noise components that alter its expression from the expected structure. The second challenge is the feature extraction and selection to represent the heart sound properties. The features should provide distinguishing quantitative measures to diagnose the disease. The last challenge is the construction of the classifiers. Due to the limited amount of available data, there might be considerable amount of bias if the classifier was not conducted properly.

The aim of this paper is to establish an efficient method to extract the features from pre-processed heart sound signals then identify the normal and five types of abnormal heart sounds, using a combination of wavelet packet signal processing technology and support vector machines (SVM). The paper is organized as follows. In Section 2, we design the structure diagram of heart sound identification system, and introduce the basic theories and realization process of the technologies used in this paper. In Section 3, the actual heart sound signals (including normal and five types of abnormal heart sound signals) are processed according to the proposed feature extraction method, so as to obtain their feature vectors. The performance of the proposed method for identification of heart sound signals in diagnosis of heart diseases is demonstrated in Section 4. Finally, Section 5 presents discussion and conclusion.

2. Methodology

In this paper, the features of the heart sound signals are extracted based on the optimum multi-scale wavelet packet decomposition (OMS-WPD) and the wavelet-time entropy. Then the support vector machine (SVM) [16] is employed as a classifier to train and identify the normal and abnormal heart sound signals. Fig. 1 shows the structure diagram of heart sound identification process we designed, which consists of three parts: (1) preprocessing (2) feature extraction and (3) identification.

In the next sections (2.1–2.3), we will introduce the theoretical basis of the WPD algorithm, the OMS-WPD algorithm and the wavelet-time entropy, respectively.

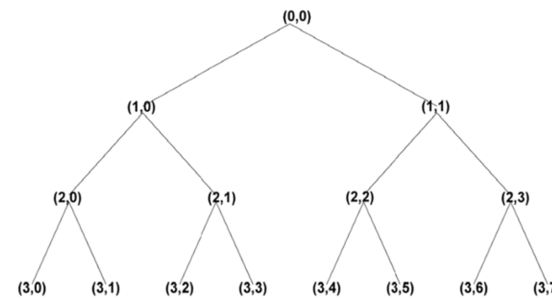

Fig. 2. Tree diagram of WPD—depth 3.

2.1. WPD algorithm

Wavelet transform (WT) can be used to decompose a signal into sub-bands with low frequency (approximate components) and sub-bands with high frequency (detail components) [17], and the wavelet technology has been used in many applications [18–21]. The structure of WPD is similar to wavelet transform. Both of them form the framework of multi-resolution analysis. The main difference of WT and WPD is that the WPD can simultaneously break up approximation and detail versions, while WT only breaks up as an approximation version. More specifically, in the WT, each level is calculated by passing only the previous wavelet approximation coefficients (cA_j) through the discrete-time low and high pass quadrature mirror filters. While in the WPD, both the detail (cD_j) and approximation coefficients are decomposed to create the full binary tree. Therefore, the WPD has the same frequency bandwidths in each resolution. Orthogonal wavelet packet is defined as [22]:

$$\mu_{2n}(t) = 2^{\frac{1}{2}} \sum_{k\in Z} h_k \mu_n(2t-k) \tag{1}$$

$$\mu_{2n+1}(t) = 2^{\frac{1}{2}} \sum_{k\in Z} g_k \mu_n(2t-k) \tag{2}$$

where h_k and g_k are the quadrature mirror filters associated with the predefined scaling function and mother wavelet function, respectively. The wavelet packet coefficients are given by:

$$d_{j,n}(k) = \int_{-\infty}^{+\infty} x(t) 2^{\frac{j}{2}} u_n(2^j t - k) dt \tag{3}$$

where $x(t)$, j, n, and k are the signal, scale, band and surge parameter, respectively.

As a simple example, the binary tree diagram associated with a depth 3 WPD is shown in Fig. 2.

Moving from top to bottom of Fig. 2, frequencies are divided into ever smaller segments. Each layer that emanates down and to the left of a node represents a low-pass filtering operation (h), and to the right a high-pass filtering operation (g). The nodes that have no further nodes emanating down are referred to as terminal nodes, leaves or sub-bands. We refer the other nodes as non-terminal, or internal nodes. The first layer represents the original signal bandwidth. The other nodes are computed from their father by one application of either the low-pass or high-pass quadrature mirror filters. The bandwidth is 50% decreased with each filtering operation. In the bottom layer, each sub-band is an eighth of the original signal bandwidth. Thus multi-resolution is achieved.