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An innovative intelligent system based on automatic diagnostic feature extraction for diagnosing heart diseases

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ABSTRACT

An innovative intelligent diagnostic system is proposed in this study, which is primarily reflected in first heart sound (S1) and second heart sound (S2) automatic extraction, frequency feature matrix (FFM) automatic extraction, diagnostic feature y_1 and y_2 generation based on principal components analysis (PCA) and diagnostic method definition based on the classification boundary curves. Four stages corresponding to the diagnostic system implementation are summarized as follows. Stage 1 describes an envelope E_T extraction from heart sound signals. In stage 2, heart sound segmentation points and peaks are first automatically located based on a novel method STMHT, and then S1 and S2 are automatically extracted according to the relationship between the systolic time interval and the diastolic time interval. In stage 3, in the frequency domain, a novel method is first proposed to generate the secondary envelopes SE_{S1} and SE_{S2} for S1 and S2, respectively, and then an STMHT-based FFM is automatically extracted from SE_{S1} and SE_{S2}. Finally, the PCA-based diagnostic features y_1 and y_2 are generated from the FFM. In stage 4, support vector machine (SVM)-based classification curves for the dataset consisting of y_1 and y_2 are first generated, and then, based on the classification curves, the scatter diagram diagnostic result (SDDR) and numerical diagnostic result (NDR) are defined for diagnosis of heart diseases. The proposed intelligent diagnosis system is validated by sounds from online heart sound databases and by sounds from clinical heart diseases. As a result, the classification accuracies (CA) achieved are 91.7%, 98.8%, 98.4%, 99.8%, 98.7%, 97.8%, 98.1% and 96.5% for the detection of atrial fibrillation (AF), aortic regurgitation(AR), mitral regurgitation (MR), normal sound (NM), pulmonary stenosis (PS), small ventricular septal defect (SVSD), medium ventricular septal defect (MVSD) and large ventricular septal defect (LVSD), respectively.

1. Introduction

Heart disease is the most common overall cause of death for people worldwide. According to the World Health Organization [47], heart diseases were the top major killers from 2000 to 2011. Thus, using a modern information processing method to diagnose heart disease is one of the most important medical research areas [44]. Currently, methods for the diagnosis of heart valve disorders include non-invasive techniques (electrocardiograms, chest X-rays, heart sound analysis and ultrasound imaging and Doppler techniques) and invasive techniques (angiography, transozefagial and echocardio-graph). Of these methods, heart sound analysis is a non-invasive, economical, easy and efficient method widely used to diagnose heart disease and evaluate heart functions during medical check-ups for adults and children, such as ventricular septal defects (VSD) diagnosis [40], fetal heart rate extraction algorithm testing [5], fetal examination [18], valvular heart disease diagnosis [8], heart valve disease identification [24] and children's congenital heart disease screening [36]. Heart sounds are generated by vibrations induced by valve closure, abnormal valve opening, vibrations in the ventricular chambers, tensing of the chordae tendineae, and by turbulent or abnormal blood flow across valves or between cardiac chambers [17]. Basic heart sound signals are primarily composed of four sound types, including S1, S2 and two weak sounds, called the third sound (S3) and the fourth sound (S4). S1 is produced by the closure of the mitral and tricuspid valves at the beginning of isovolumetric ventricular contraction. S2 is produced by the closure of the aortic and pulmonic valves at the beginning of isovolumetric ventricular relaxation. S3, when audible, occurs early in ventricular filling and may represent tensing of the chordae tendineae and the atrioventricular ring, which is the connective tissue supporting the tricuspid and mitral valves valve leaflets. S4, when audible, is

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caused by vibration of the ventricular wall during atrial contraction and is usually associated with a stiffened ventricle and is therefore heard in patients with ventricular hypertrophy, myocardial ischemia, or in older adults. Although these four sounds may be audible by the auscultation of the heart and occur in the frequency range of 20–2000 Hz, unitary murmurs such as a systolic ejection murmur (e.g., aortic stenosis) and a pan systolic murmur (e.g.,mitral regurgitation) mostly appear between S1 and S2 with different noise patterns [14]. However, S3 and S4 appear at extremely low amplitudes with low frequency components and are difficult to detect during normal auscultation. Therefore, the analysis of S1 and S2 plays an important role in heart sound analysis. To obtain more information on heart sounds to diagnose heart sounds with higher accuracy, heart sound segmentation used to extract S1 and S2 is first conducted, and then the efficient features are extracted from S1 and S2. Finally, a classification method is used to diagnose heart diseases.

In recent years, the reported studies on heart sound segmentation can be summarized into three categories. In the first category, the performance of heart sound segmentation is quite good with reference electrocardiography [25,11]. However, in children with left or right hypertrophic ventricles, the axis deviation of the heart causes an abnormality on the electrocardiograph signal, which complicates heart sound segmentation [35]. Another category makes use of the frequency domain-based segmentation algorithms, which were proposed with tracking heart sound spectra [20,19,12,29]. However, the selection of the threshold and the filtering of the unexpected noise remain difficult problems with this method type, and few studies mention this issue. The third category is the envelope-based segmentation method, which has been studied by many researchers [48,14,32]. However, the selection of the threshold and filtering of unexpected noise remain difficult problems in this method. Furthermore, the study [48] revealed that locating the local peaks of S1 and S2 remains extremely difficult with this method. Fortunately, the novel STMHT-based method of automatic heart sound segmentation and peak location proposed by the study [39] has been reported to provide sufficient performance compared with a published algorithm [48] that was demonstrated to be better than other segmentation methods.

As an efficient feature defined in the frequency domain, the frequency width of the envelope over a given threshold value (Thv) has been verified to be useful for detecting heart diseases [6] and for diagnosing VSD [40]. However, for many types of heart diseases, it is difficult to extract frequency widths with a smaller Thv (Fig. 4(b)). Moreover, to achieve higher classification accuracy for diagnosing different types of heart disease, different Thv values must be considered. For example, the study [6] indicated that the highest classification accuracy is 96.88% for diagnosing MR at $Thv = 0.8$, and the highest classification accuracy is 93.94% for detecting AF at $Thv = 0.3$. However, the highest reported classification accuracy is 98.4% for diagnosing ventricular septal defect (VSD) at $Thv = 0.2$ [40]. To avoid setting different Thv to extract features for different heart diseases, a novel frequency feature matrix FFM proposed by the study [38] was evaluated and found to be efficient at diagnosing many types of heart diseases, such as aortic regurgitation (AR), aortic stenosis (AS) and mitral regurgitation (MR). However, using FFM for features to diagnose heart diseases involves complicated computation. Therefore, to reduce the computation of the proposed diagnostic system, principal components analysis (PCA) is a linear dimensionality reduction technique for finding new principal components in high-dimension data and is used to make a diagnostic system more simple and effective in many studies, such as those involving heart disease diagnosis [3], thyroid disease diagnosis [9], cardiac death diagnosis [16], coronary artery disease diagnosis [10], data clustering [22], cardiovascular diseases diagnosis [37] and electrocardiogram arrhythmias diagnosis [50].

Recently, as a classification method, support vector machines (SVMs) have been proposed as an effective statistical learning method for the classification of different data classes using classification curves [45] and have been successfully used for the solution of many problems, such as handwritten digital recognition [27], cancer diagnosis [2], and heart murmur classification [40,6]. In the study [40], an SVM-based efficient calculation procedure for generating a classification curve was proposed that can successfully diagnose VSD.

In this study, an innovative intelligent system for diagnosing heart disease is proposed. To achieve this intelligent diagnostic system, this study is arranged into four stages. In stage 1, an envelope E_T is extracted from the heart sound signal X_T filtered using the wavelet decomposition method. In stage 2, heart sound segmentation points and peaks of E_T are first automatically located based on a novel method, STMHT, and then S1 and S2 are automatically extracted according to the relationship between the systole time interval and the diastole time interval. In stage 3, in the frequency domain, a novel method is first proposed to generate the secondary envelopes SE_{S1} and SE_{S2} for S1 and S2, respectively, and then an STMHT-based frequency feature matrix (FFM) is defined and automatically extracted from SE_{S1} and SE_{S2}. Finally, two PCA-based first principal components, y_1 and y_2, are generated from the FFM and used as the diagnostic features. In stage 4, SVM-based classification curves for the datasets consisting of y_1 and y_2, which are generated from heart disease sounds, are first generated by a novel procedure, and then, based on the classification curves, the diagnostic method are defined to diagnose detected sounds. Furthermore, to evaluate the performance of this intelligent system, a comparative analysis for the diagnosis of the sounds from online heart sound databases and clinical heart diseases in hospitals is performed to validate the proposed intelligent diagnostic system.

2. Methodology

The block diagram of the proposed innovative automatic diagnostic system is shown in Fig. 1. This system consists of four stages, i.e., the envelope extraction procedure, the automatic S1 and S2 extraction procedure, the automatic feature y_1 and y_2 generation procedure and the diagnosis method definition procedure. In stage 1, the envelope E_T is extracted from the heart sound signal X_T filtered using the wavelet decomposition method. In stage 2, based on the novel method STMHT, the segmentation points between S1 and S2 and the peaks for S1 and S2 are first automatically located, and then S1 and S2 are automatically extracted according to the diastolic time interval, which is generally greater than the systolic time interval in one periodic heart sound. In stage 3, in the frequency domain, a novel method is first proposed to generate the secondary envelopes SE_{S1} and SE_{S2} for S1 and S2, respectively, and then an STMHT-based frequency feature matrix (FFM) is automatically extracted from SE_{S1} and SE_{S2}. Finally, two PCA-based first principal components, y_1 and y_2, which simplify the diagnostic system, are generated from FFM and used as the diagnostic features. In stage 4, SVM-based classification curves (g) for the datasets consisting of y_1 and y_2 are first generated by a novel procedure, and then, based on the classification curves, the scatter diagram diagnostic result (SDDR) and numerical diagnostic result (NDR) are defined for diagnosis of heart diseases.

2.1. **Stage 1:** E_T extraction procedure

2.1.1. Heart sound acquisition and preprocessing

The heart sound signal (denoted as S_T) was tested with 16-bit depth at the sampling frequency $F_S = 44.1$ kHz. Our previous study