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A novel method based on a combination of discrete wavelet transforms, group-based Sparse and tensor decomposition for Heart Sound Classification

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Abstract

Listening to the sound signals of the heart is considered one of the most non-invasive and easy ways to diagnose the irregularities of the human heart, the correct analysis of which requires the knowledge and experience of a specialist doctor. The purpose of this paper is to design and implement a computer-aided diagnosis (CAD) system for detecting and classifying normal and abnormal heart sounds from phonocardiogram (PCG) signals. To perform experiments, the PhysioNet database was used. In the pre-processing step, noise and environmental disturbances in the PCG signals are removed using band-pass Butterworth filters. Then, discrete wavelet transforms (DWT), group-based Sparse, and tensor decomposition are used to extract features from PCG signals. Finally, the support vector machine (SVM), the k-nearest neighbors (KNN), naive Bayes (NB), the classification and regression tree (CART), and multi-layer perceptron (MLP) were used for the classification step. The employment of DWT, group-based sparse, and tensor decomposition for detection features is the novelty of this paper. The proposed method demonstrated better performance compared to other methods used in different papers. The proposed DWT, group-based sparse and tensor decomposition-NB method had a high accuracy rate of 95.3%. Also, the combination of PCG feature extraction methods increases the accuracy of the CAD system in diagnosing abnormal heart sounds. The proposed method in this paper uses different methods for extracting features, and their classification has high accuracy for abnormal sound detection.

Keywords: Classification of heart sounds, Murmur, Feature extraction, Group-based sparse, tensor decom-position, Discrete wavelet transform.

1. INTRODUCTION

Heart disease is one of the most common causes of death worldwide [1]. Cardiac

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valvular abnormalities include a wide range of diseases such as aortic valve stenosis, mitral valve stenosis, aortic and mitral valve insufficiency, etc. Timely diagnosis of valvular abnormalities of the heart will help prevent the spread of the disease, treat and eradicate it [2]. Auscultation of the heart is a method that has been used for a long time to diagnose cardiac abnormalities [3]. The main sounds of the heart are low-frequency sounds called s1 and s2 [4]. In sick people, in addition to the main sounds of the heart, other high-frequency sounds are heard as murmurs. Due to the transient and non-stationary nature of the heart sound, it is difficult to recognize heart abnormalities from the heart sound, which requires years of practice and experience [5]. Due to the importance of timely diagnosis of heart diseases, signal processing specialists have conducted research to solve this problem in recent years for the automatic detection and classification of heart sounds.

There are various approaches for heart sound classification, which can generally be classified into four stages: noise elimination, feature extraction, feature selection, and signal classification [6, 7]. The accuracy of heart sound detection and classification is generally influenced by these four stages. In [8], multi-domain features and SVM are presented to classify healthy and unhealthy heart sounds. In [9], a short-time Fourier transform is used to extract features, and a deep neural network (DNN) algorithm is used to classify heart sounds. In [10], fast Fourier transform and Levinson-Durbin auto-regression algorithms are used to extract features, and multilayer perceptron algorithms and RBF are used to classify heart sounds. In [11], the fast Fourier transform of the energy spectrum is used to extract the features, and the artificial neural network is used to classify the heart sound. In [2], Mel Frequency Cepstral Coefficient (MFCCs) and discrete wavelet transform (DWT) algorithms are used to extract the features, and then the deep neural network algorithm is used to classify the heart signal. In [12], sparse coding and SVM algorithms are proposed to identify spectral features and heart sound classification, respectively. This method has classified the sound of the heart into two classes: normal and abnormal sound. In [13], wavelet transform, short-time Fourier transform, and wavelet entropy are used to extract features, and least-squares support vector machine (LS-SVM) classification is used to distinguish normal sounds from abnormal sounds. In [14], DWT and Shannon entropy are used to extract features and reduce the dimensions of the feature vector, respectively, and finally, the adaptive neuro-fuzzy inference classifier is used effectively for diagnosing heart valve disease. In [15], the tensor decomposition method and SVM algorithm are proposed for heart sound classification. In this method, important information on the pathology and physiology of the heart sound signal is extracted using tensor analysis, and then the SVM algorithm is used to classify the sick heart sound signal from the healthy heart sound signal.

Most heart sound detection methods are sensitive to the location of the sound recording. The main reason for this issue comes from the fact that the sounds related to heart function and breathing sounds in the lungs have a short period of time, and therefore, in this short period of time, several different sounds will be heard from the chest area. This limitation motivated the proposal of a combination of methods. In this proposed method, DWT, group-based sparse, and tensor decomposition are used to extract features. Although these methods alone have been used in some articles, the use of these three methods to identify the features is a completely new solution that results in the best characteristics of the signal. In the sparse method, the relationship between the steps is not considered. In this article, to solve the mentioned problem, group-based sparse representation is used in order to increase sparse efficiency. Therefore, another innovation is the use of group-based sparse, which will increase efficiency and reduce computational complexity. Another innovation of the article is the review of classification algorithms such as SVM, KNN, NB, CART, and MLP.

The organization of the paper is as follows: In Section 2, methods are described, and in Section 3, the simulation results are reviewed. Finally, Section 4 concludes the paper.

2. MATERIALS AND METHODS

In this paper, the proposed method for heart sound classification is composed of main stages: noise removal by Butterworth filter, extracting features by DWT, group-based sparse, and tensor decomposition and classification using famous algorithms such as SVM [16], KNN [17], NB [18], CART [19], and MLP [20], according to Figure 1.

2.1. Preprocessing

The audio signal is affected by disturbances and noises inside or outside the body, and for this reason, a filter is needed that can remove the unwanted parts of the audio signal of the heart to a significant extent. In noise analysis, it has been shown that often, the frequency of the original signal is different from the noise frequency. If a quiet environment is used to record heart sound signals, then only residual disturbances inside the body will accompany the original signal. Most body noises are low-amplitude signals with high frequencies. In this article, the bandpass Butterworth filter is used to remove noise. The frequency range of heart sounds is usually between 40 and 400 Hz [21]. To maintain this frequency range and remove other noises, a second-order bandpass Butterworth filter with a lower cutoff frequency of 30 Hz and an upper cutoff frequency of 450 Hz was used.

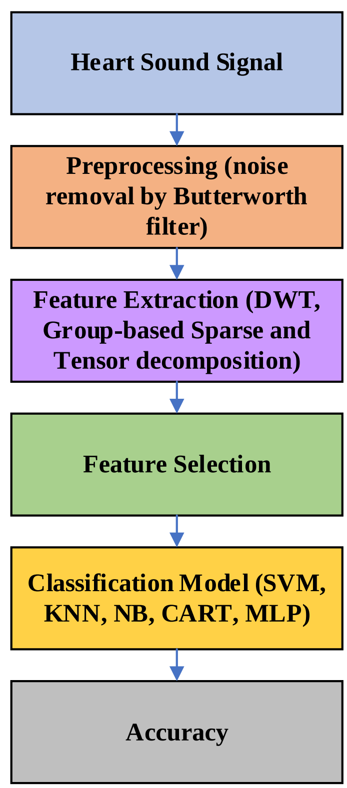

Fig. 1. Flowchart of the Proposed Heart Sounds Classification Process.

2.2. Extracting features

In this section, the DWT method, group-based sparse method, and tensor decomposition algorithm are used to extract the features of the heart signal.

- ***Discrete wavelet transforms***

In this section, the DWT method is used to analyze the PCG signal in different frequency bands. Discrete wavelet functions are defined by pairs of high-pass and low-pass filters. These filters separate the high and low-frequency components of the input signal. In the first stage, the output of the high-pass filter is the detail coefficients of (D1), and the output of the low-pass filter is the approximation coefficients of (A1). The coefficients of (A1) are decomposed again and continue up to seven stages.

- ***Group-based Sparse***

Group-based sparse was proposed by Zhang et al. for image restoration [22]. In this method, the signal is first divided into n overlapped blocks x_i of $\sqrt{b}\times\sqrt{b}$ $i=1,2,,....,n$ size. Then, different from block-based sparse representation, for each exemplar block x_i, the most similar m blocks are selected from a $W\times W$ sizeable searching window to form a set S_{Gi}. all blocks are stacked into matrix X_{Gi} , which contains every block in S_{Gi} as its column $X_{Gi}=\{x_{i,1},x_{i,2,....,}x_{i,m}\}$. This matrix X_{Gi} consisting of all blocks with similar structures is thus called a block group, where $x_{i,j}$ denotes the. group block i^{th} in j^{th} Finally, similar to block-based sparse representation, given a dictionary $D_{Gi}\in R^{b\times k}$ each block group X_{Gi} can be sparsely represented by solving.

$$\beta^*_{Gi}=\arg\min_{\beta^*_{Gi}}\left(\frac{1}{2}\left\|X_{Gi}-D_{Gi}\beta^*{}_{Gi}\right\|_2^2+\lambda\left\|\beta^*_{Gi}\right\|\right) \qquad (1)$$

where β^*_{Gi} represents the group-based sparse coefficient of each block group X_{Gi} and $\|\ \|_0$ signifies the ℓ_0-norm, *i.e.*, counting the nonzero entries of each column in β^*_{Gi}.

- ***Tensor analysis***

Heart signal processing is very important for disease diagnosis, so tensor analysis is used. Each of the received PCG signals is converted into a matrix by drawing a spectrogram, and a tensor is formed by putting them together.

2.3. Classification

In this section, various classification algorithms have been used to classify normal and abnormal heart sounds. Below is a brief description of each algorithms.

- ***Support Vector Machine***

The SVM method is one of the most popular and best classification methods [23]. This method is widely used in various two-class and multi-class classification problems with significantly high performance. In the SVM method, the two class or multiclass classification is performed using various kernels such as linear, polynomial, and RBF [23, 24]. In this article, the RBF kernel is used to classify heart sounds.

- ***K-Nearest Neighbors***

The KNN method, also used as a classification method, operates such that it finds the nearest neighbor using Euclidean distance for each data point [17, 25]. Afterward, it selects the K-nearest neighbor, specifying the data label based on the label of the majority. In this article, K is considered to be three.

- ***Naive Bayes***

The Naive Bayes algorithm is one of the supervised classification algorithms and uses probability techniques to classify samples into different classes [18]. In this algorithm, the Bayes theorem is used.

- ***Classification and Regression Tree***

The CART algorithm is one of the most popular and the simplest decision tree algorithms. This algorithm is widely used in classification and regression. The CART algorithm divides the data into binary parts to build a decision tree and builds a binary tree based on them. CART uses the Gini index criterion to select tree nodes [19].

- ***Multi-Layer Perceptron***

Multi-layer perceptron neural networks are the most well-known neural networks. This algorithm is the most used among different types of neural structures. These networks consist of three layers, input, hidden (intermediate), and output [20]. The number of hidden layers increases according to the complexity of the issues.

3. RESULTS AND DISCUSSION

In order to evaluate the feasibility of the proposed method and its efficiency in heart sound classification, three experiments were performed. In the first experiment, the performance of the combination of three algorithms including DWT, group-based sparse, and tensor decomposition is investigated for feature extraction. In the second experiment, the performance of different classification algorithms, such as SVM, KNN, NB, CART, and MLP, is evaluated for heart sound classification. Finally, in the third test, the performance of the proposed method is investigated with other methods.

3.1. Evaluation Criteria

In order to evaluate the performance of the proposed method, criteria of accuracy according to (2), precision according to (3), sensitivity according to (4), and specificity according to (5) are used. As the accuracy, precision, sensitivity and specificity, are higher, they are more suitable.

$$Acc = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{2}$$

$$precision = \frac{T_P}{T_P + F_P} \tag{3}$$

$$sensitivity = \frac{T_P}{T_P + F_N} \tag{4}$$

$$specificity = \frac{TN}{TN + FP} \tag{5}$$

In Equations (2)-(5), TP, TN, FN, and FP denote true positives, true negatives, false positives, and false negatives, respectively.

3.2. Database

In this article, the PhysioNet dataset is used, which describes the general heart sound database [26]. It includes 2435 heart sound recordings, of which 1138 are sick heart sound recordings and 1297 are healthy heart sound recordings. Heart sound recordings were taken in various environments and conditions (clinical environment and nonclinical environment). For more details on the database, refer to article [27].

3.3. Investigating the Performance of the Proposed Feature Extraction Methods

In this section, an experiment has been conducted to check the performance of the proposed feature extraction algorithms. The results are shown in Table 1. Table (1) implies that the combined use of DWT, group-based sparse method, and tensor decomposition method yields better results in terms of feature extraction for heart sound classification compared to other methods or combinations mentioned. It suggests that this particular combination is more effective in capturing relevant information from heart sound signals, potentially leading to improved classification performance.

TABLE 1. ***The performance of the proposed methods for feature extraction.***

Methods	Accuracy	Sensitivity	Specificity
DWT SVM	0.685	0.68	0.69
Group-based sparse SVM	0.725	0.74	0.71
DWT, Group-based sparse SVM	0.765	0.80	0.73
DWT, Tensor decomposition SVM	0.795	0.86	0.74
DWT, Tensor decomposition and group-based Sparse SVM	0.868	0.95	0.77

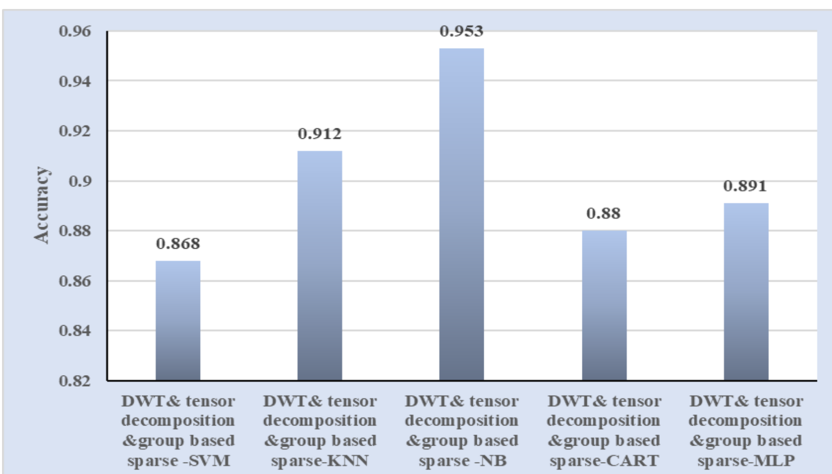

Fig. 2. Investigating the performance of different classification methods in heart sound classification.

3.4. Investigating the Performance of Classification Algorithms

In this experiment, classification algorithms such as SVM, KNN, NB, CART, and MLP are investigated for heart sound classification. Figure 2 shows the classification accuracy of each classification algorithm. The best and worst accuracies

TABLE 2. ***Checking the performance of the proposed method with other recent methods.***

Methods	Sensitivity	Specificity
Dominguez-Morales et al. [28]	0.9512	0.9320
Kay et al. [29]	0.848	0.8330
Tang et al [8]	0.88	0.87
Raymond See et al [7]	0.85	0.80
Proposed DWT, Tensor decomposition and group based sparse-NB	0.987	0.9613

were achieved by NB, KNN, MLP, CART, and SVM, respectively.

3.5. Checking the Performance of the Proposed Method with Other Recent Methods

In this section, the performance of the proposed method is compared with other recent methods, as shown in Table 2. The proposed DWT and tensor decomposition, and group-based sparse-NB methods perform better than other methods in terms of sensitivity and specificity (Table 2). In general, it can be concluded that the proposed method is very effective in heart sound classification.

4. CONCLUTION

In this article, a new system for automatic detection of abnormal heart sounds using pre-processing, feature extraction, and classification was introduced. At first, a bandpass Butterworth filter is used to remove noise and DWT, group-based sparse, tensor decomposition are used to extract information from the complex and unstable PCG signal. Finally, different algorithms such as SVM, KNN, NB, CART, and MLP are used to classify the PCG signals of normal heart sound and abnormal sound. The proposed method is effective in the automatic classification of heart sounds.

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