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Heart Sound Signal Classification Algorithm: A Combination of Wavelet Scattering Transform and Twin Support Vector Machine

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ABSTRACT By classifying the heart sound signals, it can provide very favorable clinical information to the diagnosis of cardiovascular diseases. According to the characteristics of heart sound signals which are complex and difficult to classify and recognize, a new method of feature extraction and classification about heart sound signal is proposed by a combination of wavelet scattering transform and twin support vector machine in this paper. The method is as follows: The heart sound signal data set is firstly divided into two parts, one as a training set and the other as a testing set. Then the wavelet scattering transform is applied to the heart sound signals in the training set and the testing set. The scattering transform is a new time-frequency analysis method. It overcomes the shortcomings of the traditional wavelet transform which has the time-shift changes. It has the advantages of translation invariance and elastic deformation stability. Thus obtain the scattering feature matrix of the heart sound signal. Due to the large dimension of scattering feature matrix, this paper uses multidimensional scaling (MDS) method to reduce the dimension. This method is compared with the classical dimension reduction method—principal component analysis (PCA). Finally, the dimensionality-reduced feature matrix is input into the twin support vector machine (TWSVM) for training. After training the classifier to get the optimal parameters, the dimensionality-reduced scattering feature matrix of the testing signal is input into the classifier for testing. Experimental results show that the classification accuracy of the proposed method can reach 98% or more, and the running time is greatly reduced compared with support vector machine (SVM).

INDEX TERMS Wavelet scattering transform, multidimensional scaling (MDS), twin support vector machine (TWSVM), signal classification.

I. INTRODUCTION

Heart sounds are the vibration signals produced by heart movements, which contain the information about atrium, ventricle, blood vessel and valve associated with cardiovascular disease. Therefore, there is an intrinsic relationship between heart sounds and cardiovascular diseases. In the early stage of cardiovascular disease, before the pathological changes have occurred in the heart, the important pathological information about the functional status of various parts of the heart will appear in the heart sounds. The pathological information is characteristic in many diseases, which is helpful for diagnosis. Its importance is unquestionable. It is very meaningful to the diagnosis and estimation of cardiovascular diseases. Therefore, heart sound analysis is an important means of non-invasive detection of cardiovascular disease. It has become one of the effective methods for clinical diagnosis of the cardiac disease [1].

There are many analysis methods for heart sounds. Here we mainly focus on the feature extraction and classification methods of heart sounds such as time-domain features, wavelet features, frequency-domain features, support vector

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machine (SVM), Hidden Markov Models (HMMs), k-neareast neighbor (KNN), deep neural networks (DNN) and so on [2], [3]. In 2009, Amit Guy et al. proposed the algorithm based on hierarchical clustering and compact data to identify distinct morphologies of heart sounds. The proposed algorithm was applied to two heart sound datasets. The average classification accuracy of 82.7% on the first dataset of 12 subjects was achieved. On the second dataset including 11 subjects, the average classification accuracy was 86.7% [4]. In 2011, Guraksin G.E proposed the algorithm by using the Shannon entropy to calculate the entropy of each sub-band for reducing the dimensionality of the feature vectors with the help of the discrete wavelet transform. The least square support vector machine was used to classify the heart sounds. Finally, the proposed algorithm obtained 96.6% of the classification performance [5]. In 2012, Xiefeng Cheng et al. proposed a synthetic heart sounds model based on a family of wavelets. The heart sounds linear band frequency cepstra was used to extract the features of heart sounds. The similarity distance was used to identify the heart sounds. To highlight the difference between the time domain and frequency domain in two heart sound signals, the heart sound wavelet was constructed and the parameters of a synthetic model were calculated [6]. In 2013, Fatemeh Safara proposed the method based on multi-level basis selection (MLBS). The method used wavelet packet transform to decompose the signal. Then obtain a set of orthonormal bases. Select an appropriate base for feature extraction. Multi-level basis selection (MLBS) was proposed to retain the most useful bases of the wavelet packet decomposition tree. The classification accuracy of heart sound signals was 97.56% [7]. In 2014, Patidar Shivnarayan et al. proposed the method based on constrained TQWT. The features were obtained from heart beat cycles of reconstructed heart sounds and murmur separately. The heart sounds were separated based on constrained TQWT. Then create the feature set using the optimized parameters while constraining the output of TQWT together with that of extracted by using time-domain representation and Fourier-Bessel (FB) expansion. The subsequent classification of heart sounds used the least squares support vector machine (LSSVM). The proposed algorithm obtained the classification accuracy of 94.01% [8]. In 2015, Safara proposed the heart sound classification method based on the higher-order cumulants (HOC). The features of heart sounds were obtained by wavelet packet decomposition tree. Define the information measures based on HOC of wavelet packet coefficients. Extract HOC features from the coefficients of selected nodes. The classifier used the support vector machine. Experimental data included the different categories: normal heart sounds, aortic stenosis, mitral regurgitation, and aortic regurgitation. The results were promising to achieve indicate the capabilities of HOC of wavelet packet coefficients [9]. In 2016, Deng Shiwen proposed a novel heart sound classification method based on the autocorrelation feature and diffusion map. Firstly, extract the autocorrelation features from the sub-band envelopes which were calculated using the discrete wavelet decomposition (DWT). The autocorrelation features were fused with diffusion maps. The heart sound classification used the Support Vector Machines (SVM) classifier [10]. In 2017, Chen T.E. proposed the method based on DNN. This method was based on acoustic characteristics without using the ECG reference or incorporating the assumptions of the time intervals of S1-S2 and S2-S1and individual durations of S1 and S2. The proposed method based on DNN obtained the high recall, precision, and F-measure scores. It obtained the accuracy rate of more than 91% [11]. In 2018, Tang Hong proposed the method based on multidomain features and support vector machine (SVM). The database came from the PhysioNet/CinC Challenge 2016. They extracted a total of 515 features from nine feature domains. The experimental results showed that the sensitivity, specificity, and overall score were 0.88, 0.87, and 0.88, respectively [12]. Bozkurt Baris et al. proposed the algorithm based on CNN. They used the method for the segmentation and time-frequency representation components. The features (MFCC and Mel-Spectrogram) and a time-frequency representation were considered. The experimental results showed that the sensitivity was 0.845, the specificity was 0.785, and the accuracy was 0.815 [13]. In 2019, Abduh Zaid proposed the heart sound classification based on fractional Fourier and stacked sparse autoencoder deep neural network. They converted the time series of heart sound signal into time-frequency heat map representation based on fractional Fourier transform. The stacked sparse autoencoder deep neural network was used to classify. The experimental data came from the database of the PhysioNet/CinC Challenge 2016. The proposed algorithm obtained the accuracy, sensitivity, and specificity of 0.955, 0.893, and 0.970, respectively [14]. All of the above methods have achieved remarkable results, but the running time of the algorithm has not been described too much. Under the premise of taking into account the classification accuracy of algorithm, the proposed algorithm also considers the problem of running speed in this paper.

For the feature extraction method of heart sound signal, the wavelet scattering transform is used in this paper. By iterating the high-frequency components of the signal with wavelet modulus operation and low-pass filtering, stable signal features can be obtained, and high-frequency information lost due to low-pass filtering operation can be recovered. The scattering coefficients obtained have local translation invariance and elastic deformation stability [15]–[19]. Therefore, the ability of classification and recognition of scattering transform has been greatly improved. Scattering transform has been widely used in sound recognition, texture classification, and handwritten digit recognition. It has achieved good classification results. At present, there are few experiments that apply scattering transform to the classification of heart sound signal.

For the classification of heart sound signal, the twin support vector machine (TWSVM) is used in this paper. The support vector machine (SVM) has strong generalization ability and classification ability. It is often used to classify the heart sounds. However, the SVM method has a long training time and is not suitable for the classification of a large number of samples. In response to these problems, Jayadeva *et al.* [20] proposed a new learning method based on traditional SVM, called Twin Support Vector Machine (TWSVM). Its training is faster and has less computational complexity. TWSVM looks for a pair of non-parallel hyperplanes compared to SVM. Each of them should be as close as possible to one class of the samples and away from the other. In view of the excellent learning performance of TWSVM, it has become a research hotspot in the field of machine learning. The twin support vector machine can also effectively prevent the occurrence of samples imbalance problems.

For the above reasons, this paper proposes the heart sound signal classification method based on wavelet scattering transform and twin support vector machine. Scattering transform can scatter the information of the signal hierarchically to all layers, so that the information is not lost, but also the stability of the signal features can be maintained. The twin support vector machine (TWSVM) can achieve better classification results, and its computational overhead is much less than that of SVM. Therefore, this paper uses the wavelet scattering transform to extract the feature information of the heart sound signals, and uses the twin support vector machine to classify the heart sound signals. For the problem that the dimension of scattering feature matrix is too large, this paper uses multidimensional scaling (MDS) method to reduce dimension, and compares it with the classical principal component analysis (PCA) method. Finally, the feature matrix obtained by MDS dimension reduction method obtains better classification accuracy. The following sections show the implement process and results of the proposed algorithm in details.

II. METHODS

The processing procedures of heart sound signal include heart sound signal acquisition, heart sound signal de-noise, heart sound signal segmentation, feature extraction, and classification. The heart sound signal acquisition and heart sound signal de-noise have been firstly finished in the proposed algorithm. Heart sound signal segmentation is not required here. The major work of this paper is feature extraction and heart sound signal classification. The implementation flow of this algorithm is shown in the Figure 1. The figure shows also the comparison algorithm using PCA and SVM respectively.

A. WAVELET SCATTERING TRANSFORM

Wavelet transform is the typical time-frequency analysis method, which has the stability of local deformation and multi-scale. It can extract the local feature information of signals well, but it will change with time and easily cause the omission of signal features. Scattering transform is an improved time-frequency analysis method based on wavelet transform. The process is essentially an iterative process of complex wavelet transform, modulus operation and low-pass filtering averaging. It solves the disadvantage of wavelet

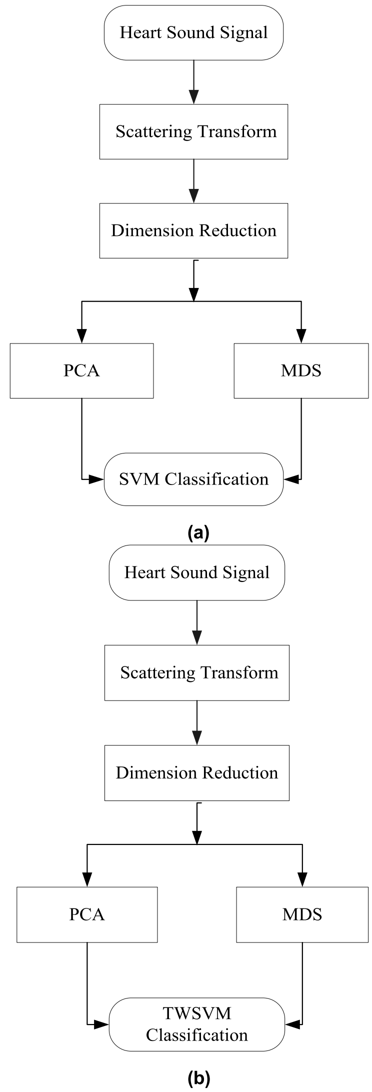

FIGURE 1. The steps to implement this algorithm: (a) Comparison algorithm using SVM; (b) Proposed algorithm using TWSVM.

transform changing with time, and has the advantages of translation invariance, local deformation stability and rich feature information representation. Its algorithm principle is as follows:

Assume that ψ_λ is the wavelet cluster which is scaled by a mother wavelet in the range $1 \leq 2^j \leq 2^J$:

$$\psi_j(u) = 2^{-2j}\psi(2^{-j}u) \tag{1}$$

When the input signal is two-dimensional, the mother wavelet will also rotate at an angle θ, and the wavelet cluster becomes:

$$\psi_{j,\theta}(u) = 2^{-2j}\psi(2^{-j}r_{-\theta}u) \tag{2}$$

In order to facilitate calculation, the wavelet clusters $\psi_j(u)$ and $\psi_{j,\theta}(u)$ are collectively called as $\psi_\lambda(u)$. In addition, define a wavelet modular operator. The content is the combination of wavelet operation and modular operation:

$$|Wx| = \{x * \phi_J, |x * \psi_\lambda|\}_\lambda \tag{3}$$

It consists of two parts: the first part is to average the low-pass filtering of the input signal, giving the operator translation invariance, which essentially extracts the low-frequency main information of the input signal; the second part is the modulus of the nonlinear wavelet transform, giving the operator stable deformation.

Scattering transform constructs invariant, stable and informative signal feature representation by iterative wavelet decomposition, modular operation and low pass filter. The essence of the process is an iteration process which calculates the input signal and the wavelet modulus operator. The first part of the wavelet modulus operator is called the invariant part Sx, and it is used as the coefficient output of this order. The second part is called the covariant part Ux, which is the input of the next order transformation. The purpose is to recover the high frequency information lost by the operation of the invariant part. Therefore, the invariant part and the covariant part of the scattering transform at the 0th order are:

$$S_0 x = x * \phi_J(u) \tag{4}$$

$$U_1 x(u, \lambda) = |x * \psi_\lambda(u)| \tag{5}$$

Then, let $U_1 x(u, \lambda)$ as the input of the first order of the scattering transform, a new wavelet modulus operator is used to calculate the results.

$$S_1 x(u, \lambda) = U_1 x(u, \lambda) * \phi_J(u) = |x * \psi_\lambda| * \phi_J(u) \tag{6}$$

$$\begin{aligned} U_2 x(u, \lambda_1, \lambda_2) &= \left| U_1 x(u, \lambda_1) * \psi_{\lambda_2}(u) \right| \\ &= \left| \left| x * \psi_{\lambda_1} \right| * \psi_{\lambda_2}(u) \right| \end{aligned} \tag{7}$$

The wavelet cluster ψ_{λ_2} in $U_2 x(u, \lambda_1, \lambda_2)$ needs to satisfy the scale $j_2 > j_1$. Because the energy is very small, when $j_1 > j_2$. Then the iteration operation is repeated, and the scattering output at m-order is as follows:

$$\begin{aligned} & S_m x(u, \lambda_1, \ldots, \lambda_m) \\ & \quad = \left| \ldots \left| x * \psi_{\lambda_1} \right| \ldots * \psi_{\lambda_m} \right| * \phi_J(u) \end{aligned} \tag{8}$$

$$\begin{aligned} & U_{m+1} x(u, \lambda_1, \ldots, \lambda_{m+1}) \\ & \quad = \left| \ldots \left| x * \psi_{\lambda_1} \right| \ldots * \psi_{\lambda_{m+1}}(u) \right| \end{aligned} \tag{9}$$

The final scattering coefficients are all the output sets of the scattering transform from the 0th to the m-th order [21]:

$$Sx = \{S_0 x, S_1 x, \ldots S_m x\} \tag{10}$$

The scattering transform structure diagram is shown in the Figure 2.

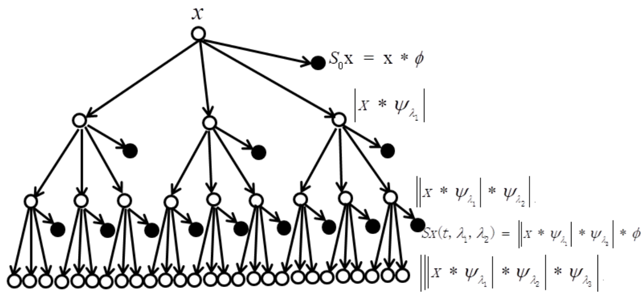

FIGURE 2. Scatter network structure diagram.

B. TWIN SUPPORT VECTOR MACHINE (TWSVM)

Twin support vector machine is different from support vector machine. It obtains a pair of non-parallel hyperplanes by solving two smaller quadratic programming problems. The objective function of each quadratic programming corresponds to a specific class. Its constraints are affected by another class of samples. Each hyperplane is as close as possible to the sample points of this class and as far as possible from the sample points of another class. TWSVM is similar to classical support vector machines in form, but it converts a large classification problem into solving two small-scale classification problems, so that the number of constraints for each quadratic programming problem becomes 1/2 of the original, thus reducing the training time to 1/4 of SVM. This algorithm improves the computational performance and generalization ability of SVM.

TWSVM is a two-class classifier. The classification principle is to obtain two non-parallel classification hyperplanes by two convex quadratic programming problems (QP). Then the vertical distances from each sample point to two hyperplanes are calculated separately. Finally, the classification of sample points is determined according to the vertical distances between the sample points and the two classification hyperplanes. Sample points belonging to the hyperplane are defined as class '+1' and those not belonging to the hyperplane are defined as class '-1'. Figure 3 is a classification sketch of TWSVM. Squares and circles represent sample points '+1' and sample points '-1' respectively. The corresponding classification hyperplanes of the two-class sample points are H_1 and H_2, respectively.

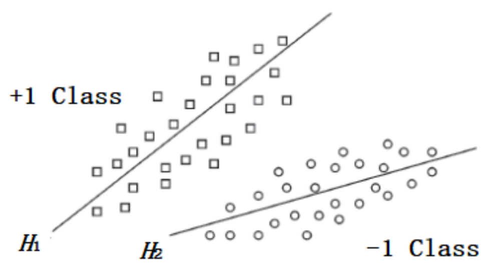

FIGURE 3. Twin support vector machine classification diagram.

In this paper, the heart sound classification belongs to the non-linear classification problem. The heart sound signals are divided into two categories: normal heart sound signals and abnormal heart sound signals. TWSVM is suitable for the classification of heart sound signals. TWSVM uses the Gaussian kernel method to deal with it. The principle of this method is as follows: The data in the original feature space are mapped into the high-dimensional regenerative space. The mapped data are linearly separable. Establish two hyperplanes in the high-dimensional space. The following $K(x, y)$ is the kernel function. Assume that the number of training sample points is m in R^n space. Among them,

m_1 training sample points belong to class '+1' and m_2 training sample points belong to class '-1'. Matrix A represents the training sample points of class '+1' and matrix B represents the training sample points of class '-1'. Each row of matrix A represents a sample point belonging to class '+1'. Each row of matrix B represents a sample point belonging to class '−1'. The thought of TWSVM is to construct the two non-parallel hyperplanes based on kernel function for the classification:

$$K(x^T, C^T)u_1 + b_1 = 0 \quad \text{and } K(x^T, C^T)u_2 + b_2 = 0$$

where u_1 and u_2 are the normal vectors of two hyperplanes, b_1 and b_2 is the offsets of two hyperplanes. The offsets and normal vectors of two non-parallel hyperplanes are obtained by the following quadratic programming problem:

$$\left.\begin{array}{l}(\text{TWSVM1}) \quad \min \frac{1}{2}\left\|K(A, C^T)u_1 + e_1 b_1\right\|^2 + c_1 e_2^T \zeta \\ \textit{subject to } -(K(B, C^T)u_1 + e_2 b_1) + \zeta \geq e_2, \zeta \geq 0\end{array}\right\} \tag{11}$$

$$\left.\begin{array}{l}(\text{TWSVM2}) \quad \min \frac{1}{2}\left\|K(B, C^T)u_2 + e_2 b_2\right\|^2 + c_2 e_1^T \eta \\ \textit{subject to } (K(A, C^T)u_2 + e_1 b_2) + \eta \geq e_1, \eta \geq 0\end{array}\right\} \tag{12}$$

where matrix C represents all training sample points, and each row of matrix C is a training sample point. e_1 and e_2 are the unit column vectors. c_1 and c_2 are the penalty parameters. ζ and η are the slack variables. The kernel function $K(x, y)$ maps the finite dimensional data into the high dimensional space. Make the data linear separable in high dimensional space. Two hyperplanes based on kernel function are obtained by solving Equations (11) and (12). The decision rule of TWSVM is that the testing sample point belongs to the class which hyperplane is close to it. The decision function is as follows [22], [23]:

$$Label(x) = \underset{k=1,2,\ldots,K}{\arg\min} \left(K(x, C^T)u_k + b_k / \sqrt{u_k^T K(C, C^T)u_k}\right) \tag{13}$$

The classifier can be used to divide the heart sound signals into two categories quickly and effectively based on the above principle.

C. DIMENSION REDUCTION ALGORITHM

Dimensional disaster mitigation by dimensionality reduction means that the original high-dimensional attribute space is transformed into the low dimensional subspace by some mathematical transformation to improve the density of sample and simplify the distance calculation. At present, the commonly used dimensionality reduction methods include principal component analysis (PCA), multidimensional scaling analysis (MDS) and so on. Principal Component Analysis (PCA) transforms the original feature into linear independent feature by orthogonal transformation, which maximizes the variance of sample points after projection. However, the principal components with small contribution may also contain important information about sample differences [24]. MDS algorithm requires that the distance between sample points in the original space be maintained in low-dimensional space. MDS dimension reduction can effectively reduce the amount of data processing and retain the topological structure of the original data to the greatest extent.

The essence of MDS method is to find a matrix $B_{n\times k}$ in low-dimensional space, so as to make $B_{n\times k}$ maintain the connection between data points of high-dimensional matrix $A_{n\times m}$. For the sample consisting of n points $x_1, x_2, \cdots, x_n$ in $m\_$ dimensional space, the MDS dimension reduction process is as follows [25]:

Step1: Compute the distance matrix D (d_{rs} is the element of the matrix D, representing the distance between x_r and x_s). D is a real symmetric matrix with all diagonals of 0. Compute the d_{rs}^2.

$$d_{rs}^2 = (x_r - x_s)^T(x_r - x_s) \tag{14}$$

Available from Equation (14)

$$d_{rs}^2 = x_r^T x_r + x_s^T x_s - 2x_r^T x_s \tag{15}$$

Step2: Define the inner product matrix B (b_{rs} is the element of the matrix B), where

$$b_{rs} = x_r^T x_s \tag{16}$$

Available from Equation (15)

$$\frac{1}{n}\sum_{x=1}^{n} d_{rs}^2 = \frac{1}{n}\sum_{r=1}^{n} x_r^T x_r + x_s^T x_s \tag{17}$$

$$\frac{1}{n}\sum_{s=1}^{n} d_{rs}^2 = \frac{1}{n}\sum_{s=1}^{n} x_s^T x_s + x_r^T x_r \tag{18}$$

$$\frac{1}{n^2}\sum_{r=1}^{n}\sum_{s=1}^{n} d_{rs}^2 = \frac{2}{n}\sum_{r=1}^{n} x_r^T x_r \tag{19}$$

Available from Equation (16) to Equation (19)

$$b_{rs} = a_{rs} - a_{r1} - a_{s1} + a_{11} \tag{20}$$

where

$$a_{rs} = -\frac{1}{2}d_{rs}^2 \tag{21}$$

$$a_{r1} = \frac{1}{n}\sum_{s=1}^{n} a_{rs} \tag{22}$$

$$a_{s1} = \frac{1}{n}\sum_{r=1}^{n} a_{rs} \tag{23}$$

$$a_{11} = \frac{1}{n^2}\sum_{r=1}^{n}\sum_{s=1}^{n} d_{rs}^2 \tag{24}$$

So obtain B from the matrix D.

$$B = -\frac{1}{2}HD^2H \tag{25}$$

where $H = I - \frac{1}{n}ii^T$, i is the column vector whose elements are 1.

Step3: Calculate the k largest eigenvalues of the matrix B and their corresponding eigenvectors.

Step4: Assume V is a diagonal matrix composed of k largest eigenvalues, $V = diag(\lambda_1, \lambda_2, \ldots, \lambda_k)$ and Λ is a $n \times k$ matrix composed of k standard orthogonalized eigenvectors, $\Lambda = (\overrightarrow{k_1}, \overrightarrow{k_2}, \cdots, \overrightarrow{k_k})$, then the coordinate matrix in k-dimensional space is

$$X = (\sqrt{\lambda_1} \cdot \overrightarrow{k_1}, \sqrt{\lambda_2} \cdot \overrightarrow{k_2}, \cdots, \sqrt{\lambda_k} \cdot \overrightarrow{k_k}) = \Lambda\sqrt{V} \quad (26)$$

III. IMPLEMENTATION OF THE PROPOSED ALGORITHM

The experimental data come from the PhysioNet/CinC Challenge 2016 heart sound database. The heart sound data are collected from the healthy individuals and patients with valvular heart disease and coronary artery disease. The duration of heart sound recording varies from seconds to minutes. A sub-database is chosen to implement the algorithm proposed in this paper. The sub-database contains 409 records of heart sound signals, 117 normal heart sound signals and 292 abnormal heart sound signals [26], [27].

The experimental steps are as follows:

Step1: Collect the heart sound signals. The heart sound signals come from the heart sound database. The heart sound signals in the database are all sound waveform files, and the acquisition duration is different, so the sampling points of the signals are different. In order to facilitate post-processing, waveform files need to be represented by data, and their amplitude information should be extracted according to the number of sampling points. By observing the duration of heart sound signal and its sampling points, all heart sound signals are sampled at 30 000 sampling points to satisfy the unification of signal dimensions.

Step2: Set the wavelet scattering network according to the properties of the signal. The length of the signal must match the 'SignalLength' of the wavelet scattering decomposition framework. The wavelet scattering coefficients are obtained through the scattering channels, and the 0th channel represents the original signal. The scattering transform scale is also set according to the signal length. The following Figure 4 is the partial scattering results obtained.

Step3: Determine the training and testing sets. In order to verify the classification accuracy of the proposed algorithm, the heart sound signals in the database are divided into two parts: training set and testing set. 70% of the heart sound signals are used for training and 30% for testing.

Step4: Extract the scattering features of heart sound signals. The above-mentioned heart sound signals for training are extracted by using the built wavelet scattering network to obtain the scattering features of the training signals. The feature display is three-dimensional, which is 'scattering path × wavelet scale × number of signals'. Because the twin support vector machine requires the two-dimensional feature vectors as input, the three-dimensional feature matrix is integrated into two-dimensional matrix. Similarly, the heart sound signal

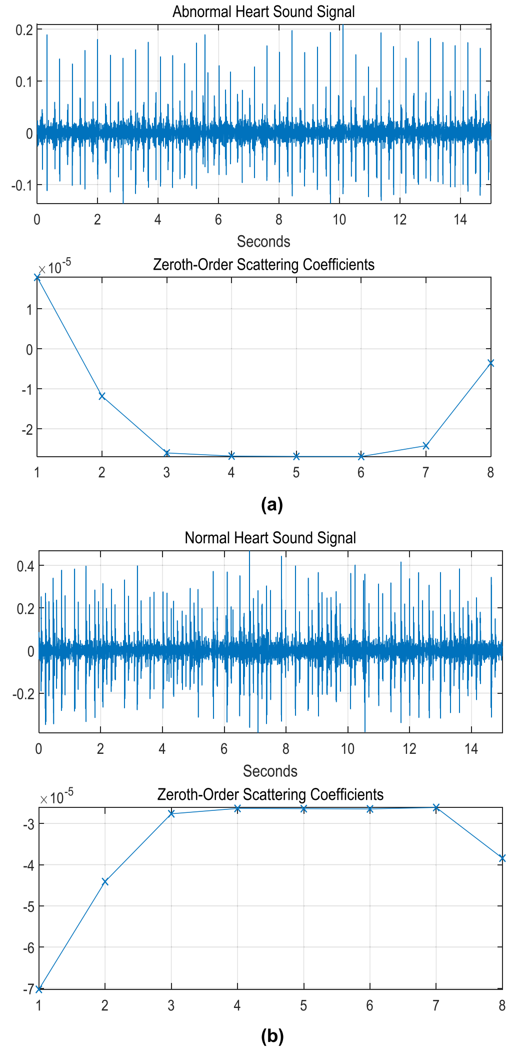

FIGURE 4. **Heart sound signal and zero-order scattering coefficient distribution: (a) Abnormal heart sound; (b) Normal heart sound.**

used for testing is also extracted by using the wavelet scattering network. Finally, the three-dimensional feature matrix is transformed into two-dimensional pattern. The calculation results of the 'wavelet scale × number of signals' is taken as one dimension of the feature matrix, and then the scattering path is taken as another dimension of the feature matrix. The following Figure 5 is the integrated feature vectors. The size of the feature vectors matrix is 56 × 498. From the figure, we can see that the number of vectors of the feature vectors matrix is very large, and the dimension of the feature vectors matrix is too large.

Step5: MDS (Multidimensional Scaling) method is used to reduce the dimension of feature vectors. Because the dimension of the feature matrix is too large, it needs to use dimension reduction algorithm to reduce the dimension of the feature matrix. In this paper, MDS dimension reduction method is chosen. The following Figure 6 is the representation of feature vectors after dimension reduction. The size of feature matrix after dimension reduction is 56 × 12. Under the premise of retaining the important feature information,

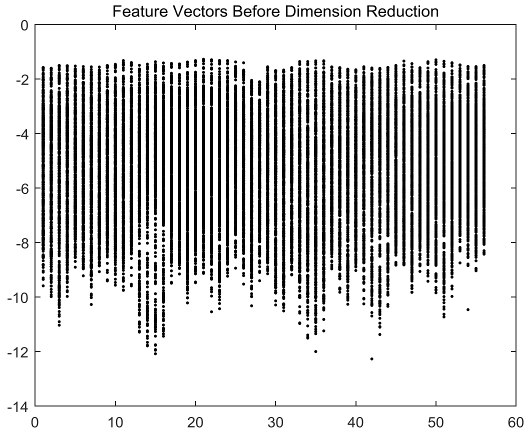

FIGURE 5. Feature vectors before dimension reduction.

FIGURE 6. Feature vectors after dimension reduction.

the feature vectors are reduced, which greatly reduces the burden of subsequent classifier.

Step6: Twin Support Vector Machine is used to train and test the feature vectors. The optimal parameters of TWSVM are found through training. The feature vectors of the samples to be tested after dimension reduction are input into the trained TWSVM. Then the classification effect is evaluated. Select the Gaussian kernel $K(x, y) = e^{-\frac{\|x-y\|^2}{2\sigma^2}}$ as the kernel function for twin support vector (TWSVM). σ is the kernel parameter which controls the radial action range. In addition, two hyperplanes of TWSVM need to be determined. Choose the optimal parameters about kernel parameters σ_1, σ_2 and penalty parameters c_1, c_2 [28]–[33]. Through a lot of experiments, the best classification accuracy is obtained when c_1, c_2, σ_1, σ_2 are all chosen as 2. The accuracy changes with σ are showed in Figure 7. However, choosing the optimal parameters is still a problem to be solved for twin support vector machine (TWSVM).

IV. RESULTS AND DISCUSSION

A. EXPERIMENTAL DATA AND ENVIRONMENT

The PhysioNet/CinC Challenge 2016 heart sound database is used for the proposed algorithm in this paper. The heart

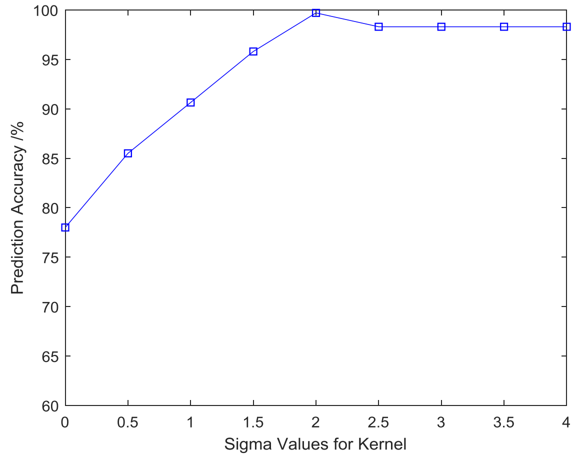

FIGURE 7. The accuracy changes with sigma values.

sound database includes more than 2000 records of normal and abnormal heart sound signals which are collected from healthy people and the patients with heart disease. In this paper, a sub-database from PhysioNet/CinC Challenge 2016 which contains 409 heart sound records is chosen for this experiment. This experiment is implemented on the computer system which processor is Intel (R) Celeron (R) CPU N3450 1.10 GHz, RAM is 4.00 GB and operating system is 64-bit Windows 10. The MATLAB 2018b is used to simulate.

B. RESULTS AND ANALYSIS

The SVM classification method is compared with the classification method proposed in this paper based on twin support vector machine (TWSVM). Comparing the traditional dimension reduction method PCA with the MDS method used in this paper, four kinds of contrast combinations are formed: PCA + SVM, PCA + TWSVM, MDS + SVM, MDS + TWSVM. They are compared in terms of running time and classification accuracy. 50, 100, 150, 200, 409 records of heart sound signals are randomly selected from the heart sound database for this experiment. Of these, 70% are trained and 30% are tested. In order to highlight the advantages of the proposed algorithm, the proposed algorithm (MDS+TWSVM) is compared with PCA+SVM, PCA+TWSVM and MDS+SVM. Table 1 is the comparison of feature vector dimensions before and after dimension reduction. Table 2 is the comparison of classification accuracy. Table 3 is the comparison of running time.

In order to facilitate the observation of the comparison results, the comparison results are also displayed in Figure 8 and Figure 9. It can be seen from Figure 8 that the classification accuracy of the proposed algorithm (MDS+TWSVM) is obviously better than that of other algorithms. About the running time, it can be seen from Figure 9 that the PCA+TWSVM and MDS+TWSVM are superior to other algorithms. Although the running time of PCA+TWSVM is sometimes less than that of the proposed algorithm (MDS+TWSVM), the classification accuracy of

TABLE 1. Feature vector dimensions before and after dimension reduction.

Feature Vector Dimension Before Dimension Reduction	56×498	120×498	180×498	240×498	492×498
Feature Vector Dimension After Dimension Reduction	56×12	120×12	180×12	240×12	492×12

TABLE 2. Comparison of classification accuracy of different methods.

Classification Method	Dimension Reduction Method	56×12	120×12	180×12	240×12	492×12
SVM	PCA	69.44%	71.43%	72.38%	77.5%	71.33%
	MDS	86.81%	81.43%	80.71%	79.82%	75.63%
TWSVM	PCA	93.06%	84.29%	81.90%	83.93%	77.80%
	MDS	100%	98.33%	98.33%	98.75%	98.58%

TABLE 3. Comparison of running time of different methods.

Classification Method	Dimension Reduction Method	56×12	120×12	180×12	240×12	492×12
SVM	PCA	2.641s	2.771s	2.965s	3.031s	4.197s
	MDS	3.193s	4.766s	4.789s	5.396s	5.047s
TWSVM	PCA	0.19s	0.794s	0.963s	1.817s	2.736s
	MDS	0.18s	0.706s	1.661s	2.359s	2.819s

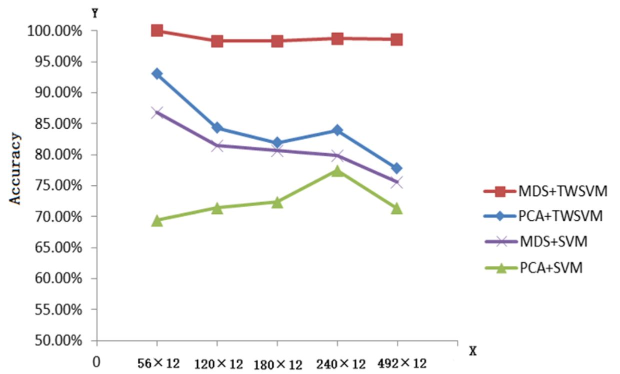

FIGURE 8. Comparison of classification accuracy.

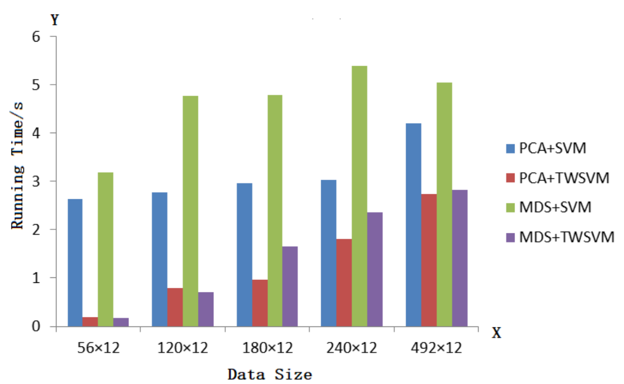

FIGURE 9. Comparison of running time.

PCA+TWSVM is not as good as that of the proposed algorithm (MDS+TWSVM).

To evaluate the performance of the proposed algorithm, the classification accuracy, specificity, sensitivity, precision and F1 Score are used. The Equations (27)–(31) are given to calculate the performance parameters. In the equations, TP represents the true positive number, TN represents the true negative number, FN represents the false negative number, and FP represents the false positive number [34], [35].

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \times 100\% \tag{27}$$

$$Sensitivity = Recall = \frac{TP}{TP + FN} \times 100\% \tag{28}$$

$$Specificity = \frac{TN}{FP + TN} \times 100\% \tag{29}$$

$$Precision = \frac{TP}{TP + FP} \times 100\% \tag{30}$$

$$F1Score = \frac{2 \times Recall \times Precision}{Recall + Precision} \times 100\% \tag{31}$$

Under the same dimension reduction method (MDS), the performance parameters of traditional classifier SVM and TWSVM used in this paper are compared. According to the above equations, the classification accuracy, precision, sensitivity, specificity and F1 score are obtained to evaluate the performance of this proposed method. Table 4 shows the comparison results of different dimensions of feature vectors using SVM and TWSVM respectively. Under the same dimension, the performance parameters of TWSVM method are superior to the SVM method.

The algorithm proposed in this paper is compared with other literatures, as shown in Table 5. It can be seen from the table that the classification accuracy, sensitivity and specificity of the algorithm proposed in this paper are better than those mentioned literature. The running speed of the algorithm proposed also has greater advantages.

TABLE 4. Comparison of sensitivity, specificity, precision, accuracy and F1 Score about different dimensions of feature vectors based on SVM and TWSVM.

Classifiers	Feature Matrix	Sensitivity	Specificity	Precision	Accuracy	F1 Score
SVM	56×12	87.53%	81.25%	92.11%	86.81%	89.76%
	120×12	83.33%	77.78%	89.74%	81.43%	86.42%
	180×12	82.03%	76.92%	89.74%	80.71%	85.71%
	240×12	81.98%	75.00%	89.24%	79.82%	85.46%
	492×12	77.27%	71.43%	87.18%	75.63%	81.93%
TWSVM	56×12	100%	100%	100%	100%	100.00%
	120×12	97.65%	97.22%	98.81%	98.33%	98.23%
	180×12	98.44%	98.08%	99.21%	98.33%	98.82%
	240×12	98.84%	98.53%	99.42%	98.75%	99.13%
	492×12	98.58%	98.57%	99.43%	98.58%	99.00%

TABLE 5. Comparison of the proposed algorithm and other literature.

Methods	Sensitivity	Specificity	Accuracy
STFT[36]	70.59%	86%	77.12%
Spectrogram analysis[37]	77.94%	82%	79.66%
WPT[38]	79.41%	84%	81.36%
HHT[39]	80.88%	92%	85.59%
OMS-WPD [40]	85.29%	94%	88.98%
DFT/ANN [41]	97.29%	82.6%	91.67%
DFT/Burg AR-PCA-ANN [42]	97.44%	90.48%	95%
Proposed algorithm	98.58%	98.57%	98.58%

V. CONCLUSION

This paper proposed a novel algorithm for the heart sound signal classification based on wavelet scattering transform and twin support vector machine (TWSVM). The signal features are extracted by using wavelet scattering transform. Then obtain the feature vectors of the signal. However, the dimension of feature vectors is too large, which affects the classification speed. Therefore, multidimensional scaling (MDS) method is used to reduce the dimension of feature vectors. Finally, the feature vectors after dimension reduction are input into the twin support vector machine for training and testing. In the operation of the algorithm, the signal features extracted by the wavelet scattering transform can more fully express the feature information of the signal. The twin support vector machine is used to classify the heart sound signal. It can reduce the calculation complexity of the classification. The proposed algorithm can effectively shorten the classification time under the premise of ensuring classification accuracy. In the next research work, we can consider the use of other feature information to further shorten the running time. The number of samples should be also expanded. In addition, TWSVM algorithm still needs to be improved in terms of parameters optimization.

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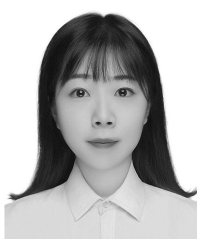

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