Diagnosis of Ventricular Septal Defect Based on Mel Frequency Cepstrum Analysis

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Abstract: This research aims at the heart sound modeling for a typical congenital heart defect, ventricular septal defect (VSD). VSD will threaten the health and life of the children seriously if they can't be detected and cured timely. Hence, an easy-operation diagnosis model based on Mel-scale is proposed to give an early detection. Firstly, an improved Mel-scale feature extraction is applied for the clinical normal and VSD heart sounds. And then the diagnosis model is built by defining the Mel-scale features as the mathematical parameters. Lastly, a visible and primary diagnosis result can be obtained by the heart sound model easily. A set of clinical data is used to validate the efficiency of the proposed diagnosis model. The identify model can detect the VSD heart sounds effectively and it has the potential for analyzing other heart diseases.

Key-Words: *Heart sound, Ventricular septal defect (VSD), Mel-scale, Modeling*

1. Introduction

Congenital heart disease (CHD) is one of the typical cardiovascular diseases, which is a congenital defect in the heart structure before birth. In China, the 30.4%～59.69% of CHDs is ventricular septal defect (VSD). Some single defects can be healed up naturally during one year after birth, like the healing probability of the VSD is about 20.5%~52.9% [1]. However, if the defects exist for a long time, it will affect the growth of the children and may become serious and lead to pathological changes. So the early detection and appropriate treatment is necessary.

With the development of the auscultation and signal processing technique, the heart diseases diagnosis algorithm based on heart sound becomes a hot point. Among the various heart sound analysis means in time domain, frequency domain and spectrum energy, Mel frequency cepstrum coefficient (MFCC) algorithm is introduced recently. MFCC, widely used in the speech signal processing, can perceptive identify of the human ear to frequency components of the sound [2]. Ping Wang et.al. [3] built a computer-aided automatic heart sound auscultation system based on MFCC coefficients and the classifier, hidden Markov model. Wenjie Fu et.al. [4] combined the wavelet algorithm to improve the MFCC algorithm for high accuracy. Wei Chen et.al. [5] extracted the MFCC features and done the dimension reduction by principal component analysis for the individual identification.

In our pervious study, the MFCC algorithm is applied in the heart sound signal segments (S1, S2，the systolic murmurs and the diastolic murmurs) and the MFCC coefficients of VSD have noticeable features on the heart systole which have the potential to be distinguished from normal and another CHD case [6].

In this study, the MFCC is extended and modified for CHD diagnosis in the early stage. In the second section, the MFCC algorithm on the segmented heart sound signal is supplemented. And the Mel-scale feature extraction based on

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Mel frequency cepstrum analysis is discussed. In the third section, the diagnosis model is built based on the features extraction and the experiments on clinical data validate the efficiency. In the final, the conclusion and future work are summarized.

2. MFCC and Mel-scale feature extraction

Mel frequency cepstrum coefficients (MFCCs) are derived from the short time spectrum of a signal and widely used both for speech and speaker recognition. MFCCs can represent the low frequency region more accurately than the high frequency region and it can capture formants lying in the low frequency range which is suitable for heart sound analysis [7].

2.1 The MFCC features of the segment heart sound

There are five steps in the procedure of the MFCC algorithm. Heart sound framing and windowing are processed firstly, and FFT transform is followed to compute the heart sound frequency energy spectrum. Then a triangle filter bank is applied to transform the real frequency to Mel frequency. The Mel-scale comes from Equation 1.

$$Mel(f)=\frac{1000\times\ln(1+f/700)}{\ln(1+1000/700)} \tag{1}$$

Lastly, the logarithm and discrete cosine transform (DCT) is used to reduce the computation complexity and transform the signal into time domain. The 12 MFCC coefficients can be obtained by

$$MFCC_{\mathrm{i}}=\sum_{k=1}^{K}X_k\cdot\cos(i\cdot(k-\frac{1}{2})\cdot\frac{\pi}{K}),i=0,1,...N \tag{2}$$

Where, N is the dimension of MFCC, k is the number of filters in filter bank.

The heart sound signal is segmented which defined as the S1 part, S2 part, the systolic murmurs (SM) part and the diastolic murmurs (DM) part. The SM part, between the S1 part and S2 part, lasts about 0.17s and the DM part, between the S2 part and the next S1 part, lasts about 0.4s according to the clinical experiments.

After down sampling from 40 kHz to 2 kHz, the clinical heart sound data collected by BIOPAC system, including 23 normal case, 17 VSD and 6 atrial septal defect (ASD) cases are used to extract MFCC features in the above four segments.

The average values in each segment for each MFCC features are shown in Fig.1.

From the Fig.1, we can see that for VSD case, the MFCCs have the distinguished difference in SM part from the ASD and normal cases. And the DM part seems to be potential to diagnose the normal from CHD cases by MFCC. In a word, the SM part performs better than DM part and is selected for the following VSD experiments in this research.

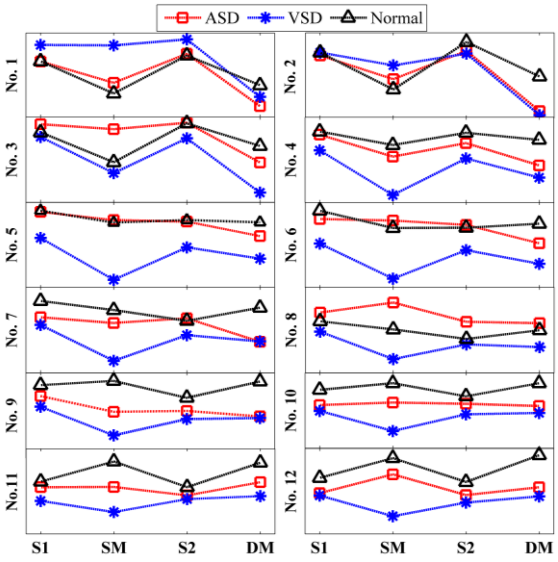

Fig.1 The average of each MFCC in four segments

2.2 The Mel-scale feature extraction

In order to get more accurate heart sound features, some modifications have been done for MFCC algorithm and the Mel-scale feature extraction is proposed.

As shown in Fig.2, the energy computation by the FFT is replaced by power spectrum density directly and the discrete cosine transform is deleted.

The essence of MFCC algorithm is a serious of transforms in the frequency domain. The FFT waveform has lots of burrs which will cause the confusion, hence the power spectrum density is considered to get a much smoother frequency envelope.

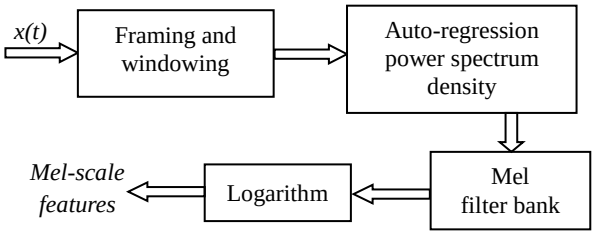

Fig.2 The flow chart of Mel-scale feature extraction

The power spectrum density estimation reflects the energy distribution in the frequency domain. And autoregressive method is the most frequently used parametric method because the estimation of AR parameters can be done easily by solving linear equation [8]. Here Yule-Walker's method is selected and the order of an autoregressive prediction model for the signal is set as 32. According to the waveforms shown in Fig.3, the AR-PSD envelope is smoother and shows the same variation trend as the energy spectrum gotten by FFT transform.

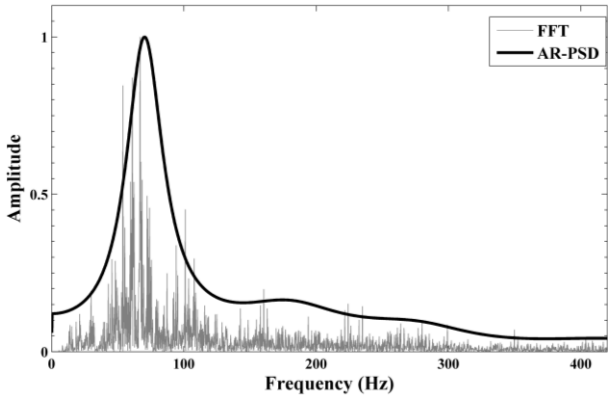

Fig.3 Comparison of the AR-PSD waveform and the FFT energy spectrum for a VSD case

3. The identify model based on Mel-scale

For speech signal processing, the MFCC features are considered as a whole to simulate the speech signal's patterns. Here a identify model is built following this concept.

3.1 The identify model built for VSD detection

According to the experiments above, the 12 Mel-scale features are extracted in SM part, and then the mean value μ and the standard deviation σ of each feature are calculated which can reflect the changing trend of the samples and the discrete degree of the samples respectively. The data is saved as Excel file for the following modeling.

The boundaries of the distribution zones for normal and VSD identification are defined by the $\mu\pm\sigma$ from a training data set (30 normal and 17 VSD). As shown in Figure 4, the VSD zone is calculated by $\mu_{VSD}\pm\sigma_{VSD}$, and the normal zone is obtained using $\mu_{Normal}\pm\sigma_{Normal}$.

Based on the experimental results, there are large overlaps in the first 2 and the last 2 features in the normal and VSD zones. Hence, in this study, from the No.3 to No.10 Mel-scale features are kept for modeling and the identify model is shown in Fig.4.

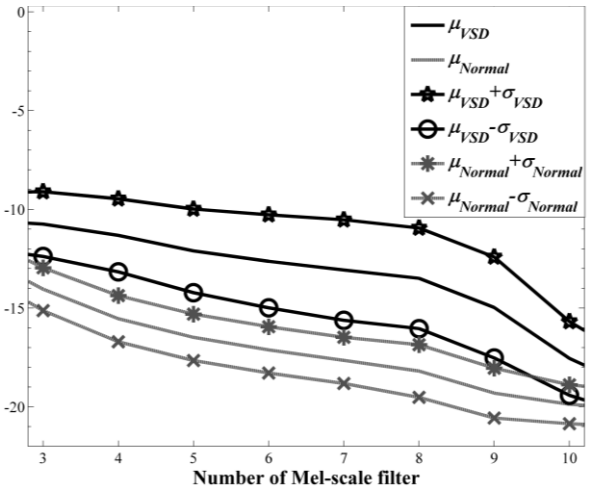

Fig.4 Identify model for the normal and VSD cases

For VSD detection, if more than half of the features distributed in normal zone, it will be identified as normal, vice versa it will be VSD. In addition, if more than half of the features are outside both VSD and normal zones, it will be distinguished as other heart diseases.

3.2 The identify model applied in clinical data

A test data set containing 5 VSD, 5 normal cases and 4 other CHD cases (2 ASD and 2 tetralogy of fallot (TOF)) are selected to test the efficiency of the identify model. In Table 1, Y/N represents the diagnosis right or wrong.

From the experiment results shown in Table 1, we can see that the normal cases and VSD cases are diagnosed correctly and for other cases, except an ASD can be identified

as other heart disease, another ASD and 2 TOF are misdiagnosed as normal cases.

As the TOF is a kind of the complex CHDs which accompanys other three heart diseases except for VSD and the heart murmurs of ASD are not mainly distributed in heart systole, the existing model can't show the characteristics of the above two cases exactly. A model which can show the outstanding pathological features of other CHDs need to be built in the future.

Table 1 Model identify results for clinical heart sounds

Zones / Test case	Normal zone	VSD zone	Other zone	Identify result	Y/N
Normal1	8	0	0	Normal	Y
Normal2	8	0	0	Normal	Y
Normal3	8	1	0	Normal	Y
Normal4	8	0	0	Normal	Y
Normal5	8	0	0	Normal	Y
VSD1	0	8	0	VSD	Y
VSD2	0	8	0	VSD	Y
VSD3	0	8	0	VSD	Y
VSD4	0	8	0	VSD	Y
VSD5	0	8	0	VSD	Y
ASD1	8	0	0	Normal	N
ASD2	3	0	5	Other	Y
TOF1	5	3	0	Normal	N
TOF2	6	0	2	Normal	N

4. Conclusion

To satisfy the need of the remote medical treatment and the portable diagnosis device, the VSD detection based on heart sound was discussed and the MFCC algorithm was introduced and applied for heart sound modeling. By the clinical heart sound experiments, the Mel-scale features were extracted and applied to build the VSD and normal diagnosis model. The proposed identify model can diagnose the VSD from the normal cases successfully, but it had a low discriminability for other CHD cases. In other words, the Mel-scale features show a good performance for VSD diagnosis at present.

In the future, more effective statistic means will be applied to complete the heart sound mathematic modeling and accomplish the heart disease intelligent diagnosis finally.

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