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A Review of Heart Sound and Its Research Methods

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Abstract: *In this paper, heart sound and its research methods are discussed. The traditional methods and the novel deep learning algorithm methods of heart sound research are introduced respectively. For traditional methods, there are short-time Fourier transform, Wavelet transform, Wigner-Ville Distribution and Hilbert analysis. For novel deep learning algorithm methods, CNN, RNN and U-net framework are mainly introduced. Their characteristics and applications are compared through comparative analysis, and the main research direction and significance of heart sound signal analysis and processing are comprehensively explained.*

Keywords: *Heart sound; Heart sound classification; Signal processing; Feature extraction*

1. Introduction

Heart sound signals are important physiological signals in the human body, carrying a large number of physiological characteristics. As a physical signal that responds to human heart activity and cardiovascular function, it can be evaluated by a specialist through heart sound auscultation, which in turn gives information on the pathology of cardiovascular disease. In addition, the heart sound signal contains a part of information that is not reflected in the ECG. Therefore, heart sound signal classification is a key technology in the research and application of computer-aided diagnosis of cardiovascular diseases. A number of international researchers have experimented with different methods to analyse heart sound signals. There are two broad types of analysis methods that have been studied for heart sound signals, namely traditional analysis methods and novel deep learning analysis methods.

2. Basic concepts and classification of heart sounds

During the cardiac cycle, turbulence caused by the contraction of the heart muscle, the opening and closing of valves, changes in blood flow and vibrations caused by blood flow against the walls of the ventricles and aorta are transmitted through the surrounding tissue to the chest wall, where they can be heard with a stethoscope in certain parts of the chest as heart sounds. If these mechanical vibrations are converted into electrical signals by a transducer and recorded, a heart sound map can be obtained.

Heart sounds occur at specific times in the cardiac cycle and are characterised by their pitch and duration. In heart sound segmentation, the heart sounds are generally segmented into basic heart sounds, namely the first heart sound (s1), the second heart sound (s2), the third heart sound (s3), and the fourth heart sound (s4). Of these, the first and second heart sounds are normally heard, the third heart sound is usually heard only in children and adolescents, and the fourth heart sound is rarely heard in normal circumstances. When a heart valve is diseased, abnormal mechanical fluctuations in the valve can cause changes in blood flow, resulting in an abnormal heart sound, known as a heart murmur.

The different frequency bands of heart murmurs that occur at different times represent different cardiac diseases, and the use of heart sounds to aid in the diagnosis of cardiac disease begins with an analysis of their temporal frequency distribution. For this reason, a combination of mathematical and computer methods can be used to analyse the time-frequency distribution of heart sounds.

3. Traditional methods of heart sound studies

Traditional methods for heart sound research include short-time Fourier transform, wavelet transform, Wigner-Ville distribution, Hilbert analysis, etc. Traditional Fourier-based methods cannot effectively analyze non-smooth signals, and Hilbert spectral analysis can make a more accurate description of the signal's time-frequency distribution than short-time Fourier transform and wavelet analysis. The traditional heart sound classification method consists of three steps: heart sound segmentation, feature extraction and classifier design.

3.1. Short-time Fourier transform

The Short Time Fourier Transform method, created by Gabor [1] in 1946, is one of the most basic methods of time-frequency analysis, analysing a signal with a sliding window and then applying a Fourier transform to the windowed signal, h(t) is the window function, defined as follows.

$$\mathrm{S}(\omega t)=\frac{1}{2\pi}\int_{-\infty}^{+\infty}\mathrm{e}^{-\mathrm{i}\omega}\mathrm{s}(\tau)\mathrm{h}(\tau-\mathrm{t})\,d\tau$$

This is a modification of the Fourier transform and is relatively common and effective for the analysis and processing of smooth signals. The analysis results of short-time Fourier transform can be displayed in two-dimensional and three-dimensional ways to show its display results, which is intuitive and easy to understand. However, when dealing with non-stationary signals, Fourier analysis does not reveal the characteristics of the signal, and the results are not easily distinguishable when the murmur and s1 and s2 heart sounds are in the same low to medium frequency band, which limits the application of this method. The Fourier transform is an overall transform, which cannot show the moment and change of a certain frequency component.

In 1992, G. Jamous et al. applied the short-time Fourier transform to analyze the time-frequency characteristics of heart sound signals in dogs. The experimental results show that the optimal length of the window is 16-32ms. When the length of the window is less than 16ms, the low frequency components will be confused into high frequency components, thus decreasing the frequency resolution; when the length of the window is greater than 32ms, the frequency resolution of the signal is increased while the time resolution is decreased. Vikhe et al. [2] used STFT to determine the frequency composition and duration of s1 and s2. With the help of STFT and other tools, Wei Zhe et al. [3] transformed the one-dimensional heart sound signal graph into the form of an intensity map with strong identifying features.

The STFT solves the problem of the traditional Fourier transform not reflecting the time domain of the signal and is relatively easy to implement, which is essentially a Fourier analysis with a restricted time window length, so that the signal under analysis must be segmentally smooth. Then, for small smooth segments with different time scales, one needs a window length and type appropriate to oneself in order to obtain the best results.

However, by the definition of STFT, only a fixed window function can be selected, i.e. the time and frequency resolution is fixed in the whole time-frequency plane. This is a major drawback of this method. It has to be selected through several experiments to find the right length and type of window to be added. STFT analysis is limited by the uncertainty principle, where longer windows improve the frequency domain solution but make the time domain solution worse. A shorter window gives a good time domain solution, but the frequency domain solution becomes blurred. The uncertainty principle tells us that the uncertainty principle tells us that it is impossible to obtain a clear solution in both the time and frequency domains, which also limits the application of this method.

3.2. Wavelet transform

Wavelet transform was proposed on the basis of STFT. The main difference between the two methods of analysis lies in the multi-resolution nature of the wavelet transform, which is defined for non-smooth signals as follows.

$$\mathrm{W}(\mathrm{a},\mathrm{b})=|\mathrm{a}|^{-\frac{1}{2}}\int_{-\infty}^{+\infty}\mathrm{s}(\mathrm{t})\varphi(\frac{\mathrm{t}-\mathrm{b}}{\mathrm{a}})\,dt$$

In the formula, a is the scale stretch, b is the time translation and φ is the window function.

Wavelet analysis is a time-frequency localized analysis method in which both time and frequency windows can be changed, it has high frequency resolution and low time resolution in the low frequency part and high time resolution and low frequency resolution in the high frequency part, it is this characteristic that makes the wavelet transform be adaptive to the signal.

The wavelet transform can be used to estimate the energy-frequency distribution of a heart sound using the power spectrum, extracting the eigenvalues of the heart sound from different perspectives and providing a comprehensive overview of the characteristics of the heart sound. The continuous wavelet transform shows the dynamic changes of the heart sound signal. The eigenvalues obtained by this analysis method can be applied to artificial neural networks for the automatic diagnosis of organic heart disease. Simulation experiments have also demonstrated that this analysis method is effective in differentiating heart sound signals and is useful in the diagnosis of organic heart disease. The wavelet transform provides a comprehensive picture of the frequency components, time of occurrence, intensity and trend of heart sounds, adductory sounds and heart murmurs, but the graphical presentation is not intuitive.

In 1997, Yuan-Yuan Wang from China described a method to analyze heart sound signals using wavelet transform. The experiments on the analysis of computer-simulated heart sound signals found that the wavelet transform could be used to effectively analyze heart sound signals, thus providing a new method for diagnosing heart diseases using heart sound signals. Subsequently, L.Khadra et al. applied wavelet transform to decompose the high frequency and middle frequency information of heart sound signals of patients with irregular heart rate thus achieving the desired effect of differentiating normal from abnormal individuals. Babaei et al. [4] proposed a versatile multi-resolution wavelet algorithm for the main features of three heart valve lesions. Dokur et al. [5-6] used wavelet transform for segmentation and feature extraction of S1 and S2 with good application.

The multi-resolution of WT is still a fixed characteristic and once the basic wavelet function is selected, we have to use it to analyse all the data of the whole signal, which is a drawback of wavelet analysis. Furthermore, as with STFT, wavelet analysis cannot give satisfactory time-frequency results in the time-frequency domain due to the uncertainty principle, and improvements in the frequency domain are necessarily accompanied by ambiguities in the time-domain results. However, wavelet analysis is still a very effective and desirable time-frequency analysis method for non-stationary signals, the STFT is not as good as the WT in analyzing the details of the intensity and trend of the murmur and the applied tones.

The wavelet transform has good prospects for application in heart sound signal processing. The time-varying spectral analysis of the heart tone signal can be achieved so that the signal can be analyzed in arbitrary details, but in the analysis of the heart tone signal in some cases the choice of different wavelet basis functions can yield very different results. Therefore, the wavelet coefficients can better reflect the characteristics of the heart sound signal by selecting the appropriate wavelet basis functions.

3.3. Wigner-Ville Distribution

The Wigner-Ville distribution was originally proposed by Wigner in 1932 for the study of quantum mechanics; it was used by Ville in 1948 for signal analysis. The Wigner-Ville distribution is a quadratic transformation with the following Wigner-Ville distribution for the signal x (t).

$$\mathrm{WVD}(t,w)=\int_{-\infty}^{+\infty} s(t+\frac{\tau}{2})s*(t-\frac{\tau}{2})e^{-j\tau\omega}\,d\tau$$

In the formula, s (t) is the analytic signal of x(t) and s*(t) is the complex conjugate of s(t). WVD performs signal processing by mapping a one-dimensional function of time or frequency into a two-dimensional function of time-frequency, which in turn reflects the variation of signal energy with time and frequency.

Gavrovska et al. [7] proposed a joint time-frequency representation based on a pseudo-affine Wigner-Ville distribution for automatic detection of heart sound signals. Djebbari et al. [8-9] proposed a new algorithm based on a redistributed smoothed pseudo-Wigner-Ville distribution to detect aortic and pulmonary valvular splitting in second heart sounds.

The Wigner-Ville distribution has a high time-frequency resolution, but cross terms appear and the time-frequency characteristics of the signal are affected and become obscure, as well as affecting the analysis and processing of the signal. The suppression of cross terms also results in a reduction in resolution.

3.4. Hilbert analysis

Huang proposed the analysis of signals by empirical mode decomposition analysis in 1996, introducing the Hilbert spectrum, an analysis method named Hilbert-Huang Transform, or HHT for

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short.

The HHT is divided into two parts: empirical mode decomposition and Hilbert transform. The signal is adaptively decomposed by EMD into a series of eigenmode functions, a Hilbert transform is applied to each IMF to obtain the corresponding instantaneous time-frequency and energy distributions, and the time-frequency-energy distributions of all IMFs are constructed and aggregated to obtain the Hilbert spectrum of the original signal. For the component x (t) of the decomposed IMF, the Hilbert transform is as follows.

$$H[x(t)] = P\frac{1}{\pi}\int_{-\infty}^{+\infty}\frac{x(\tau)}{t-\tau}d\tau$$

In the formula, P is the principal value of Corsi.

The Hilbert spectrum clearly describes the variation of the signal frequency and gives a fine frequency domain solution, while the wavelet analysis gives a very vague frequency domain solution, especially at the high frequency end, where the signal frequency band is greatly broadened. The frequency domain solution of the wavelet analysis is again very vague, especially at the high frequency end, where the signal frequency band is greatly broadened. For non-stationary signals, the Hilbert time-frequency analysis method gives more satisfactory results than wavelet analysis.

Tseng et al. [10] demonstrated the superiority of the method by applying the Hilbert-Yellow transform to detect S3 and S4. Hung et al. [11-18] proposed a heart sound time-frequency analysis method based on the Hilbert-Yellow transform and demonstrated that it could provide higher frequency resolution.

The HHT can decompose the non-linear non-stationary signal adaptively according to the characteristics of the signal to be analysed, achieving high temporal resolution and high frequency resolution, and can be applied to the analysis of abrupt signals.

Compared to the traditional Fourier analysis method, the Hilbert analysis method is innovative in that it introduces a method of localised signal decomposition, which gives accurate results of signal frequency variation at both the high and low frequency ends. Hilbert analysis has a higher time-frequency resolution than wavelet analysis and shows a finer and more consistent time-frequency distribution.

4. Novel deep learning algorithm methods

New approaches to heart sound research draw on deep learning and artificial intelligence for better classification and subsequent processing of heart sound signals, including CNN, RNN, U-net framework and other methods. The difference between traditional classification algorithms and deep learning methods is mainly that traditional pattern recognition methods require manual extraction of features, while deep learning methods can do the job of feature extraction by self-learning from a large number of samples, i.e. feature extraction and classification recognition are fused together.

4.1. Convolutional neural network (CNN)

Convolutional neural network is a relative mature network framework which has been widely used in the image domain, but is also gradually being used in speech semantic recognition and biomedical signal classification.

CNN is a special type of deep feed-forward neural network consisting of an input layer, a hidden layer, a fully connected layer and an output layer. The hidden layer consists of alternating convolutional and pooling layers, where features are extracted by convolutional operations and more abstract features are obtained by pooling operations, which are fed into one or more fully connected layers.[19] CNN is able to achieve good classification results in various speech and image areas due to three important features: sparse connectivity, weight sharing and pooling. These properties can help improve machine learning systems and make CNN somewhat translation, scaling and torsion invariant.

The existing heart sound classification algorithm has poor universality, relies on accurate segmentation, and has a single classification model structure, etc. A deep convolutional neural network (CNN) approach can be adopted: the CNN is trained with a large number of two-dimensional feature maps of heart sounds that have not undergone accurate segmentation, and the heart sound signal is pre-processed to obtain a large number of heart sound feature maps that have not undergone accurate segmentation; the CNN model is used to train and test the heart sound feature maps. The experimental results show that CNN do not rely on the exact segmentation of the underlying heart sounds compared to other heart sound classification algorithms, and have improved classification accuracy, sensitivity and specificity. Another advantage of CNN over other classifiers is the ability to automatically extract features, which is expected to be used for machine-assisted auscultation.

Experiments showed that the densely connected convolutional network model showed a significant advantage in the task of heart sound classification due to its feature reuse function; the classification result of the jump connection-based convolutional nerve network was only second to that of the densely connected convolutional nerve network, and the classification result of the single connection-based convolutional nerve network was the worst among the three. Compared to other existing heart sound classification algorithms, the The CNN heart sound classification algorithm does not rely on basic heart sound segmentation, and the training sample size is larger and the model structure is more representative, which makes the heart sound classification algorithm more universal and robust. The CNN network has much higher training parameters than the other networks, and due to its own characteristics, the difference in time between each iteration is small, the algorithm is more robust and has better classification performance.

CNN heart sound classification methods have shortcomings, such as most heart sound classification algorithms rely on the accurate segmentation of basic heart sounds, which is a tedious process and affects the classification performance; due to the single structure of the classification model, the heart sound signal features cannot be fully explored and extracted. Moreover, the heart sound classification algorithms are often trained on small samples and their generalizability cannot be effectively verified.

4.2. Recurrent neural network (RNN)

The RNN is a structure that recurs over time, i.e. a recurrent neural network on a time axis. It is a directed acyclic structure consisting of an input layer, a hidden layer and an output layer. The "loop" in an RNN keeps the output of the system's hidden layers in the network and determines the output together with the input at the next moment. RNN networks have been widely used for text prediction and time series analysis, and have achieved good results.

The Long Short Term Memor (LSTM) is a special RNN structure, proposed by Prof. Schmidhuber in 1997, which aims to solve the problem of long time dependence. Theoretically, the current state of an RNN can be determined by an infinite number of previous states, however, RNNs face the same problem of gradient explosion or gradient disappearance in the process of correcting weights, and the problem of long time dependence arises.

2019, Tan et al. [20-21] showed that CNN has high accuracy in heart sound classification compared to RNN and LSTM, and LSTM network performs second only to CNN network, while RNN performs poorly. RNN has strong model oscillation during training, and it is easy to fall into local minima and overfitting phenomenon. The LSTM network is widely used in text prediction and has been used in semantic analysis, and its application in heart sound processing has certain advantages, but on the whole the CNN neural network has more potential for heart sound signals.

CNN use stacked convolutional kernels to extract features layer by layer, with each kernel focusing on one feature and sharing weights across the image. Compared to fully connected neural networks, CNN improve the efficiency of feature extraction and greatly reduce computational effort, enabling efficient processing of gridded data.

In contrast, RNN use recurrent cells as the core of the structure, each receiving as input the input of the current time step and the processed state of the previous time step. Due to the increased correlation between individual time steps, RNN can better handle sequences with temporal relationships.

4.3. U-net Framework

The U-Net framework originated from full convolutional networks and is commonly used for medical image segmentation. The model is a classical coder-decoder structure, with the left part used for feature extraction and the right part for upsampling and feature fusion.

The single-channel sampling structure of the left-hand side of the original U-shaped array model was replaced by a three-channel structure, and normal convolution was replaced by zero convolution. As the ECG signal is low-frequency and amplitude-based data, it is difficult to capture a wide spectrum of ECG signal amplitude changes with a small perceptual field [22-24]; moreover, the heartbeat itself is a short and one-dimensional signal, and it is important not to focus too much on the whole and ignore local information. In this study, the three channels on the left side of the model perform convolution, stack normalization (BN) and activation (ReLU) on the input signal [25]; in the model, hole convolution is used instead of normal convolution, and some pixels are ignored for convolution when hole convolution is performed. At the same time, the output neurons can obtain different receptive fields by setting different void rates for each channel.[26-29]

This multi-channel and cavity convolution design is most suitable for extracting feature information from one-dimensional data such as ECG signals. Once each layer in each channel has undergone the above process, the results are combined according to the channel dimension, and this result is used to merge the features with the sampling results in the right-hand section.

The U-net model was used to segment the heart sounds in the dataset, and then an Adaboost integrated classifier, a CNN-based classifier and a CNN-LSTM based classifier were used on the public dataset. The experimental results show that the CNN-LSTM model performs well and can be used to classify different diseases. The U-net based heart sound segmentation algorithm combined with the CNN-LSTM heart sound classification algorithm can show good performance in the study of heart sound signals.[30-33]

5. Summary

As the standard of living increases, people are becoming more and more concerned about their health. The heart sound signal is one of the most important physiological signals in the human body. As a result, there has been a lot of interest in heart sound diagnosis as an important tool for monitoring heart-related diseases. While heart sounds are usually performed in hospitals by experienced physicians, automated heart sound diagnostics can help to protect the health of the heart by making it easier to detect abnormal heart sounds in a variety of settings. With the help of deep learning and the development of big data, the segmentation-independent automatic heart sound determination method makes full use of the global information of heart sounds, using CNN and RNN automatically extracted time-frequency features and trained with data augmentation methods, resulting in high classification accuracy. This will be of great help in heart sound assisted auscultation, which will help people to detect cardiac abnormalities in a timely and accurate manner and prevent them early.

Compared to traditional methods, the deep learning approach ensures a larger sample size and greater generalisability, eliminates the need for manual feature extraction, facilitates real-time decision-making for future machine-aided auscultation, and has greater potential for heart sound classification. Further research on the application of CNN to heart sound classification can be devoted to improving the accuracy and practical application of the algorithm. Researchers can further develop the use of CNN or RNN structures with more reasonable and effective modules and super-parameters or more audio data augmentation operations to improve the classification accuracy, and in addition, with a better understanding of heart sound auscultation, the classification effectiveness of the model can be improved by setting up more reasonable transfer rules from heart sound segment judgments to heart sound sample judgments.

In practice there is no one analysis method that is ideal for any study or application. In practice, the choice of analysis method depends on the characteristics of the signal being analysed, and a combination of these methods or an innovation based on one method may be considered. The use of deep learning perspectives and ideas to investigate methods for determining heart sound abnormalities would be a very promising direction. With the further development of heart sound research and the widespread use of modern digital signal processing techniques, heart sounds will play a greater role in clinical diagnosis and basic physiological research.

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