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Classification of Heart Sound Based on EMD

Feng Mengdie

***Abstract*— This groundbreaking research introduces a novel model for classifying heart sound signals, which utilizes Empirical Mode Decomposition (EMD) for detailed signal analysis. The model decomposes these signals into Intrinsic Mode Functions (IMFs) and further categorizes them into four fundamental stages of the cardiac cycle. By employing Hilbert-Huang Transform (HHT) to extract crucial time-frequency features, accurate classification is achieved. Despite the presence of internal and external noise interference, the model maintains significant accuracy, owing to the inherent denoising capability of EMD, thereby circumventing complex preprocessing steps. Through extensive experimental validation, employing a hybrid Convolutional Neural Network-Long Short Term Memory (CNN-LSTM) framework, the model demonstrates outstanding precision, approaching a threshold of approximately 95% in initial stages. Serving as a cutting-edge model for deepening understanding of cardiac activity and early diagnosis of cardiac ailments, it adeptly addresses common noise issues encountered in traditional systems. With wide-ranging applications in clinical and home health monitoring, this pioneering model lays the groundwork for future advancements in cardiac healthcare.**

***Index Terms*—Empirical Mode Decomposition (EMD), Intrinsic Mode Functions (IMFs) , Hilbert-Huang Transform , Convolutional Neural Network-Long Short Term Memory (CNN-LSTM)**

I. INTRODUCTION

Cardiovascular diseases(CVDs) affects more than 500 million people worldwide by 2022 which number of death ranks first in the number of deaths each year,representing about 0.4 of the global mortality. Early diagnosis through pervasive approaches can help detect heart disease in patients at earlier stages and consequently improve the survival rate. However,effective cardiac auscultation which is a subjective practice requires trained physicians and extensive training. Thus,automatic analysis of heart sounds has been presented as an alternative to auscultation with significant impact for early diagnosis of cardiac diseases.

Automated classification of the Phonocardiogram(PCG) have been extensively researched in the past few decades. Analysis of the heart sound can be broadly divided into two principal areas,including segmentation and classification of recordings.Below is a list of several works related to the two aspects of heart sound signals.Sun et al.[1]proposed an automatic heart sound signal segmentation method based on Hilbert transform. In Springer et al.[2],the hidden semi-Markov model method was extended with logistic regression to achieve the signal segmentation in noisy environment. With the study of noise,Davoud Shariat Panah et al. [3] discussed the question how noise and degradation in heart sound signals impact the overall accuracy of data-driven models. Heart sounds with preprocessing were segmented on U-net in He et al.[4].Different kinds of spectral features, including spectral parameter models, instantaneous frequency and amplitude and octave power, were extracted in Schmidt et al. [5] to characterize the time–frequency attribute. As for heart sound classification, Wang et al. [6] used a combination of hidden Markov model and MFCC features to classify abnormal heart sound signals. In Baydoun et al. [7],two integration techniques,namely Bagging and Boosting were adopted to improve the recognition rates based on low-performance classifiers. Power spectral density of the raw heart sound signal was extracted in Nilanon et al. [8] and fed to the CNN for automatic heart sound classification.O.Deperlioglu [9] applied a stacked autoencoder network to classify and obtained an efficient results. Latif et al. [10] proposed a RNN-based abnormal heartbeat detection algorithm. The paper explored the performance and computational complexity of four RNN models,namely LongShort-termMemory,GatedRecurrent Units,Bidirectional Long Short-Term Memory and Bidirectional GatedRecurrent Units.

The main contributions of this paper are threefold:(1)The Hilbert Huang Transform cepstrums are extracted with segmenting the heart sound signal.This method can analyze time-domain and frequency-domain features which are more comprehensive and the method get an efficient result. (2)There is no need to de-noising the signal.It reduced the experiment procedure and the difficulty of preprocessing. (3)The accuracy can be guaranteed even with the addition of other noises.

There are five parts in the paper. Section 1 introduces the brief information of heart sound and the related work of heart sound. Section 2 describes the techniques and methods used in the paper. Section 3 evaluates the experimental results. Section 4 is a discussion of experimental results and research techniques. Section 5 summarizes this paper.

II. METHOD

Our proposed methods is based on HHT to solve with the problem of heart sound recordings classification , which uses non-statinonary recorded signal with low amplitude and frequency as input. In this section, it provide the details of the methodology for this study. As shown in Fig 1. The proposed method could be divided into three steps: (1) Preprocessing, (2) Feature Extraction and (3) Classification.

A. *Preprocessing*

Heart sound signal preprocessing is the basis of the whole method. The objective is to prepare the raw data for the next phase by reducing the effect of noise ,resampling the data, and normalize the all recordings.Different techniques have been proposed to address the noise issue in many articles about heart sound. Although the methods are useful to improve the index of these experiments, it can't make the noise

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Feng Mengdie, Tiangong University, TianJin,18731683754

elimination completely even it may produce the negative results. In this paper, it doesn't exist the method to de-noise the signals. As illustrated in Fig 1, the signal were normalization and segmentation to finish the Pre-processing. These steps were shown in the following:

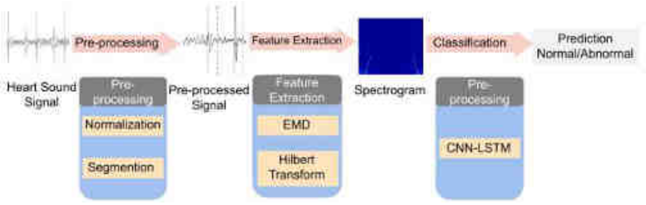

Figure1:Heart sound classification pipeline

Normalization:The amplitude of different heart sound signals were all normalized and limited to the scale of [-1,1].The equation of normalization is in the follow:

$$x_{norm}[n]=\frac{x[n]-\text{mean}\,|x[n]|}{\max|x[n]|} \tag{1}$$

Segmentation:Segmentation is used for a better method of the PCG signal and to extract more significant features. The heart sound recordings was segmented into cycles and four terms: the first heart sound(S1),the second heart sound(S2), systolic period,and diastolic period. In this work, a segmentation technique based on Hidden Semi-Markov Models [2](HSMM) is applied. The result of Segmentation is shown in Fig 2. The performance of this algorithm is ensured by using a Viterbi algorithm. In addition, the logistic regression for emission probability estimation is also converted.

B. Feature Extraction

In this work, the HHT(Hilbert-Huang Transform) spectrum is extracted as the feature. HHT is used to adaptively decompose the non-stationary and nonlinear signals and extract the instantaneous frequency. The main purpose is to obtain the Hilbert spectrum of the signals for time-frequency analysis. In Fig1, HHT consisted of two steps: Empirical Mode Decomposition(EMD) and Hilbert transform. EMD is used todecompose the signal into a series of Intrinsic Mode Functions(IMFS). Hilbert transform is the carried out to acquire instantaneous frequency and amplitude and constitute the time frequency-energy distribution, Hilbert-Huang spectrum, of the recordings.

EMD: Most non-stationary recordings may contain not only one oscillation mode, which is why the HT of original signal cannot produce an accurate instantaneous frequency. The heart sound signals is first decomposed to IMFs. To acquire the IMFs, local minima and maxima of the signal were identified. The envelopes of the local minima and maxima were respectively formed by cubic spline fitting. The mean of the upper and lower envelopes is denoted as $m_1(t)$, which is removed from the signal with normalization $x_{norm}[t]$ as the original signal $x(t)$ to obtain $h_1(t)$ .The equation is as followings:

$$x(t)-m_1(t)=h_1(t) \tag{2}$$

$h_1(t)$ as the new signal repeated the process described above until the met the criterion of the IMF. $c_1(t)$ was the first IMF. $c_1(t)$ is subtracted from the new signal,and the difference is the residue component $r_1(t)$:

$$r_1(t)=x(t)-c_1(t) \tag{3}$$

Where $r_1(t)$ is taken as the new original signal, and the second IMF component $c_2(t)$ can be obtained by using the above process.

$$r_2(t)=r_1(t)-c_2(t) \tag{4}$$

The iterative process is again executed to extract the IMFs until the component c_n or the residue component r_n is less than a predetermined threshold or the residue component r_n becomes a monotonic function. It means than no more IMF could be further extracted.The $x(t)$ was represented by

$$x(t)=\sum_{i=1}^{k}c_i(t)+r_k(t) \tag{5}$$

Hilbert Transform: The next step of HHT, Hilbert Transform extracted the instantaneous frequency and amplitude of IMFS. HT is applied to each component, which can be expressed as:

$$z_i(t)=x_i(t)-jy_i(t)=a_i(t)e^{j\theta_i(t)} \tag{6}$$

$x_i(t)$ and $y_i(\mathrm{t})$ are apart the real part and the imaginary part of analytical signal. The instantaneous amplitude is defined by the following equation:

$$a_i(t)=\sqrt{x_i^{\,2}(t)+y_i^{\,2}(t)} \tag{7}$$

The instantaneous phase is:

$$\theta_i(t)=\arctan\frac{y_i(t)}{x_i(t)} \tag{8}$$

The derivative of the instantaneous phase for time is the instantaneous frequency:

$$\omega_i(t)=\frac{d\theta_i(t)}{dt} \tag{9}$$

C. Classification

The features are used to train the classifiers after extracting.In the past few years,convolutional neural network(CNN) has been shown to be effective in large scaleand high dimensional data learning,especially in computer vision. And recurrent neural network(RNN) was investigated to be valid in long-term sequence. In this study, the CNN and LSTM were combined(CNN-LSTM) to perform feature learning on the HHT spectrum derived from the heart sound signal.

CNN-LSTM model is implemented using Pytorch deep learning library. Fig 1 shows the architecture of the model with the HHT spectrogram as input. This model consists of four convolutional layers. The first, second,third and forth convolutional layers have 64, 32, 16 and 32 kernels, respectively.The fist and second convolutional layers use the kernel size of (11,11) and (5,5). A kernel size of (3,3) was used for third and forth convolutional layers. Also, the stride was fixed at 1, and the ReLu function was used as the activation function. Each convolutional layer is followed by a max-pooling layer with a pool size of (2,2). After convolutional layers, the data is reshaped in order to be fed into the LSTM part of the network. This part is composed of two bi-LSTM, two dropout layers, one flattening layer and one fully-connected layer which outputs the result(normal or abnormal).

To train the models,Adam optimization with a learning rate of 0.001 and cross-entropy objective function is applied. CNN LSTM model are trained on the dataset for 25 epochs. This way, the model is trained on the large variety of normal and abnormal heart sounds.

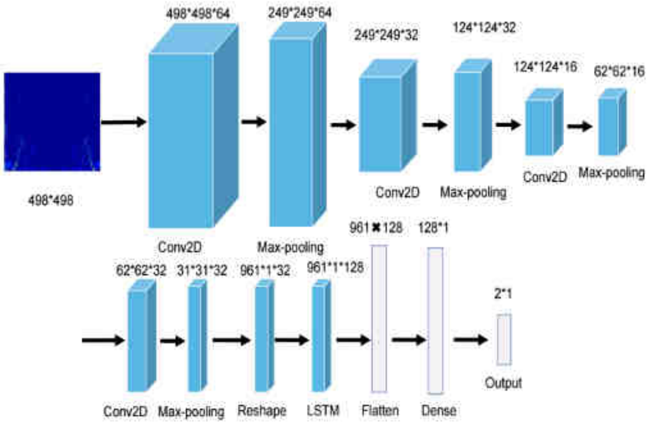

Figure1: Heart sound classifization model

III. RESULTS

A. DataSet

The PhysioNet heart sound dataset was published as part of the PhsyioNet/Computing in Cardiology 2016 challenge.This dataset with six subset datasets contains 3240 heart sound recordings,out of which 2575 samples were captured from healthy subjects while 665 samples wre collected from pathologic subjects.These signals were obtained by using various electronic stethoscopes,ranging from 5s to 120s in length,and the sampling frequency is 2000 Hz. This dataset is applied in our experiments for deep learning model.

Table1:The details of the dataset

PCG	正常	异常
a	117	292
b	384	104
c	7	24
d	27	28
e	1849	180
f	7	24
总和	2575	665

B. Evaluation Metrics

For the evaluation of the proposed method,four measure ments are used for each experiment.The features to evaluate models is balanced across normal and abnormal classes.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{10}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{11}$$

$$Specificity = \frac{TN}{TN+FP} \tag{12}$$

$$F1 = 2\frac{Accuracy * Sensitivity}{Accuracy + Sensitivity} \tag{13}$$

C. Performance comprision with methods

The experiment is to prove that the HHT method can get better performance with noise but obtain lower score with filter, and other method can’t get the result. In this experiment,the performance with different noises added into the original signals,and compared with the method by MFCC with noises.There are four noises in the study including white gaussian noise, factory noise, F16 noise and cough noise. And the butterworth filter is applied in the experiment to compare with these noises. From the above two experiments, this one chose the best SNR level noises and the best count of imfs. The SNR 20 and imf6 are applied in this experiment. The experiment uses HHT method to extract the features and CNN-LSTM model to classify the heart sound signals. And then it gets the evaluation metrics to compare the performance.

From Fig 9,it concludes that the heart sound signals with noise and using HHT method obtain the better score than applying MFCC method. It can be obviously found that the accuracy of HHT method with noise rises but MFCC method with noise is down. The result prove the aim of the experiment. It also explain MFCC method is affected by noise.

The recordings with noise are decomposed more effectively by using HHT method display the time domain and frequency domain which can provide more comprehensive features. From the experiment results,the HHT method is applied in heart sound signal is effective and it proof the the rationality of the theory in this paper.

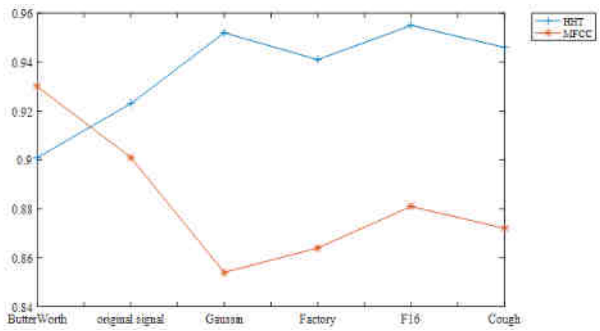

Figure 2:The accuracy of HHT and MFCC

IV. CONCLUSION

This paper investigated the heart sound signal based diagnostic tool to construct an efficient early detection system for cardiac disorders. The framework which with time-frequency features and hybrid CNN-LSTM model in the study is proposed.More precisely,the signals are decomposed into IMFs with EMD and segmented the IMFs into four parts of the cardiac cycle.Then the features are extracted using Hilbert transform and the features are input into the model.Finally,the experiment with noises achieves the superior scores comparing with MFCC.It also illustrates that the EMD has the property of denoising and the framework is more suitable in daily life.The method is expected to provide a complementary diagnostic tool in the first assessment in the case of asymptomatic heart diseases.

In the future,it need to test the performance of the proposed framework on the new data from other databases and new noise. More efficient models should be applied in heart sound signal classification.Besides,the multi-class classification problem for the recordings is another important issue in the diagnostic system for encountering frequently different heart diseases.

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Feng Mengdie

Graduated from the School of Software Engineering, Tianjin University of Technology, with a master's degree. During the postgraduate period, the research direction