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Classification of Heart Sounds Based on Topological Data Analysis Method

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Abstract. Topological data analysis (TDA) method could catch the rich geometric and topologic information of big data and find subtle differences between different signals. TDA method opens up a new way for biomedical data analysis. In this study, we applied TDA method for heart sound signals (PCG) classification. First, the sliding window method was used to build a point cloud. Then, the persistent barcode is extracted from the point cloud by using the topology technology Vietoris-Rips (VR) filtration. At last, GoogLeNet transfer learning model was applied for classifing. The proposed the model did work well on the 2016 PhysioNet/CinC challenge dataset, $Se = 99.30\%, +P = 99.57\%, F1 = 99.44\%, mAcc = 99.47\%$. The results showed that TDA can be used for the analysis of physiological signals in large quantities. The proposed method in this study has opened a new space for the application of TDA methods in physiological signal analysis.

Keywords. Topological data analysis, PCG, VR filtration, persistent barcode

1. Introduction

Cardiovascular disease is the most important cause of death in the world: 17.9 million people die from cardiovascular disease than from any other cause of death in 2019. Heart sounds could detect variable force congenital heart valve damage of the heart, which can reflect the disorder of cardiac mechanical activity caused by cardiac conduction tissue lesions. It can be used as a guide for further diagnosis, and plays a significant role in the early diagnosis of cardiovascular diseases.

In the past 50 years, the automatic detection of abnormal heart sounds has attracted the attention of researchers. The vibration of the whole heart structure, caused by the opening and closing of heart valves and the flow of blood, produce heart sounds, which include the first (S1) and second (S2) heart sounds. When the heart valve is diseased, it will cause abnormal mechanical fluctuation of the valve and changes in blood flow, resulting in abnormal heart sounds. In 1963, Gerbarg [1] first published the automatic classification of heart sound pathology. In 2016, PhysioNet/CinC held a challenge on the classification of heart sounds recordings [2, 3]. Since then, an upsurge of classifying of normal and abnormal heart sounds recordings was set off. Avendano-

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Valencia et al. [4] used the time-frequency feature and KNN for the classification. In the study[5], Hidden Markov model was used for PCG classification. Ping Wang et al. [6] applied the Mel frequency cepstrum coefficient to extract the features of PCG signals for classification.

In this study, Vietoris-Rips (VR) filtration [7] of topological data analysis method is used to extract the features of PCG signals. VR filtration could obtain the rich topological and geometric characteristics of signals which is suitable for physiological signals [8]. And GoogLeNet, a deep neural network model, was used for classifying, which is accurate and light by replacing the large size convolution kernel by a stack of multiple small size convolution kernels. First paragraph.

2. Method and Dataset

2.1. Topological data analysis method

The topological data analysis method could extract rich topological and geometric characteristics of signals by Vietoris-Rips (VR) complex, and construct the persistence statistics diagram. There are many complexes in the topological data analysis method. VR complex has high computation efficiency because it only needs to calculate 0-dimensional and 1-dimensional complex, and high-dimensional complex did not need. What's more, VR complex represented the distance between two points in the metric space, which is appropriate for the analysis of physiological signals with large amount of data.

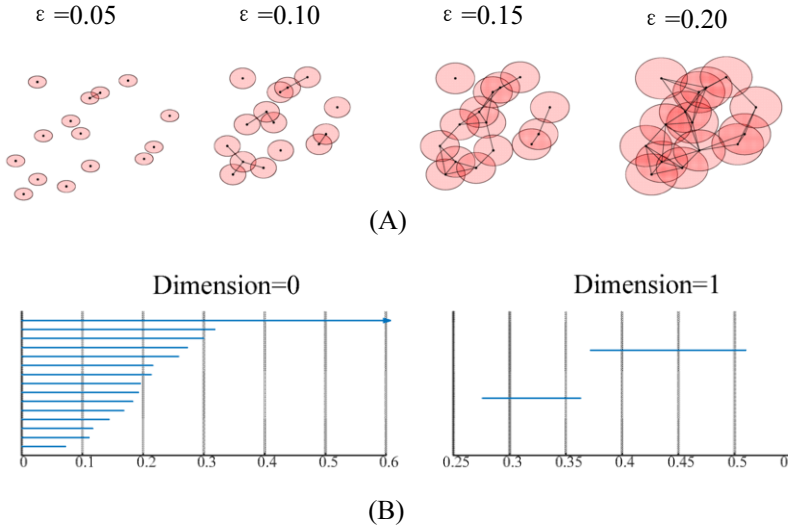

Figure 1. (A) The filtering process of the VR complex. (B) The 0-dimensional and 1-dimensional persistence barcode of VR filtration. As ε continues to increase, an increasing number of simplicial complexes are formed. In (B), the abscissa of the persistence barcode picture represents 2ε. When ε= 0.05, there are 14 connected components; when ε= 0.10, there are 7 connected components; when ε= 0.15, there are 3 connected branches; and when ε= 0.20, there are 1 connected components; when ε= 0.276 to ε=0.363 and ε= 0.372 to ε=0.51, there are a hole.

The VR complex for $X \subset R^d$ and $\varepsilon > 0$ is defined by the equation (1).

$$VR(X,\varepsilon) = \{\sigma \subseteq X \mid \max_{x,y\in\sigma} \mid x - y \mid \leq \varepsilon\} \tag{1}$$

The VR complex together with the inclusion $VR(X,r) \subset VR(X,s)$ for $r \leq s$ form a filtered simplicial complex. Figure 1 (A) shows that as the increasing, the simplicial complexes are formed. Then the Betti numbe [9] on each complex was calculated, which represented the number of A-dimensional holes in the complex. And the persistent barcode [10] was constructed based on the Betti number, which can visualize the complex life of a given filter hole for data analysis. Figure 1 (B) shows the 0-dimensional and 1-dimensional persistence barcode of VR filtration.

2.2. Dataset

The 2016 PhysioNet / CinC challenge dataset [2, 3] was used in this study, which were from six databases including 3240 heart sound records with a total duration from 5 seconds to 120 seconds. And all recordings have been resampled to 2000 Hz. Test data cannot be obtained, so only training data was used. These heart sound recordings originated from healthy subjects and patients with cardiovascular diseases, who from couple contributors around the world. All the heart sound records are divided into two types: normal (665) and abnormal (2575) heart sound records. Each recording contains only one PCG lead. Table 1 shows the details of the database.

Table 1. Dataset detail of two class dataset

Database	Abnormal	Normal	Total
a	292	117	409
b	104	386	490
c	24	7	31
d	28	27	55
e	183	1958	2141
f	34	80	114
total	665	2575	3240

2.3. Experimental procedure

As all the recordings form six different databases, the signal preprocessing was necessary. First, all PCG signals were down-sampled to 500Hz to reduce the load of calculation. Second, Z-score standardization was used to normalize the original data. And then, the 0.2-second sliding window method was applied to build the point cloud. The signal series was segmented into 0.2-second fragments no overlap. All fragments formed a multidimensional matrix, which termed as the point cloud. And then, VR filtering process was used to build the VR complex. And the persistent barcode was generated. Finally, the GoogLeNet, a deep neural network model with the Inception module launched, was used for classifying the normal and abnormal PCG signals. The persistent barcode of all signals obtained by the persistent homology method were fed into GoogLeNet model.

Four evaluation indicators sensitivity (*Se*), precision (+*P*), comprehensive index (*F*1), and correction accuracy (*mAcc*) were selected to evaluate the classification accuracy, which are defined as follows:

$$\boldsymbol{Se} = \frac{TP}{(TP + FN)} \times 100\% \tag{2}$$

$$+\boldsymbol{P} = \frac{TP}{(TP+FP)} \times 100\% \tag{3}$$

$$\boldsymbol{F}1 = \frac{TP}{TP+0.5(FR+FN)} \times 100\% \tag{4}$$

$$\boldsymbol{mAcc} = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

Among them, *TP*: normal signal is correctly predicted as an abnormal signal by the model; *TN*: abnormal signal is correctly predicted as a normal signal by the model; *FP*: abnormal signal is incorrectly predicted as a normal signal by the model; *FN*: normal signal is predicted as an abnormal signal by the model's signal.

3. Results

Figure 2 displayed the classifying results of the new proposed classification model, the box plot of 4 evaluation indexes ($\boldsymbol{mAcc}, \boldsymbol{F}_1, \boldsymbol{Se}, +\boldsymbol{P}$) for 10-fold cross validation. In the Table 1, the confusion matrix showed the test results of one test set. As shown in table 2 and figure 2, the classify performance of the topological data analysis method was quite excellent. The mean values of evaluation indicators were almost all above 99%, ($\boldsymbol{Se} = 99.30\%, +\boldsymbol{P} = 99.57\%, \boldsymbol{F}1 = 99.44\%, \boldsymbol{mAcc} = 99.47\%$).

Table 2. Confusion matrices of the test results for one test set

Confusion Matrix		Predicted class: Normal	Predicted class: Abnormal	*Se*
True class	Normal	257	1	99.6%
True class	Abnormal	1	66	98.5%
+*P*		99.6%	98.5%	*mAcc*=99.05%

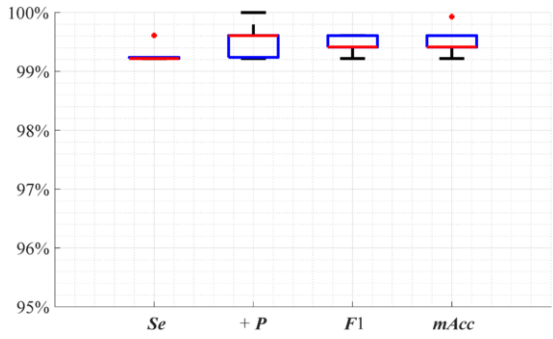

Figure 2. Box plot of 4 evaluation indexes about the classification results

4. Discussion

In this study, a new PCG signals classifying method, based on the persistent barcode of topological data analysis method and GoogLeNet deep neural network model, was proposed. This proposed new model showed a good ability for normal and abnormal PCG signals classification. The results of the proposed method were all above 99%. Table 3 shows the results comparison with other studies. The classification result of this study is better.

Table 3. Results comparison with other studies

Research	Features	Classifier	*mAcc(%)*
Mei et al. (2021) [11]	Wavelet scattering	SVM	93.64
Zen et al. (2020) [12]	PSR and ED computation	NN	97.89
Deng et al. (2020) [13]	MFCC	CRNN	98.335
Chowdhury et al. (2020) [14]	Shannon energy envelope	Five-layer DNN	97.06
Li et al.(2019) [15]	Wavelet scattering transform	TWSVM	98.575
This work	**Persistent barcode**	**GoogLeNet**	**99.6**

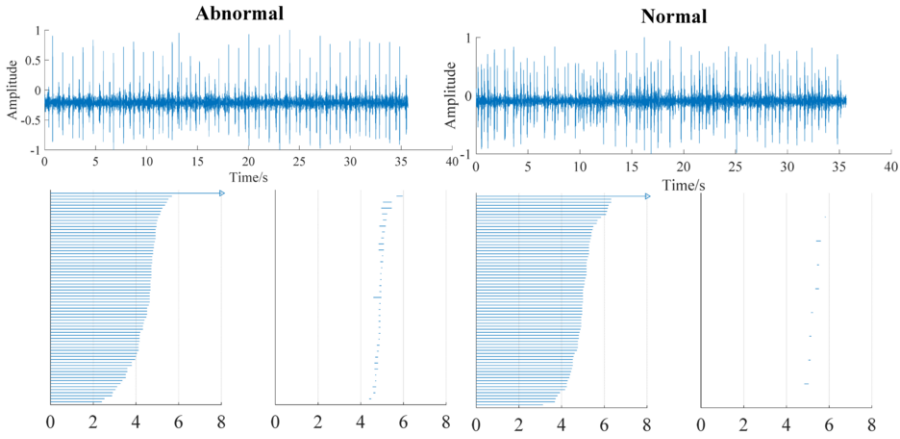

Figure 3. The abnormal and normal PCG signals and related persistent barcode

Figure 3 shows the abnormal and normal PCG signals and related persistent barcode. It was hard to identify the difference between two temporal waveforms of normal and abnormal PCG signals. However, in the persistence barcode, the difference between these two signals was obvious. For normal PCG signals, there was more information in the 0-dimensional and little information in the 1-dimensional persistence barcode. While for abnormal PCG signals, there was more information in the 1-dimensional persistence barcode. The 0-dimensional and 1-dimensional persistence barcode of VR filtration in the topological data analysis method could well capture the subtle differences between normal and abnormal PCG signals.

5. Conclusion

In this study, a new PCG signals classifying method based on the persistent barcode of topological data analysis method and GoogLeNet was proposed. This method has great performance on the classification of the 2016 PhysioNet/CinC challenge database

($Se = 99.30\%, +P = 99.57\%, F1 = 99.44\%, mAcc = 99.47\%$). The persistent barcode of VR filtration in the topological data analysis method represented the distance between two points in the metric space, which is appropriate for the analysis of physiological signals with large amount of data. In the future, we will use VR filtration in the topological data analysis method to analyze more physiological signals.

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