Multi-Frequency Decomposition with Fully Convolutional Neural Network for Time Series Classification

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Abstract

Fully convolutional neural network (FCN) has achieved state-of-the-art performance in the task of time series classification without any heavy preprocessing. However, the FCN cannot effectively capture features of different frequencies. Therefore, this paper proposed a novel FCN structure based on the multi-frequency decomposition (MFD) method. In order to extract more features of different frequencies, the MFD based on real fast Fourier transform (RFFT) is set as a layer of the FCN to decompose the original signal into n sub-signals of different frequency bands. And then the improved FCN fuse those features of different frequencies together to obtain time series classification. Finally, compared with the existing state-of-the-art methods, the proposed method is effectively verified through some datasets in UCR Time Series Classification archive.

Introduction

The existing methods based on the deep learning for time series classification are mostly drawn from its application on computer vision. However, there are some differences between pictures and signals. The pictures follow the nearest neighbor rule, and the neighboring pixels have a higher degree of correlation. Meanwhile, the signals can be regarded as the superposition of different signals, and the features are hidden in different presentation levels. Therefore, these methods above need to be modified to analyze the signals.

In this paper, we propose a multi-frequency decomposition (MFD) method based on real fast Fourier transform (RFFT) that can be added to neural networks as a layer. And then an improved FCN structure is designed to enhance the performance of fully convolutional networks.

Multi-Frequency decomposition based on RFFT

The existing methods based on the deep learning only operate the signal in the time domain, and extract sequence features with temporal convolutions. However, the MFD can decompose the original signal into n sub-signals of different frequency bands. The output from the front layer of the neural network is accepted as the input, and each sequence of the input is decomposed into n sub-sequences, which is set as the output of the next layer. Therefore, the MFD extends the ability of the neural network to process the sequence data.

Algorithm: Multi-Frequency Decomposition

Input:

$T \in \mathbb{R}^{L\times C}$: Output of the front layer
n: The number to be decomposed

Output: $H \in \mathbb{R}^{L\times n\times C}$

for each length-L signal $t \in T$ **do**
  $c \leftarrow RFFT(t)$, c is a complex vector of length-$(L/2)$
  $P \leftarrow$ Divide vector c into n parts
  for each part $p \in P$ **do**
    $q_i = \begin{cases} p_i & i \in index(p) \\ 0 & i \notin index(p) \end{cases}$, index $i \in [0, 1, \cdots, \frac{L}{2} - 1]$
    $r \leftarrow IRFFT(q)$
  end for
  Concatenate r together, and get $R \in \mathbb{R}^{L\times n}$
end for
Concatenate R together, and get the output $H \in \mathbb{R}^{L\times n\times C}$

Improved Fully Convolutional Networks Architectures

The MFD layer is added to the FCN for getting more abundant features of the sequence. And the representation of signals at different frequencies is easily exploited by neural networks. And then those signals of different frequencies are used as the input of the convolutional layer to extract features. Finally, all features are fused together for classification. This proposed approach enhances the ability of the neural network to process the sequence data, so that the desired network structure can be designed flexibly, and be used as a part of the new network structure for the feature extraction.

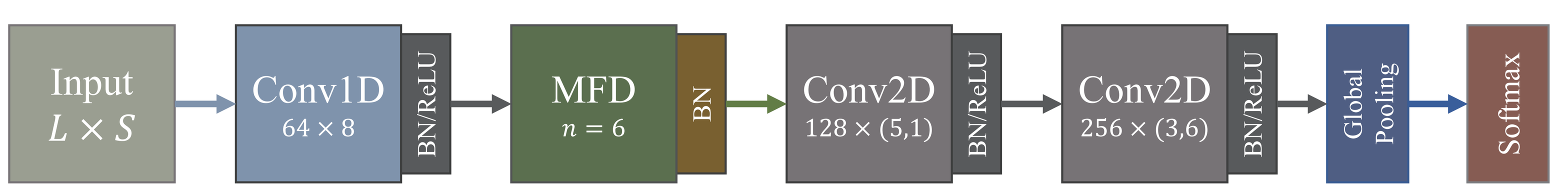
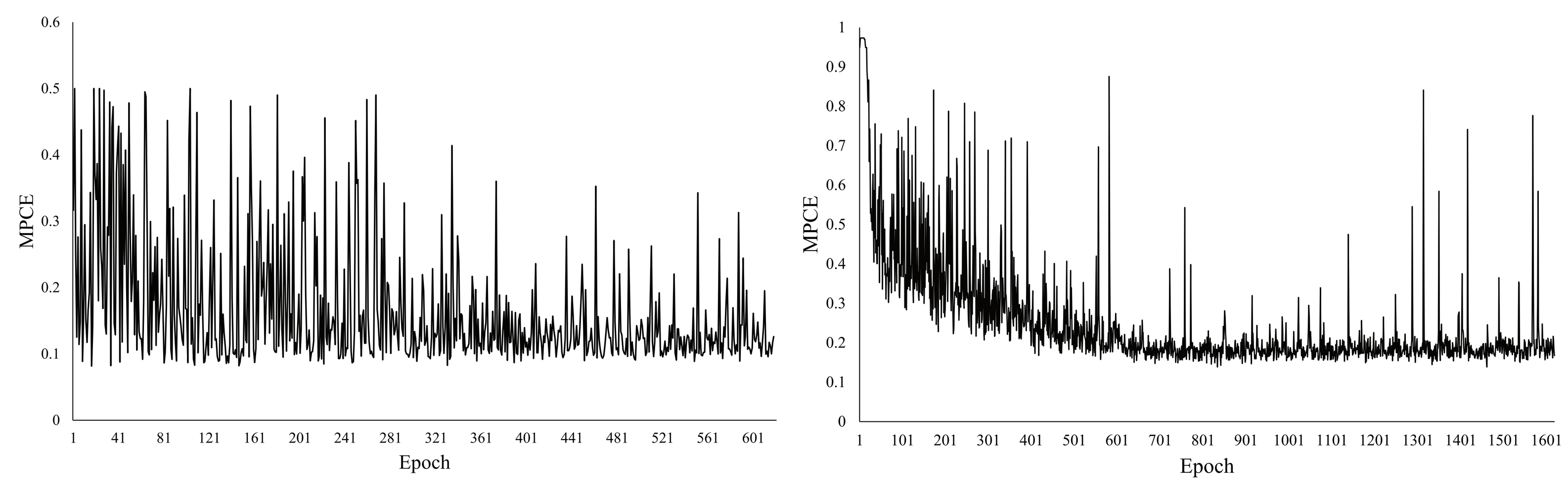


Figure: The network structure of the improved FCN

Experiments and Results

Dataset	MFD-FCN	FCN	ResNet
Adiac	**0.138**	0.143	0.174
Coffe	**0**	0	0
ArrowHead	0.148	**0.12**	0.183
ECG200	0.121	**0.1**	0.13
FordA	0.076	0.094	**0.072**
FordB	**0.078**	0.117	0.1
Beef	**0.1**	0.25	0.233
Haptics	0.453	**0.449**	0.494
BeetleFly	**0.05**	0.05	0.1
BirdChicken	**0**	0.05	0.1
CinCECGTorso	**0.129**	0.187	0.229
ECGFiveDays	**0**	0.015	0.045

Table: Performance comparison of different models



The FordB dataset The Adiac dataset

Figure: MPCE on validated set of some datasets during training

$$PCE_c = \frac{e_c}{N_c}$$
$$MPCE = \frac{1}{C}\sum_c PCE_c$$

Note: e_k denotes the error rate of category c, and C is the number of categories in dataset. The MPCE considers the ratio of each category, and can make accurate measurements even if the number of samples in each category varies widely.

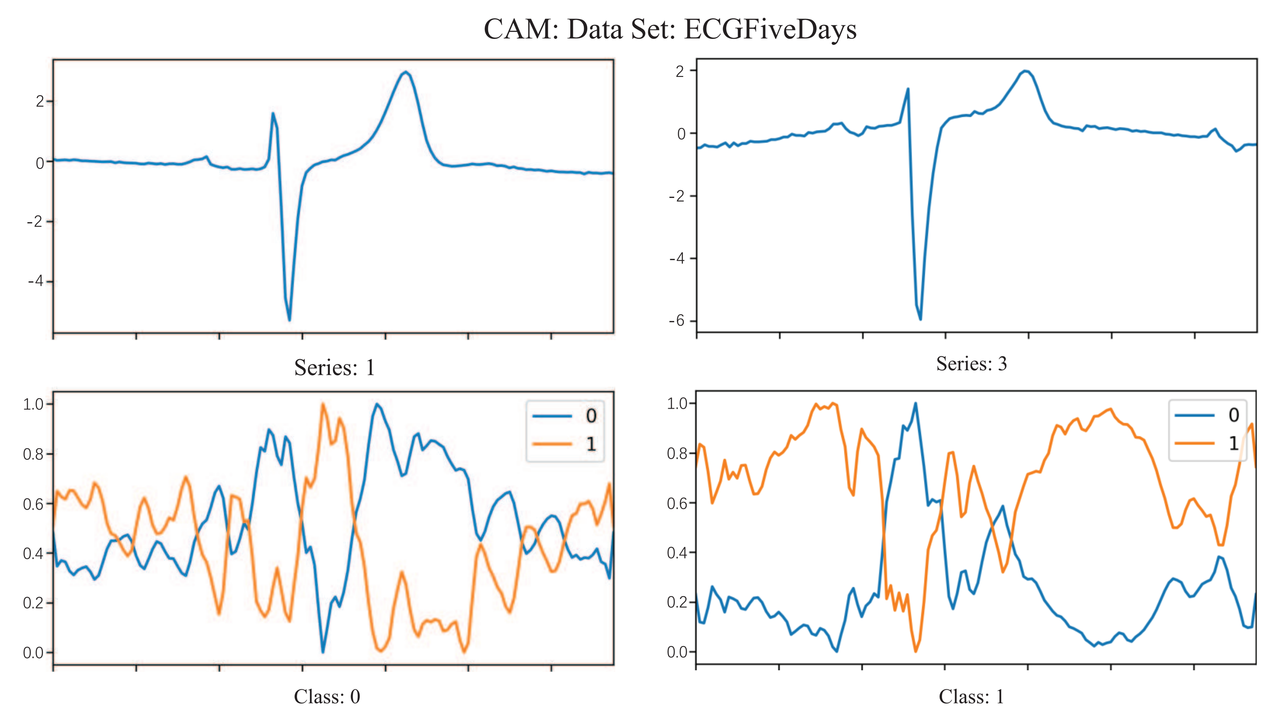


Figure: The CAM on ECGFiveDays data set

$$M_c(x, y) = \sum_k w_k^c f_k(x, y)$$

The Class Activation Maps (CAM) is computed with the weights of this fully-connected layer to indicate the contributing region in the raw data for the specific labels. It can be seen that, Class 0 is more inclined to the position where the original sequence has large fluctuations, while Class 1 tends to be the flat ones. The results of the CAM show that the added MFD layers do not change the transmission of category features in neural networks at different locations in the raw sequence.

Acknowledgements

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