Tensor Representation for Brain Signal Processing (Extended Abstract)

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Abstract

In the past decades, electroencephalograms (EEG) has been widely used for brain-computer interface (BCI). To detect the pattern from EEG signals, different kinds of algorithms have been developed. In our previous works, we already have shown that tensor presentation of EEG signals can improve the EEG signal classification. And the tensor fusion algorithm was used for a multi-modal BCI system. In the system, electroencephalography and near-infrared spectroscopy were recorded simultaneously, tensor-based fused feature vector was used for the classification. The results showed better performance than previous researches.

1 Introduction

Brain-computer interface (BCI) is a system designed to build communication between the brain and intelligent device. BCI system usually uses Electroencephalography (EEG) signals and near-infrared spectroscopy (NIRS) to record brain activities. EEG equipment consists of metal electrodes placed on the scalp [Zheng et al., 2018]. NIRS sensors can measure the hemodynamic signals from target regions of the brain.

Since recorded brain signals are usually full of noise, accurate classification and identification of EEG signals are the key to achieve real-life BCI applications. Many literature has already introduced a lot of different feature extraction and classification methods. Tensors emerged as important tools for the exploratory analysis of multidimensional data. In [Phan and Cichocki, 2010], Phan et al. proposed the tensor decomposition method for the motor imagery feature extraction and classification, which dramatically improved the classification accuracy.

In our approaches, we first generated new artificial EEG signals by proposed data augmentation strategy, and then we transformed EEG signals into integrated time, frequency, and electrode location information tensor as inputs by complex Morlet wavelets[Zhang et al., 2019]. The EEG signals were represented by 4-dimensional tensors. Finally, we used convolution neural networks (CNN)-based neural networks for the motor imagery EEG signal classification. Moreover, in multi-modal BCI system based on simultaneous EEG and NIRS signals, tensor methods was used to fuse the features for the classification [Sun et al., 2020].

2 Materials and Methods

2.1 Tensor representation for EEG signal classification

In most instances of BCI system application, a large training sample is necessary to achieve higher accuracy of EEG signals, but EEG signals are sometimes limited in amount in BCI system for invalid data caused by fatigue of subjects. To address the problems, we proposed to generate artificial EEG signals by our proposed data augmentation strategy. We firstly decomposed EEG signals into several components of representation of specific non-linear oscillation by time-frequency decomposition method, such as empirical mode decomposition (EMD)[Huang et al., 1998], and then we randomly selected original EEG frames from the set of frames belonging to the same class. The first selected EEG frame contributes with all its first decomposed components, the second one with its second ones, and successively until the nth frame, which contributes with its nth ones. In this way, artificial EEG frames will exhibit similar characteristics in time and frequency with the signals that contributes with their decomposed components.

As for original and new generated EEG data, we first transformed obtained EEG data into integrated time, frequency, and electrode location information tensor as inputs by Complex Morlet Wavelets (CMW) with bandwidth parameters
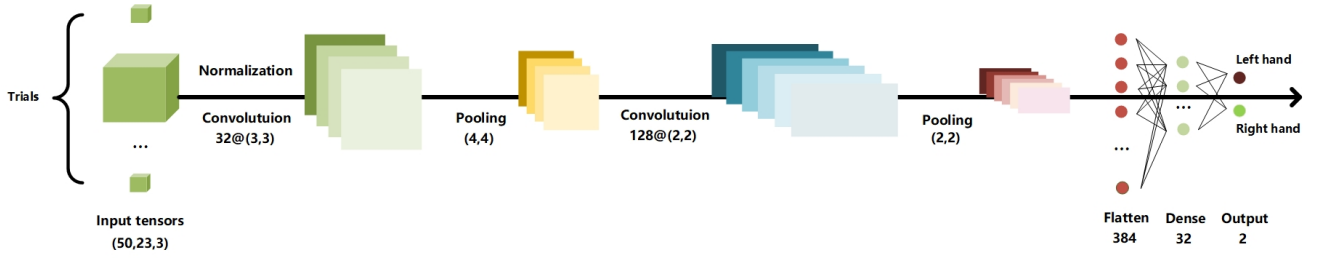

Figure 1: **The structure of CNN that we used.** The input tensors are first normalized. Two convolution layers and two pooling layers then follow. Two dense layers are at the end.

$f_b = 1Hz$ and wavelet center frequency $f_c = 1$ Hz. As a result, the training data input is a 4-dimensional tensor of N sub-tensors (N denotes the number of MI training set): $training\ samples \times frequency\ bins \times time\ frames \times channels$. And then we normalized the 4-D input tensors and used this 4-dimensional tensors to train the network. Due to that signals presented as tensors are commonly used especially in neural networks such as CNNs, in this study, we used CNN-based neural network to test our proposed combination of EEG data augmentation and tensor representations.

Our structure of CNN is presented in Fig.1. Normalization was first used to map data between zero and one. Then, the first convolution layer that had 32 filters shaped like (3,3) was followed. The proposed methods show higher classification accuracies compared to prevailing approaches.

2.2 Tensor fusion for multi-modal brain signals fusion

In [Sun *et al.*, 2020], we focused on the tri-modal task. Assuming x^1, x^2 and x^3 denote the EEG, oxy-hemoglobin NIRS (oxy-NIRS) and deoxy-hemoglobin NIRS (deoxy-NIRS), respectively. Also assume that z^1, z^2 and z^3 denote their respective feature vectors obtained from three convolutional neural networks (CNNs). To express the formula concisely, Einstein notation [Harrison and Joseph, 2016] is applied to describe multiplication between tensors or between a tensor and a vector. In particular, if we assume x_i to denote a vector and $\mathcal{W}_{ijk}$ to denote a 3rd-order tensor, their product can be written as $y_{jk} = x_i \mathcal{W}_{ijk}$, which means $y_{jk} = \sum_i^I x_i \mathcal{W}_{ijk}$. Also, when we concatenate z^1, z^2 and z^3, the result is then written as $z^{1,2,3}$. Given a vector x_{i_1}, its first copy is written as x_{i_2}, and its $(N-1)$th copy is x_{i_N}.

For the tensor fusion, the outer product is usually introduced. It is a natural way to obtain a feature containing the interaction amongst multiple feature vectors. In our task, the outer product result can be written as

$$\mathcal{Z}_{abc} = z_a^1 z_b^2 z_c^3, \qquad (1)$$

where $\mathcal{Z}_{abc}$ is a 3rd-order feature tensor, and a, b, c are the lengths of three modal feature vectors. After that, a 4th-order weight tensor $\mathcal{W}_{abco}$ is used to obtain the fused feature vector y_o:

$$y_o = \mathcal{Z}_{abc} \mathcal{W}_{abco}. \qquad (2)$$

Then, $L2$ normalization is applied to y_o. Finally, a full connected neural network is used for classification. The results indicated that all the tri-modal fusion models perform better than single-modal models. And the tensor fusion method show better results than previous researches.

3 Conclusion

In this extend abstract, we introduced two previous works about how to use tensor to represent and process brain signals. In the first method, we tested the performance of proposed CNN-based neural networks that combines tensor representations with data augmentation for the classification of MI signals. In the second method, tensor methods were used for fusion of two different brain signals, EEG signals and NIRS signals. Both of these two methods achieved better results than previous literature. We think tensor representation is a critical method for construction the robust BCI systems.

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