Motor Imagery Classification using Cascade ResNet-LSTM

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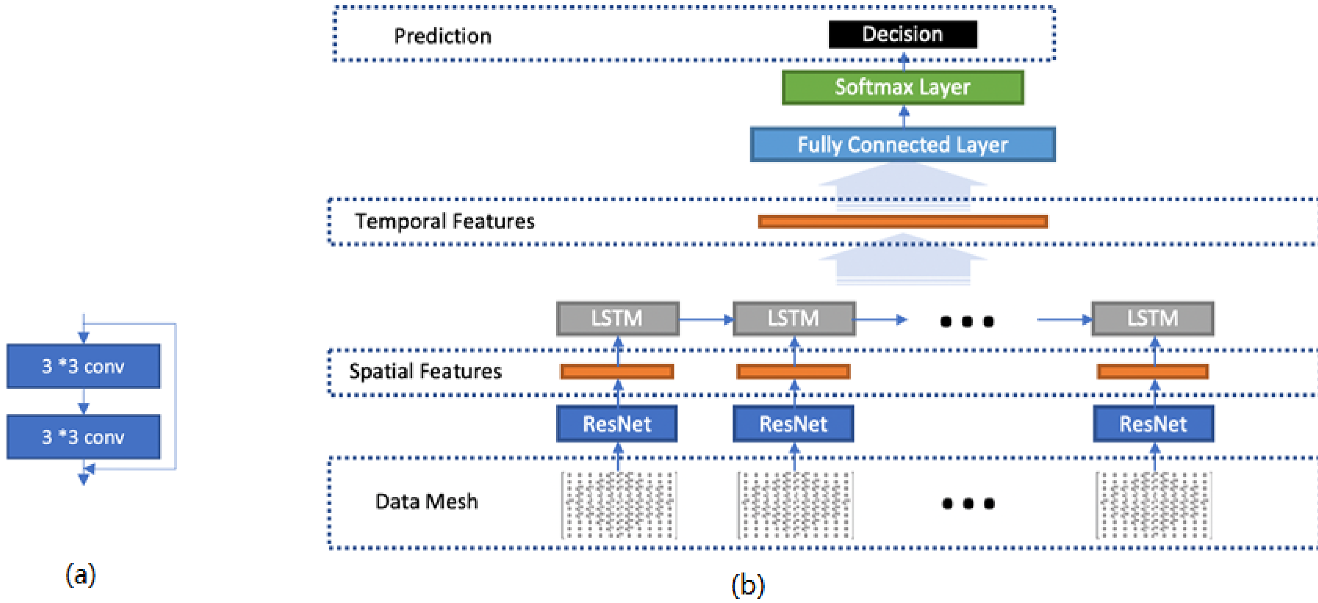
Introduction:

Many techniques have been developed to improve the classification performance of EEG-based motor imagery. Most existing works either involve extensive preprocessing or don't consider temporal and spatial features simultaneously. In this paper, we adopted a cascade Convolutional Neural Network – Recurrent Neural Network (CNN-RNN) structure (Karpathy et al., 2015) (Zhang et al., 2018) to capture spatial-temporal dynamics for imaginary motor movements. To further improve the classification performance and reduce computational cost, we applied deep Residual Nets (ResNets) (He et al., 2016) instead of vanilla CNNs.

Methods:

In motor imagery classification, the conventional non-deep learning solutions such as Common Spatial Pattern filters (Wang et al., 2005) usually require extensive preprocessing and neglect the spatial-temporal dynamics in EEG signals. Additionally, some conventional methods only handle single-subject tasks. To overcome the restrictions, we modified a CNN-RNN structure to handle the EEG sequences. 1-D EEG sequences were first mapped into 2-D meshes according to the electrodes placement map of BCI2000 instruments (Schalk et al., 2004). The mesh sequences were trimmed into individual clips with a sliding window. We first applied a ResNet to extract the spatial features of all the 2D meshes in to a sliding window. The ResNet is a variation of CNNs which converts 2D input into feature vectors. It is consisted of residual blocks which contain shortcut connections which skip the convolution operations. As shown in Fig. 1a, the shortcut connection allows the gradient to directly flow back to the previous layers during backpropagation, therefore effectively avoiding gradient vanishing during training. Batch normalization is performed after each convolutional layer, speeding up the convergence process. Instead of the max pooling performed in conventional CNNs, average pooling was performed after the convolution operation. The spatial feature embeddings extracted by the ResNet were then fed to an RNN constructed by Long Short-term Memory (LSTM) units, which computed the temporal features. Finally, a fully connected layer took in the output of the last time step of the RNN, and a softmax layer made the final prediction (Fig. 1b).



·Figure 1 (a) Residual block structure; (b) Cascade ResNet-LSTM architecture

Results:

The model was trained on the PhysioNet EEG Dataset (Goldberger et al., 2000) to predict 4 imaginary movements: moving both feet, both fists, left fist and right fist, and a rest state. The dataset contains 109 subjects, but data of subject #89 was removed because of data corruption. We trained the model on 75% of the dataset and validated it on the rest of the data (25%). The classification accuracy in the validated data was 63.57% (chance level is 20%).

Conclusions:

We proposed a cascade ResNet-LSTM model for motor imagery classification, which we hope could be used for real-time classification. The proposed method doesn't require manual feature selection nor preprocessing. This method has several other benefits; a) it has been proved to perform better in cross-subject and multi-task motor imagery classification than non-deep learning solutions, and b) application of ResNet to spatial features extraction will speed up convergence. In the future, we plan to improve the classification rate by optimizing parameters and evaluating the visualization and the features that the model has learned using the deconvolution methods.

Imaging Methods:

EEG [1]

Modeling and Analysis Methods:

Classification and Predictive Modeling [2]
EEG/MEG Modeling and Analysis

Keywords:

Electroencephaolography (EEG)
Machine Learning
Motor

[1|2]Indicates the priority used for review

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No

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Not applicable

Please indicate which methods were used in your research:

EEG/ERP

Provide references using author date format

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