Deep Learning for Motor Imagery Classification based on EEG Data

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Introduction

- In motor imagery classification, the conventional non-deep learning solutions, such as Common Spatial Pattern filters[5], usually require extensive preprocessing and neglect the spatial-temporal dynamics in EEG signals.
- Additionally, some conventional methods only handle single subject tasks.
- In this project, we adopted a cascade Convolutional Neural Network – Recurrent Neural Network (CNN-RNN) structure[3, 6] to capture spatial-temporal dynamics for imaginary motor movements.
- To further improve the classification performance and reduce computational cost, we also applied deep Residual Nets (ResNets)[2] instead of vanilla CNNs.

Methods: CNN-RNN Structure

- 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[4]. The mesh sequences were trimmed into individual clips with a sliding window.
- A ResNet was applied to extract the spatial features of all the 2D meshes into 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 to effectively avoid gradient vanishing during training.
- 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).

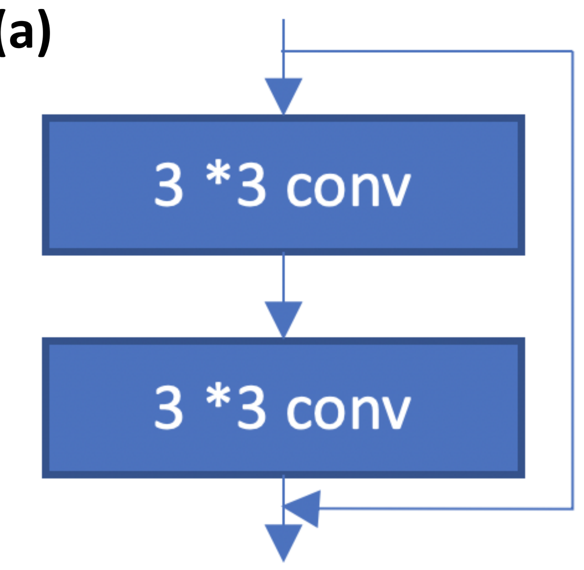
Methods: Dataset

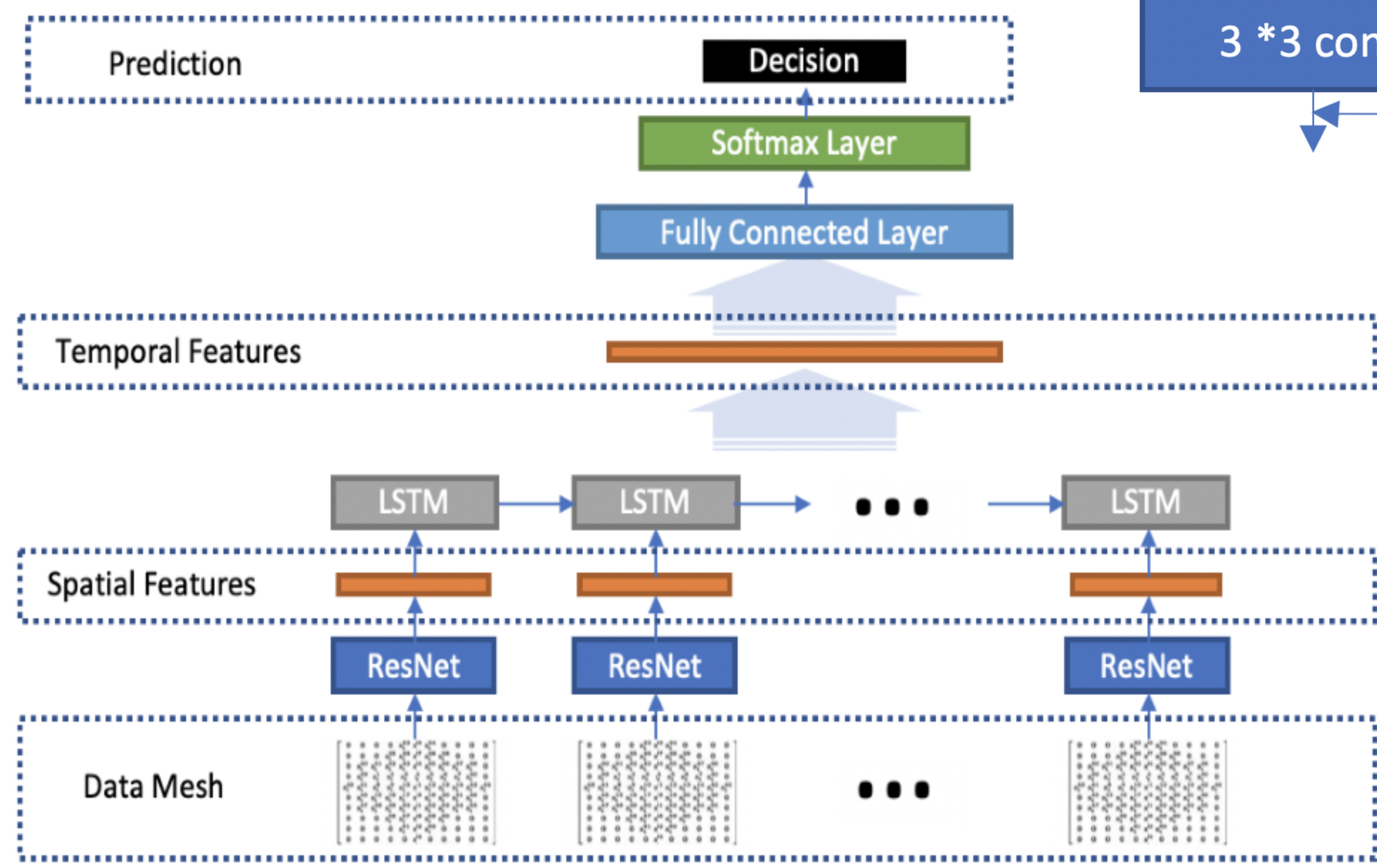
- We used the PhysioNet EEG Dataset[1] to predict resting state and 4 imaginary movements (i.e., moving both feet, both fists, left fist and right fist).
- The dataset contains 109 subjects but data of subject #89 was removed because of data corruption.
- 75% of the dataset is used as training set and the rest of the data (25%) is used as validation set.

Results

- The cascade ResNet-LSTM model exhibited high accuracy performance in this task. The classification accuracy in the validated data was 63.57% (chance level 20%).

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

(a)


(b)


Conclusion

- We demonstrated that our method achieved good results without manual feature selection nor preprocessing.
- The application of ResNet to spatial features extraction speeds up convergence.
- In the future, we plan to improve the classification rate by optimizing parameters and evaluating and visualizing the features that the model has learned using the deconvolution methods. In addition, the cascade ResNet-LSTM model could be used for real-time EEG neurofeedback.

References

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