Beijing Jiaotong University

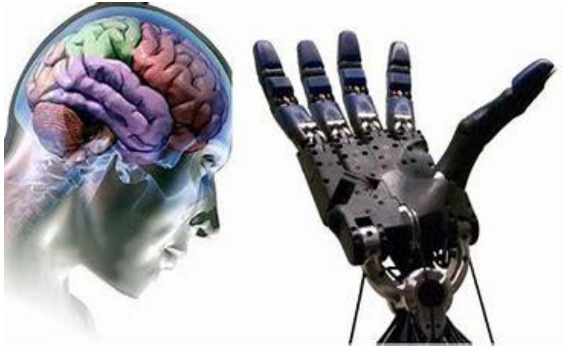
MMCNN: A Multi-branch Multi-scale Convolutional Neural Network for Motor Imagery Classification

Introduction

Brain-computer Interface (BCI):

Establishes the connection between the human brain and outside world.

Based on electrophysiological and hemodynamic brain activity.



electroencephalography(EEG):

One of electrophysiological brain activities.

Advantage: low cost, low risk

motor imagery (MI):

One of the typical EEG based BCI paradigms.

A person imagines moving different parts of the body or different control commands on the instruments.

Related Work

·traditional methods:

- spatial features: CSP[1], FBCSP[2]
- time-frequency features: Fourier transform, wavelet transform

·deep learning models:

- Shallow ConvNet [3]
- Deep ConvNet[3]
- EEGNet [4]

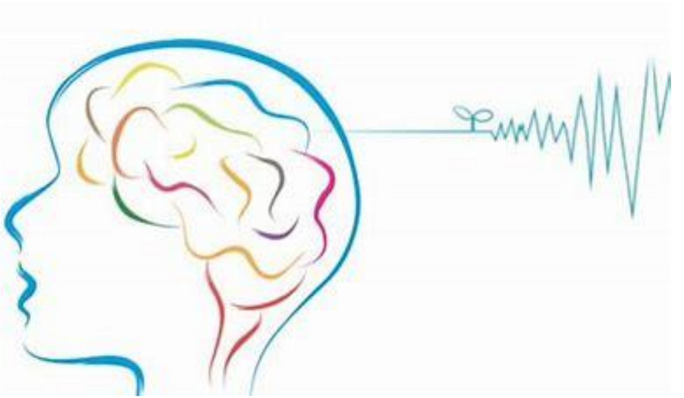
[1] Fukunaga, K.: Introduction to statistical pattern recognition (1990)
[2] Ang, K.K., et alC.: Filter bank common spatial pattern(fbcsp) in brain-computer interface. In: 2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence). pp.2390–2397. IEEE (2008)
[3] Schirrmeister, R.T., et al.: Deep learning with convolutional neural networks for eeg decoding and visualization. Human brain mapping 38(11), 5391–5420 (2017)
[4] Lawhern, V.J., et al.: Eegnet: a compact convolutional neural network for eeg-based brain–computer interfaces. Journal of neural engineering 15(5), 056013 (2018)

Challenge

EEG signals: non-linearity, non-stationarity and low signal-noise ratio.

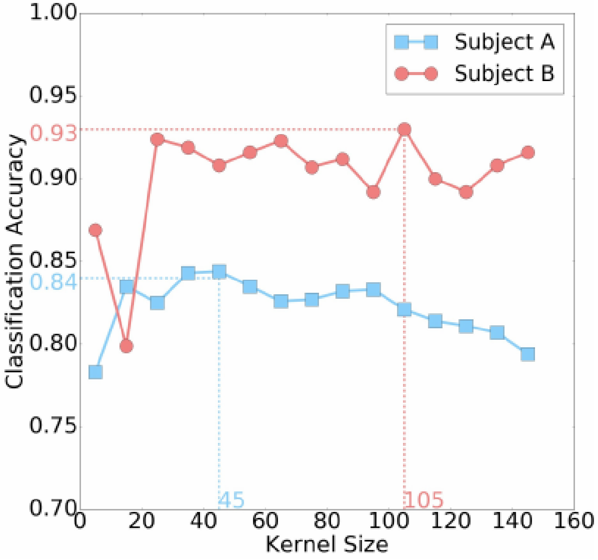
traditional methods: need manual feature extraction.

deep learning models: filter the raw EEG signals in specific frequency band.

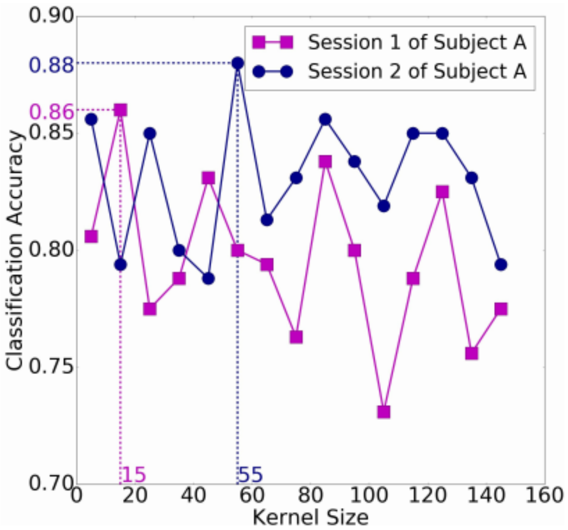


Challenge

Subject difference: the best convolution scale varies with different subject.

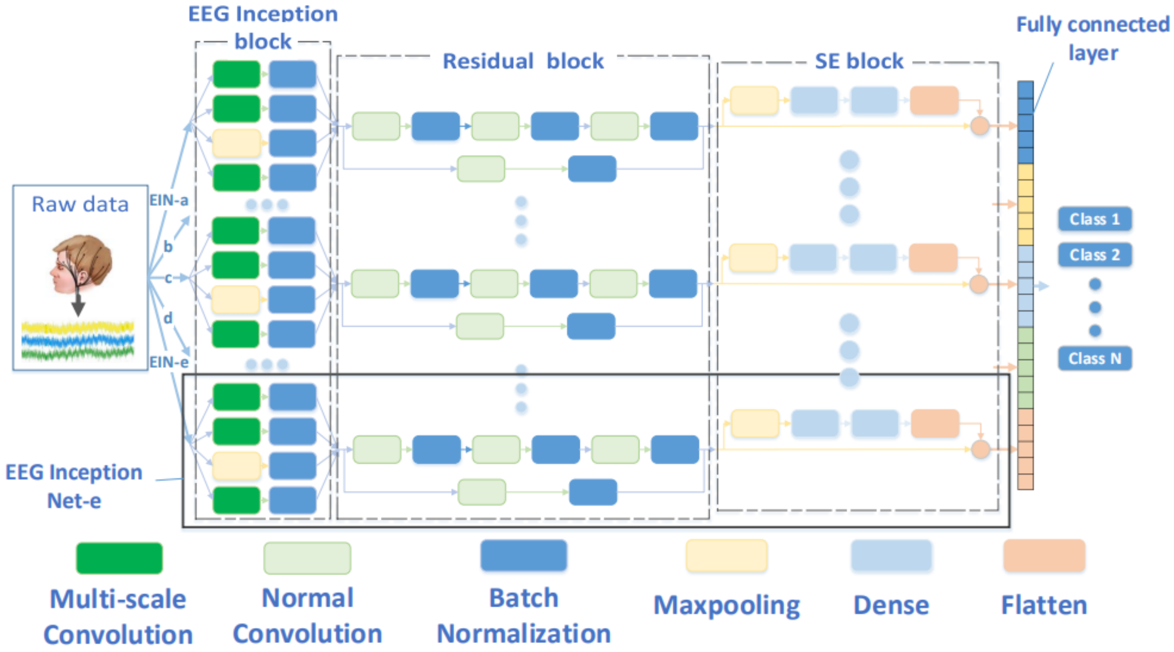


Time difference: the best convolution scale differs from time to time.



MMCNN Architecture

Multi-branch Multi-scale Convolution Neural Network



Contribution:

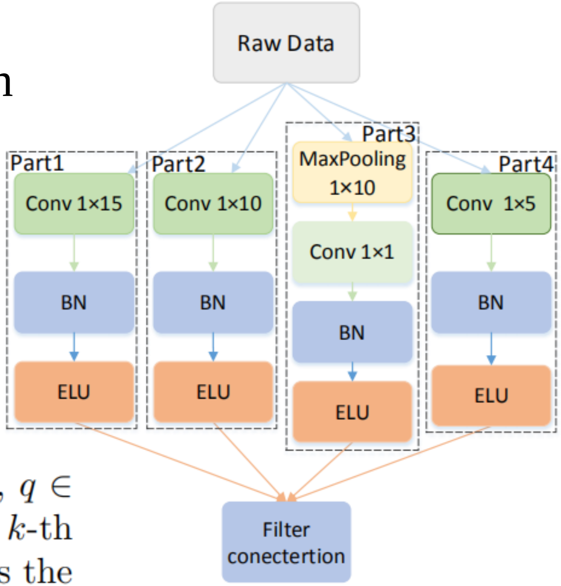
- Solve the problem: *subject difference* and *time difference*.
- Input *unfiltered data*.
- The importance of *different channels* is different.
- Obtain the superior result on *BCI Competition IV 2b* and *2a* dataset

MMCNN Architecture

EEG Inception block: implement the multi-scale convolution

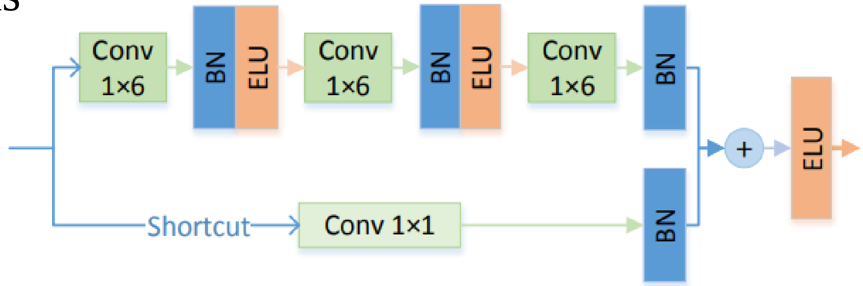
$$I_q = \left[p_q^{j=1,k} * x; p_q^{j=2,k} * x; p_q^{j=3,k} * x; F_{maxpooling}(x)\right]$$

where I_q denotes the output from EIB in different EINs and $I_q \in R^{T' \times C'}$, $q \in [a, b, c, d, e]$ with five branches in EIN, $p_q^{j,k}$ denotes parameters from the k-th filter in j-th branch, $*$ denotes the convolution operation, and the x denotes the input sample, and the T' denotes the number of time points, the C' denotes the number of channels.



MMCNN Architecture

Residual block[5]: avoid network degradation as the number of network layers increases



$$U_q = F_{res}\left(I_q\right) + I_q$$

where U_q denotes the output of the Residual block, I_q denotes the input. In this way, the features extracted from the shallow layer are transferred to the deeper layer. Therefore, Residual block largely addresses the degradation problem.

[5] He, K., Zhang, et al.: Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 770–778 (2016)

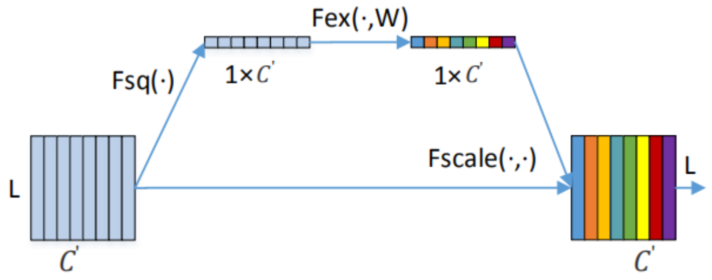
MMCNN Architecture

Squeeze and Excitation block: pay more attention to adaptive extraction of important features

Squeeze: tackles the issue of exploiting channel dependencies

$$m_q = F_{sq}(U_q) = \frac{1}{L}\sum_{n=1}^{L} U_q(n)$$

where m_q denotes the channel descriptor, L denotes the size of feature map.



MMCNN Architecture

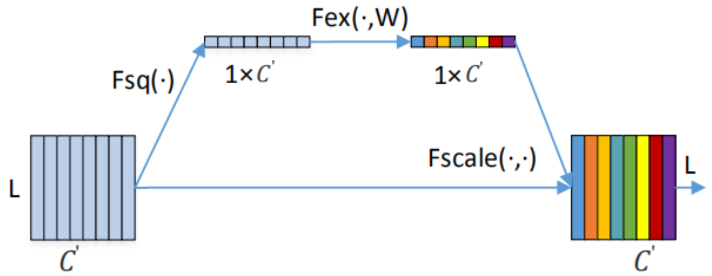
Excitation: learns sample-specific activations for each channel

$$S_q = F_{ex}\left(m_q, W\right) = \sigma\left(h\left(m_q, W\right)\right) = \sigma\left(W_2 \delta\left(W_1 m_q\right)\right)$$

where W_1 denotes dimensionality-reduction layer, and the dimension of W_1 is controlled by ratio to reduce the amount of calculation. W_2 denotes L dimensional layer and δ denotes the ELU function. Then the m_q is assigned weights:

$$f_q = F_{scale}\left(U_q, S_q\right) = U_q \cdot S_q$$

where f_q denotes the output of the SE block, F_{scale} denotes the operation of assigning weight.

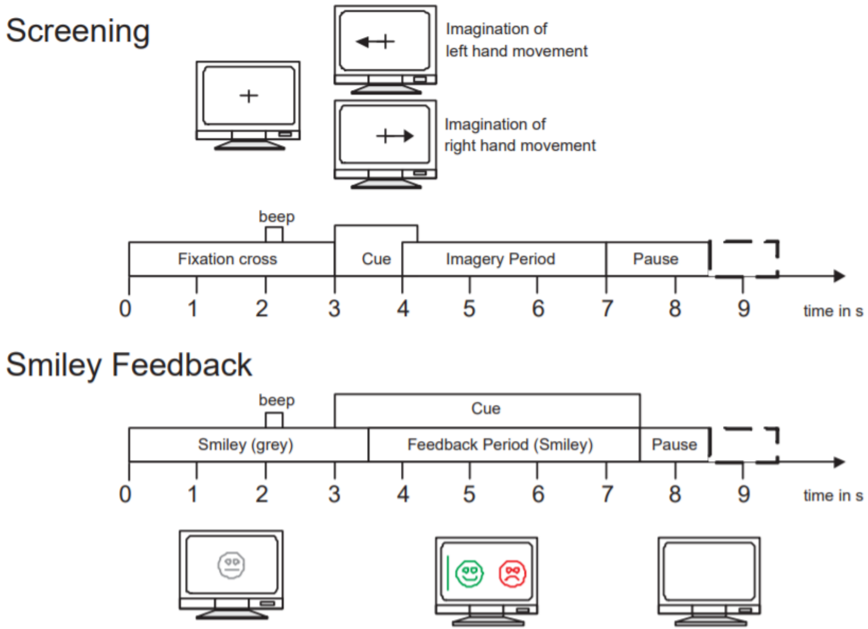


Experiments

Datasets

BCI Competition IV 2b dataset[1]: a binary classification problem dataset with MI of the left-hand movement and the right-hand movement. The dataset includes 9 subjects.

BCI Contest IV 2a dataset[2]: contains data of 9 subjects performing motor imagery classification.



1:http://www.bbci.de/competition/iv/#dataset2b
2:http://www.bbci.de/competition/iv/#dataset2a

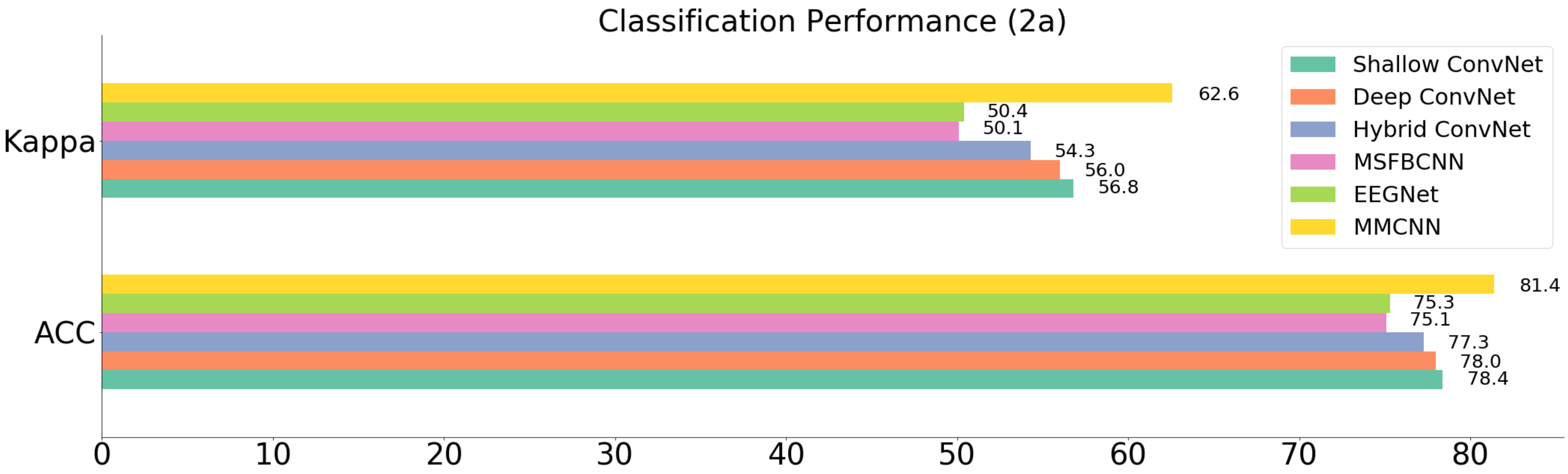
Experiments

Baseline:

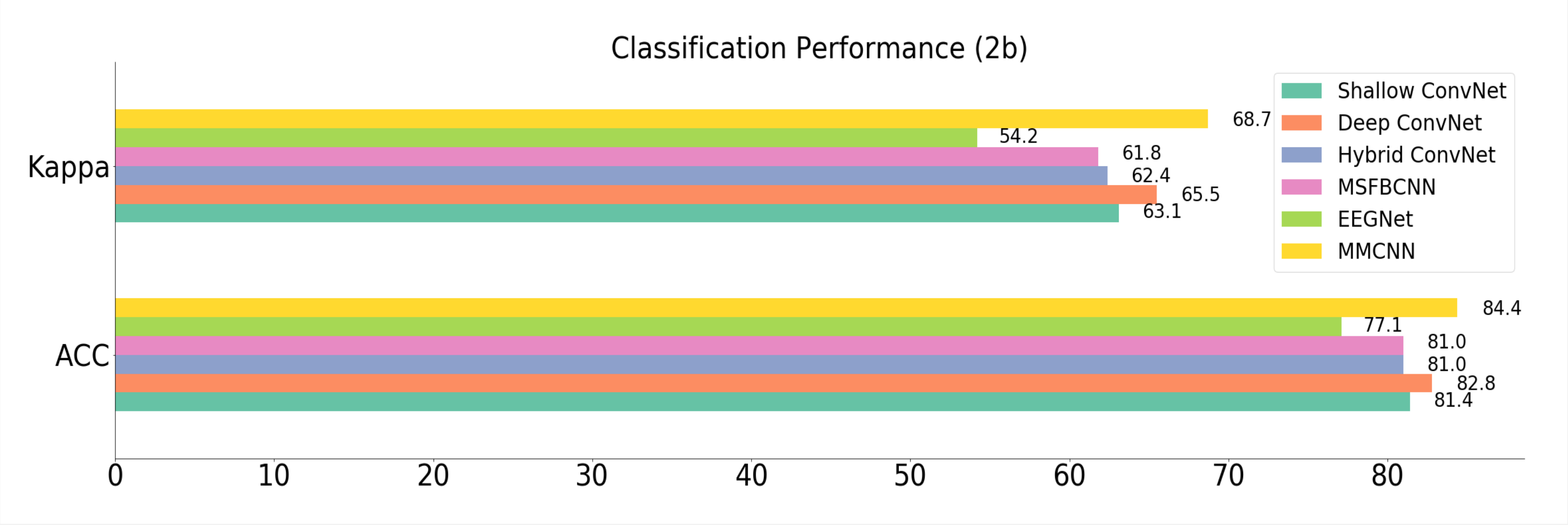
- ***Deep ConvNet***[3]: A classic end-to-end model for EGG classification with four convolution-max-pooling blocks.
- ***Shallow ConvNet***[3]: The layers in the Shallow ConvNet is less than the Deep ConvNet.
- ***Hybrid ConvNet***[3]: Hybrid ConvNet combines the structure of the Deep ConvNet and the Shallow ConvNet.
- ***EEGNet***[4]: A deep learning model utilizes a single-scale neural network with deep convolution and separable convolution.
- ***MSFBCNN***[6]: A parallel filter bank convolutional neural network.

[3] Schirrmeister, R.T., et al.: Deep learning with convolutional neural networks for eeg decoding and visualization. Human brain mapping 38(11), 5391–5420 (2017)
[4] Lawhern, V.J., et al.: Eegnet: a compact convolutional neural network for eeg-based brain–computer interfaces. Journal of neural engineering 15(5), 056013 (2018)
[6] Wu, H., et al.: A parallel multiscale filter bank convolutional neural networks for motor imagery eeg classification. Frontiers in Neuroscience 13, 1275 (2019)

Result of BCI Competition IV 2a

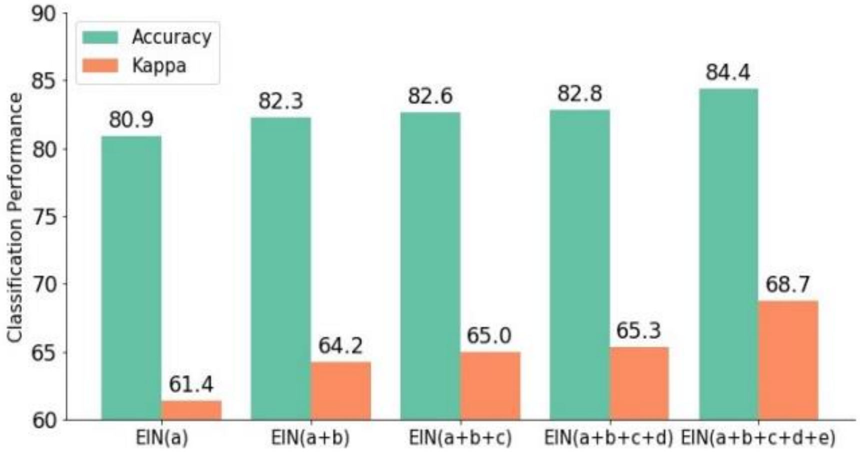


Result of BCI Competition IV 2b

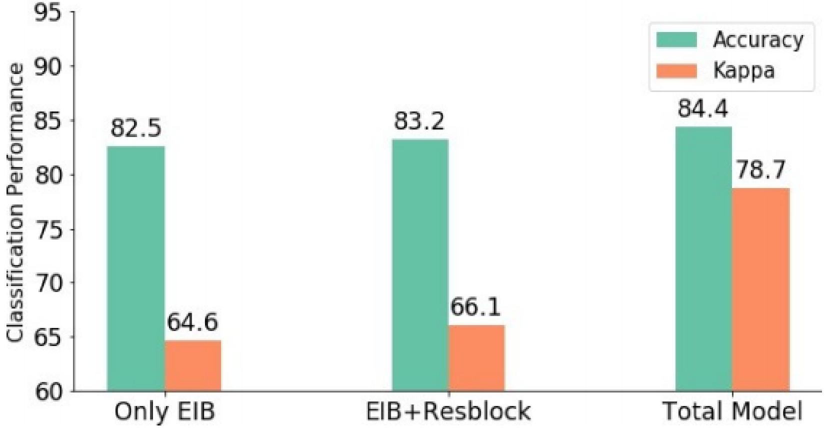


Ablation Study

Ablation Study on *Multi-scale Convolution*



Ablation Study on *different blocks*



The impact of different EEG channels

- the importance of different channels to improve the classification is different
- the combination of C4 and C3 can achieve a better result

Conclusion

Contribution:

- Solve the problem of ***subject difference*** and ***time difference***.
- The results are superior to the state-of-the-art models on two public BCI Competition datasets with unfiltered data.
- Prove the importance of different channels to improve the classification is different.

Prospect:

- The proposed model is a general framework for EEG signal classification, we can apply it to classify other BCI tasks, such as emotion recognition.
- The model is end-to-end, we can apply it to wearable equipment.

Reference

[1] Fukunaga, K.: Introduction to statistical pattern recognition (1990)

[2] Ang, K.K., Chin, Z.Y., Zhang, H., Guan, C.: Filter bank common spatial pattern(fbcsp) in brain-computer interface. In: 2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence). pp.2390–2397. IEEE (2008)

[3] Schirrmeister, R.T., Springenberg, J.T., Fiederer, L.D.J., Glasstetter, M.,Eggensperger, K., Tangermann, M., Hutter, F., Burgard, W., Ball, T.: Deep learning with convolutional neural networks for eeg decoding and visualization. Human brain mapping 38(11), 5391–5420 (2017)

[4] Lawhern, V.J., Solon, A.J., Waytowich, N.R., Gordon, S.M., Hung, C.P., Lance,B.J.: Eegnet: a compact convolutional neural network for eeg-based brain–computer interfaces. Journal of neural engineering 15(5), 056013 (2018)

[5] He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition.

In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 770–778 (2016)

[6] Wu, H., Li, F., Li, Y., Fu, B., Shi, G., Dong, M., Niu, Y.: A parallel multiscale filter

bank convolutional neural networks for motor imagery eeg classification. Frontiers in Neuroscience 13, 1275 (2019)

Thanks!