Speed Imagery EEG Classification with Spatial-temporal Feature Attention Deep Neural Networks

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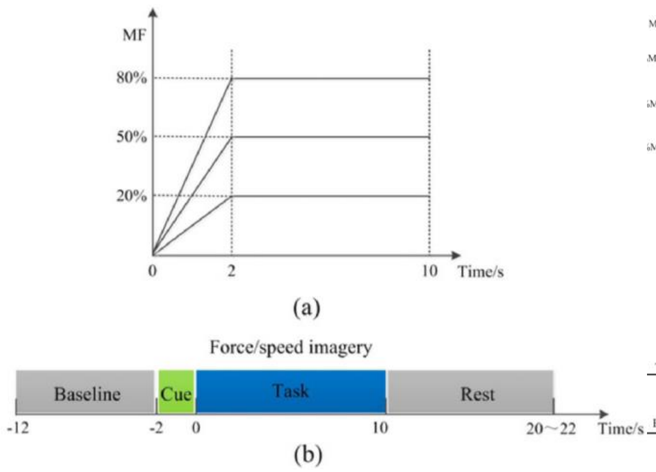
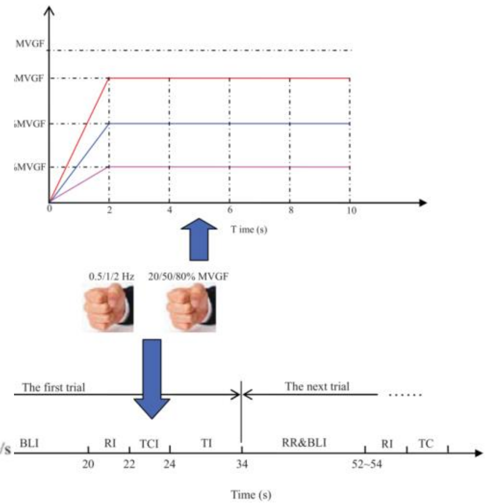
Outline

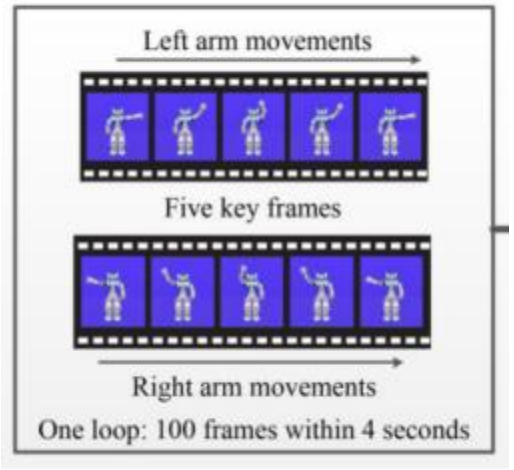
Research on Captured of Continuous Neural Intentions

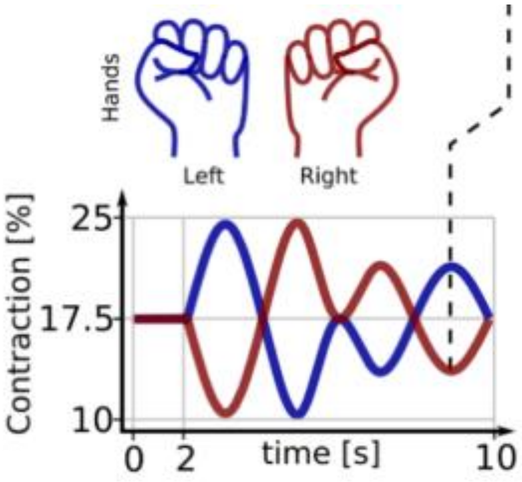
Research Process

JMI-ELMs	SVM	hMNS activations	CNN-ATT
2015	2016	2018	2021









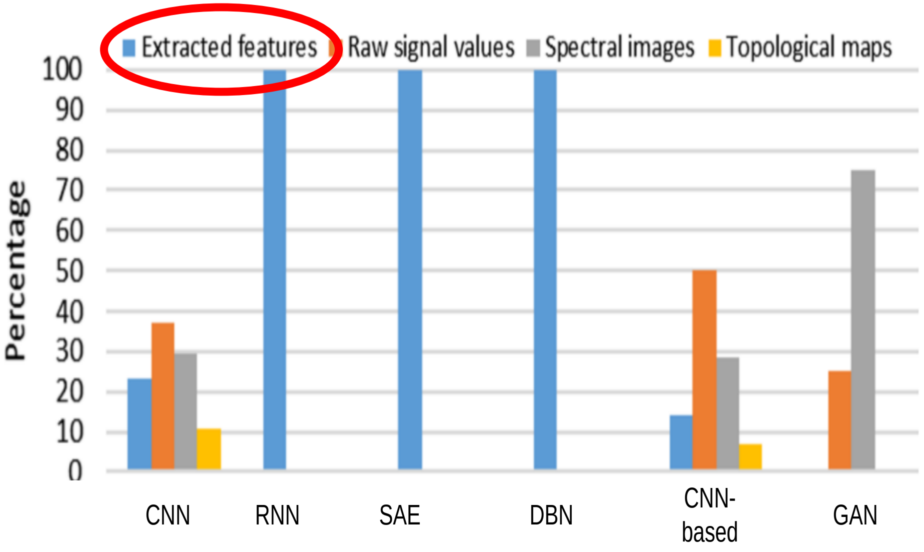
Force/speed imagery: proposed by Chinese Academy of Sciences

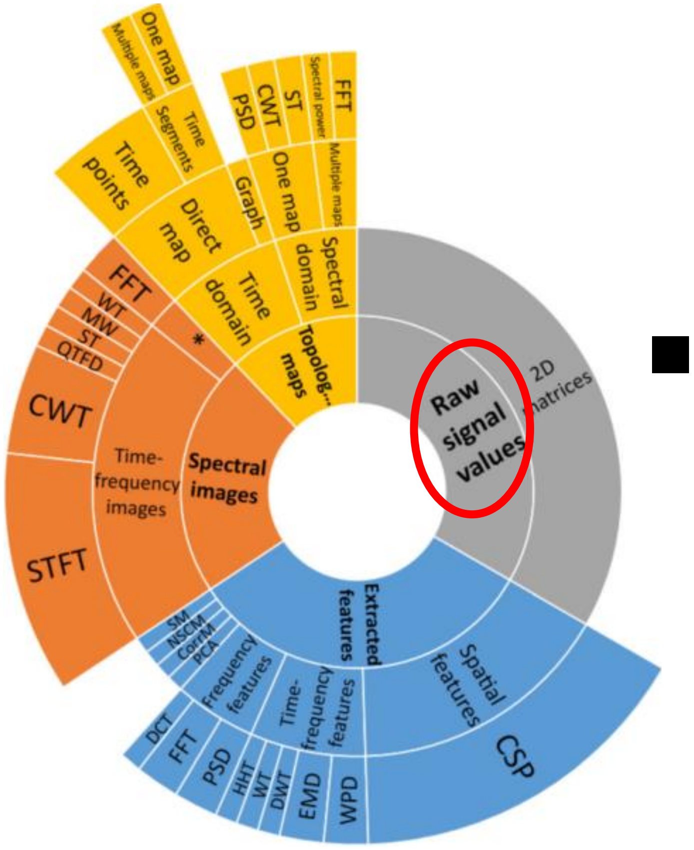
Visually evoked speed imagery

Deep learning network based on CNN and attention module

Bottleneck of Continuous Neural Intentions Decoding

- Lack of an effective capture paradigm
  - Inspired by visual or other stimuli
  - based on motor execution





- Lack of end-to-end decoding algorithms
  - Rely on hand-crafted features
  - Rely on traditional machine learning for decoding

- Lack of effective spatial-temporal feature fusion methods

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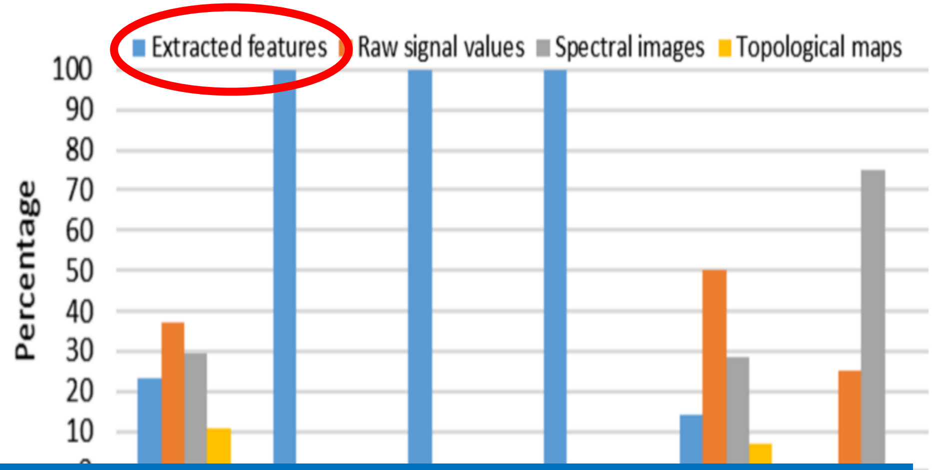

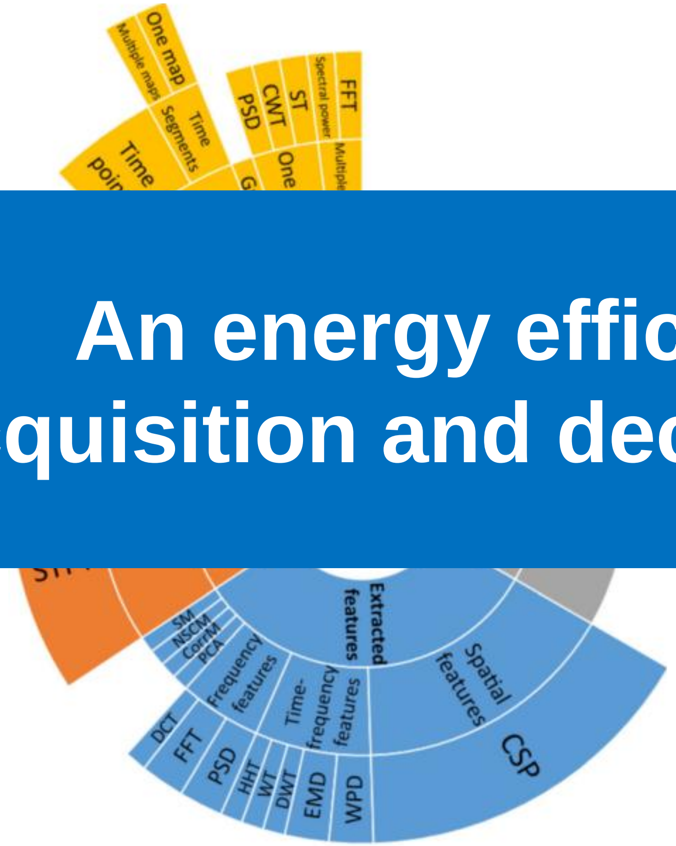

An energy efficient continuous neural signals acquisition and decoding method is highly demanded

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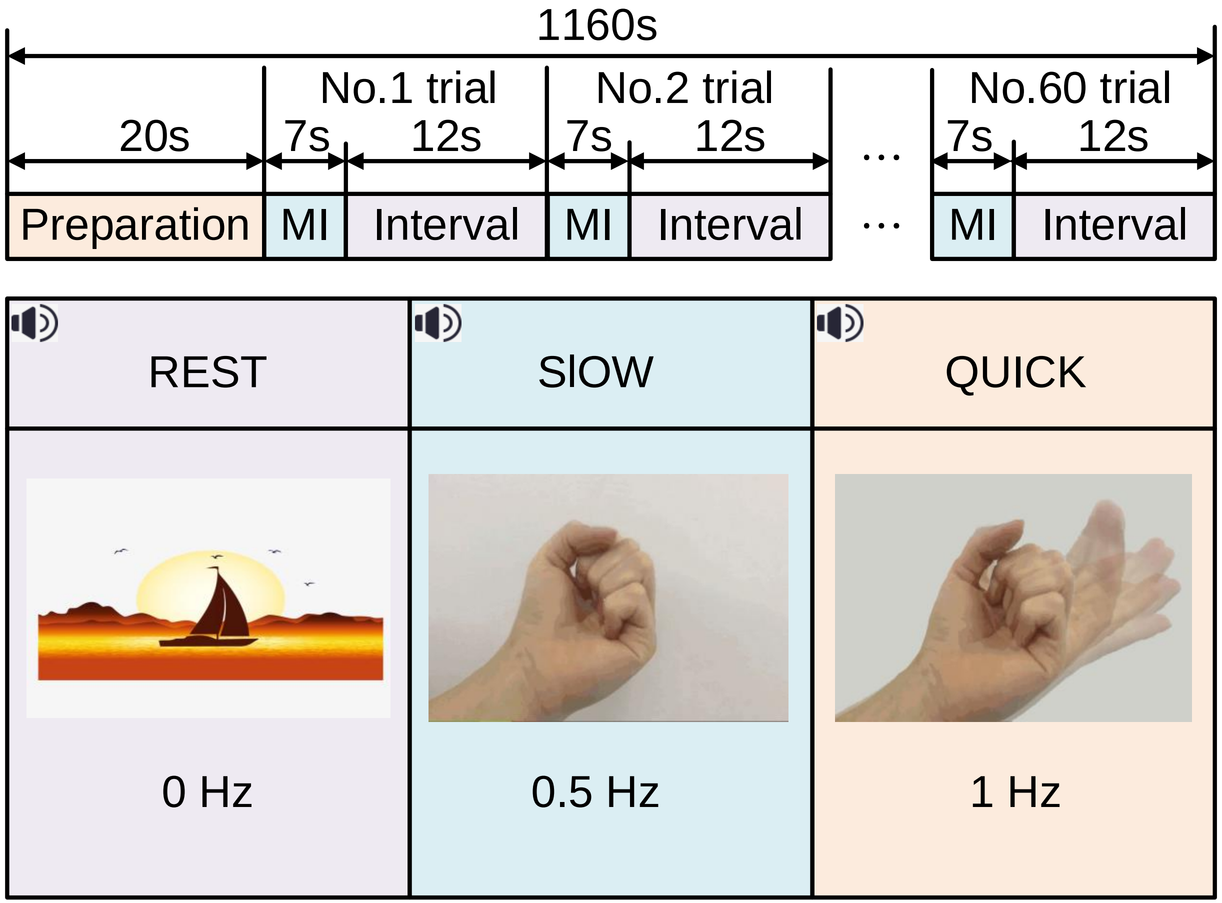
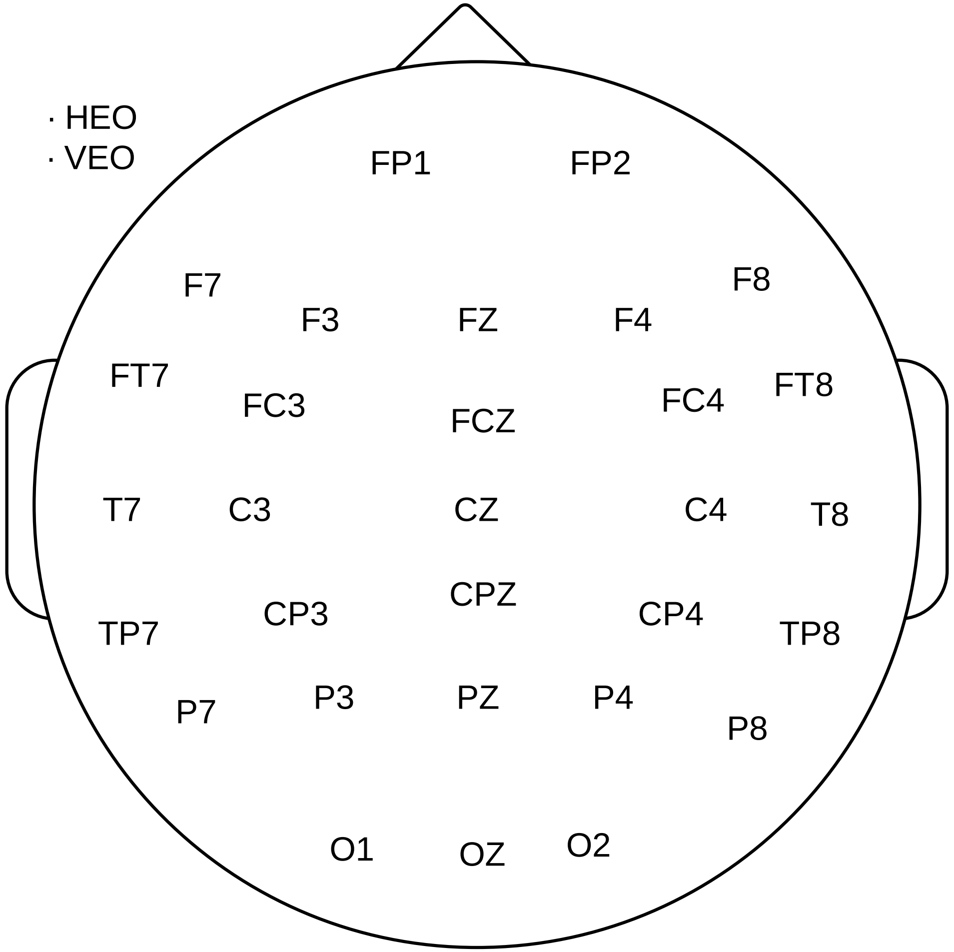
- Lack of effective spatial-temporal feature fusion methods

Deep Neural Networks for Speed Imagery EEG Classification

Contribution 1: A spontaneous speed imagery paradigm to capture continuous neural intentions





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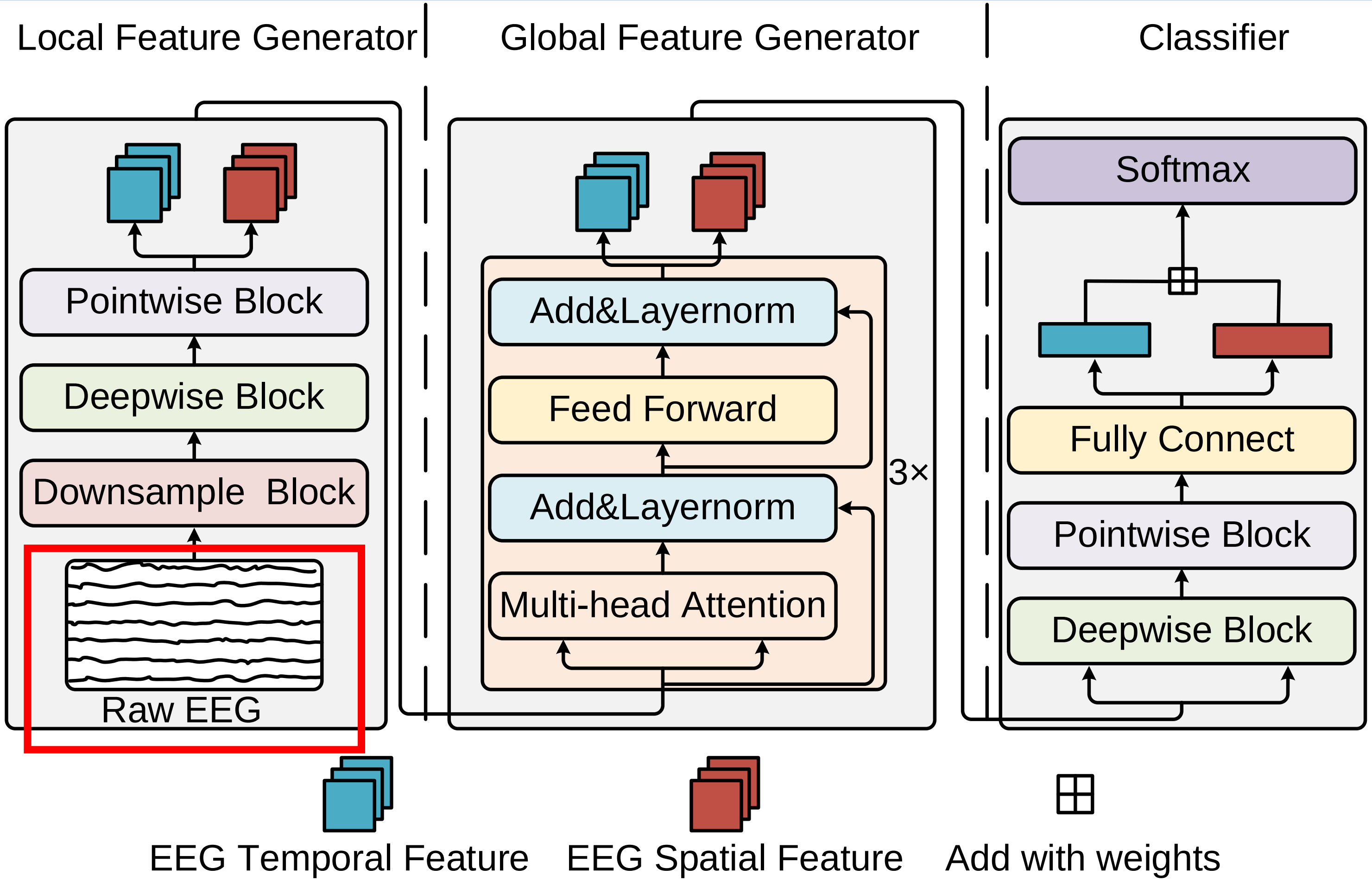
Contribution 2: An end-to-end decoding framework based on deep neural networks



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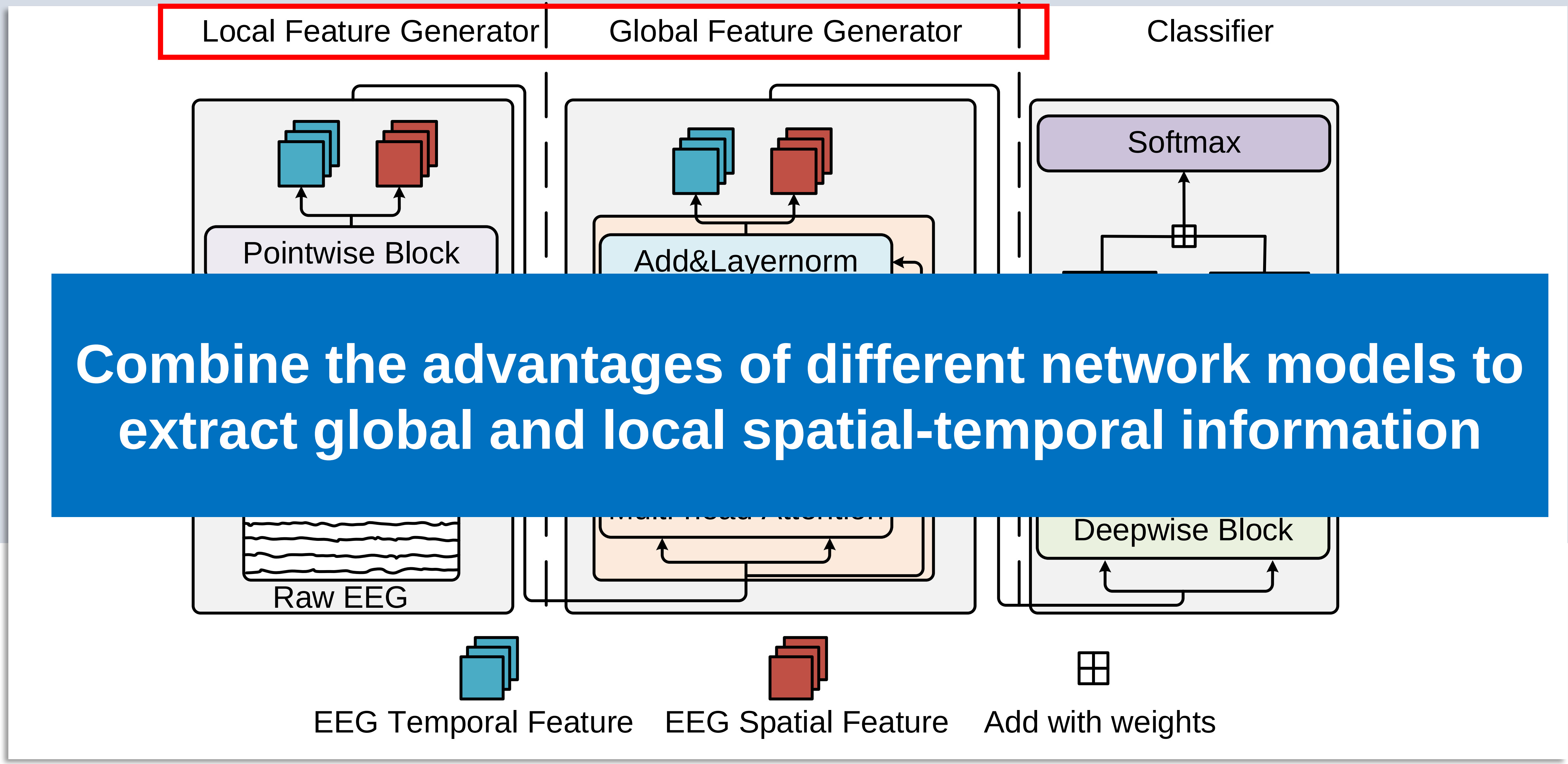
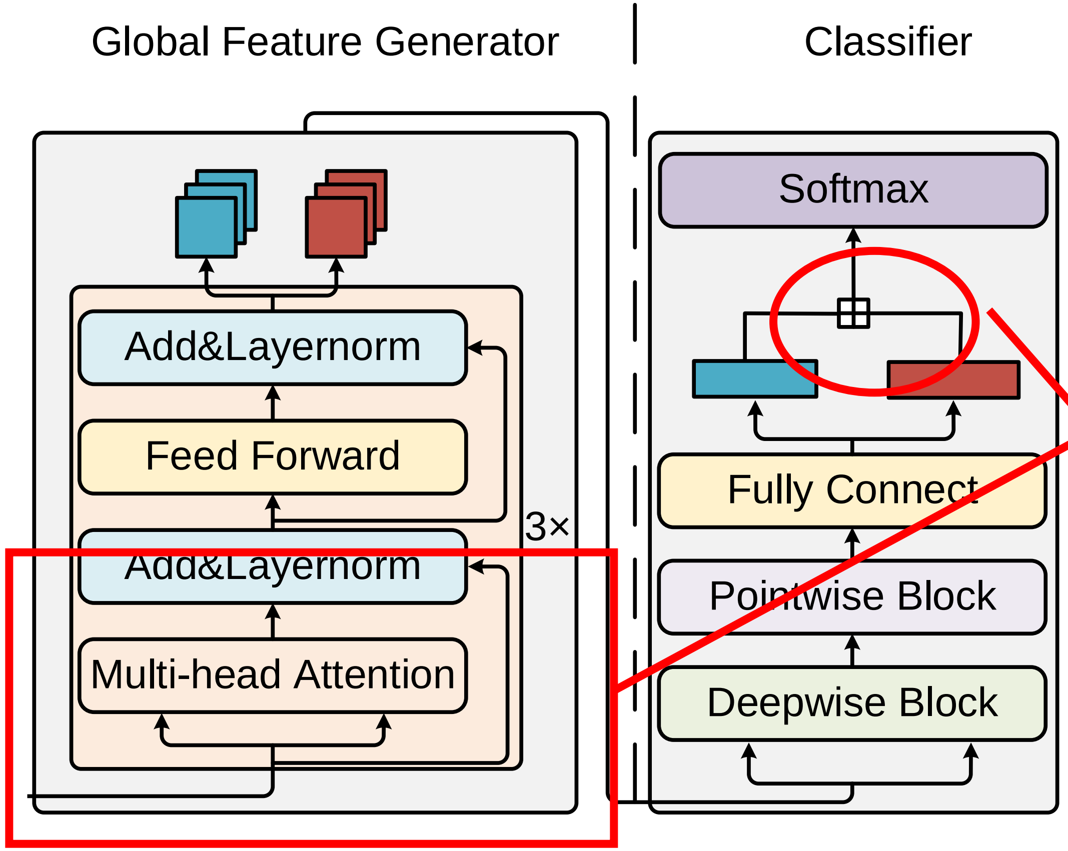


Combine the advantages of different network models to extract global and local spatial-temporal information

Deep Neural Networks for Speed Imagery EEG Classification

Contribution 3: Spatial-temporal feature attention module design



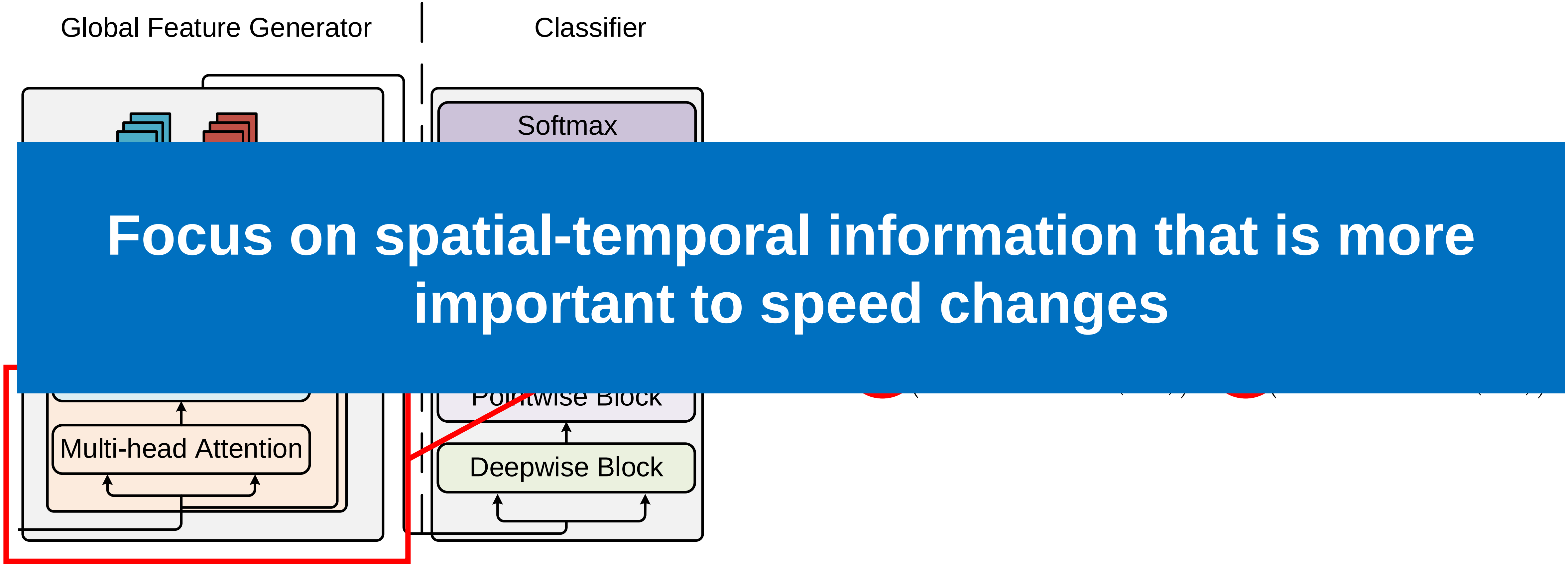
$$\mathrm{Att}(\boldsymbol{Q}^h,\boldsymbol{K}^h,\boldsymbol{V}^h)=\mathrm{softmax}\left(\frac{\boldsymbol{Q}^h\mathbf{K}^{h^{\mathrm{T}}}}{\sqrt{T}}\right)\boldsymbol{V}^h$$

$$\mathrm{MHA}(\boldsymbol{X})=\mathrm{Concat}\left(\mathrm{Att}^1,\mathrm{Att}^2,\ldots,\mathrm{Att}^H\right)$$

$$\boldsymbol{X}^{\mathrm{mix}}=\boldsymbol{W}^{\mathrm{s}}\left(\mathrm{FC}\circ\mathrm{PW}\circ\mathrm{DW}\left(\boldsymbol{X}^{\mathrm{s}}\right)\right)+\boldsymbol{W}^{\mathrm{t}}\left(\mathrm{FC}\circ\mathrm{PW}\circ\mathrm{DW}\left(\boldsymbol{X}^{\mathrm{t}}\right)\right)$$

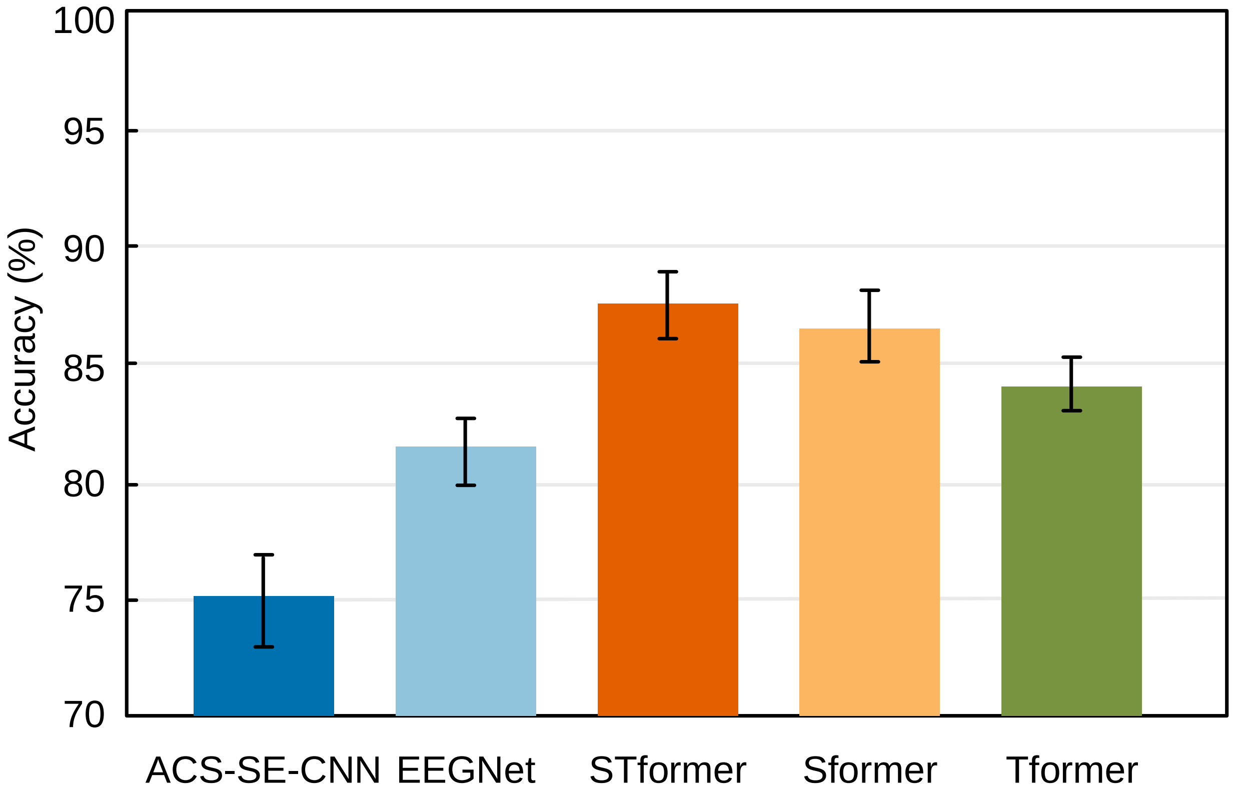
Deep Neural Networks for Speed Imagery EEG Classification

Contribution 3: Spatial-temporal feature attention module design

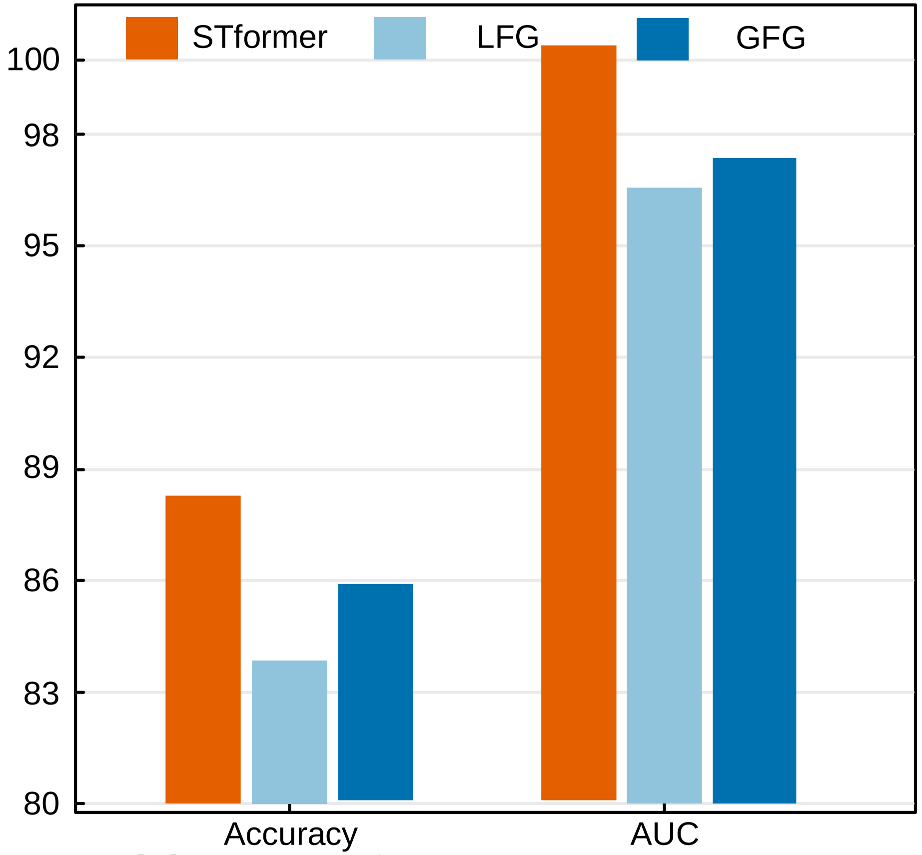


Focus on spatial-temporal information that is more important to speed changes

Experiments and results



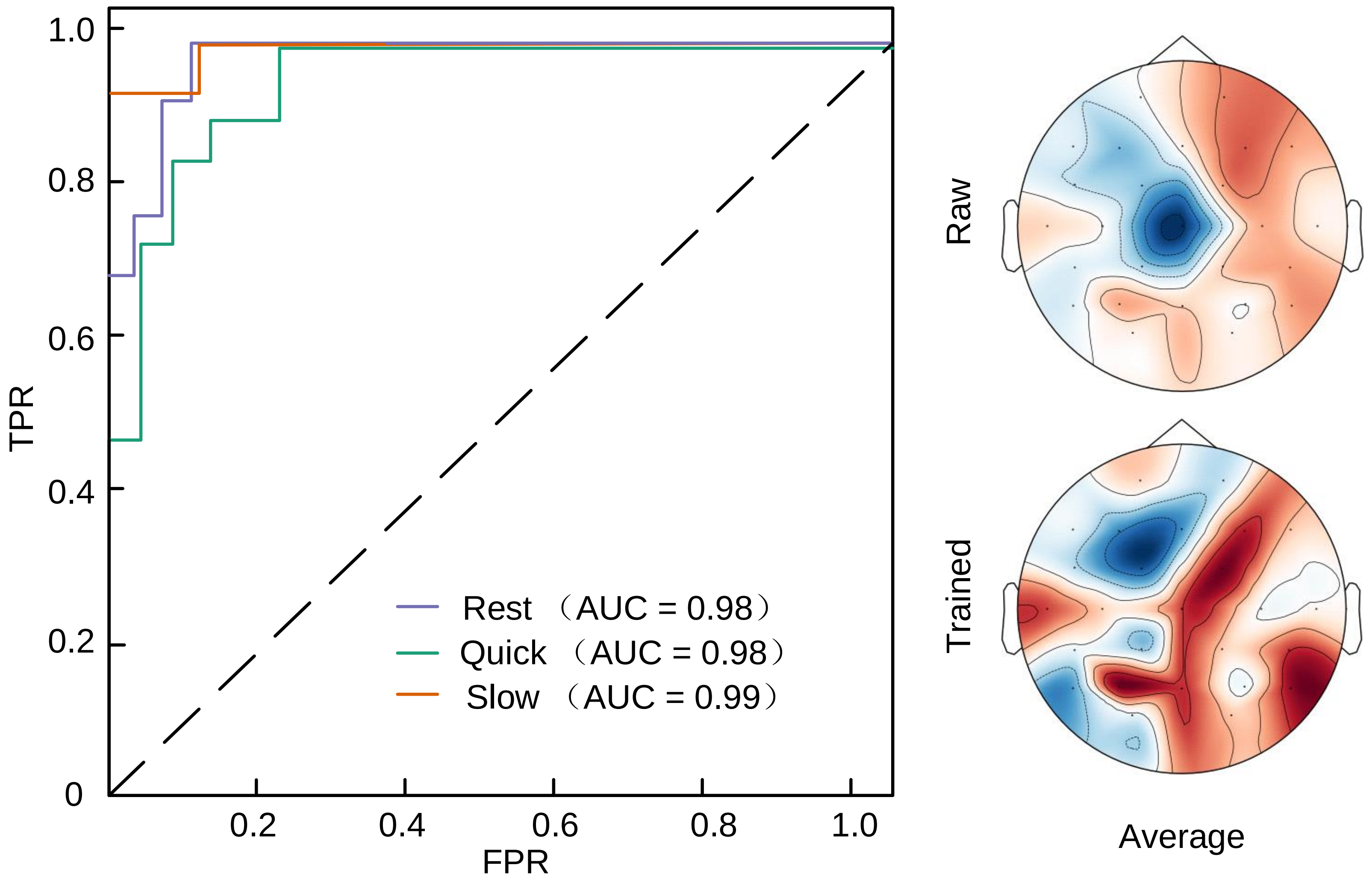
Classification accuracy and standard deviation (STD) results for different modules



Algorithm performance compares on of different modules

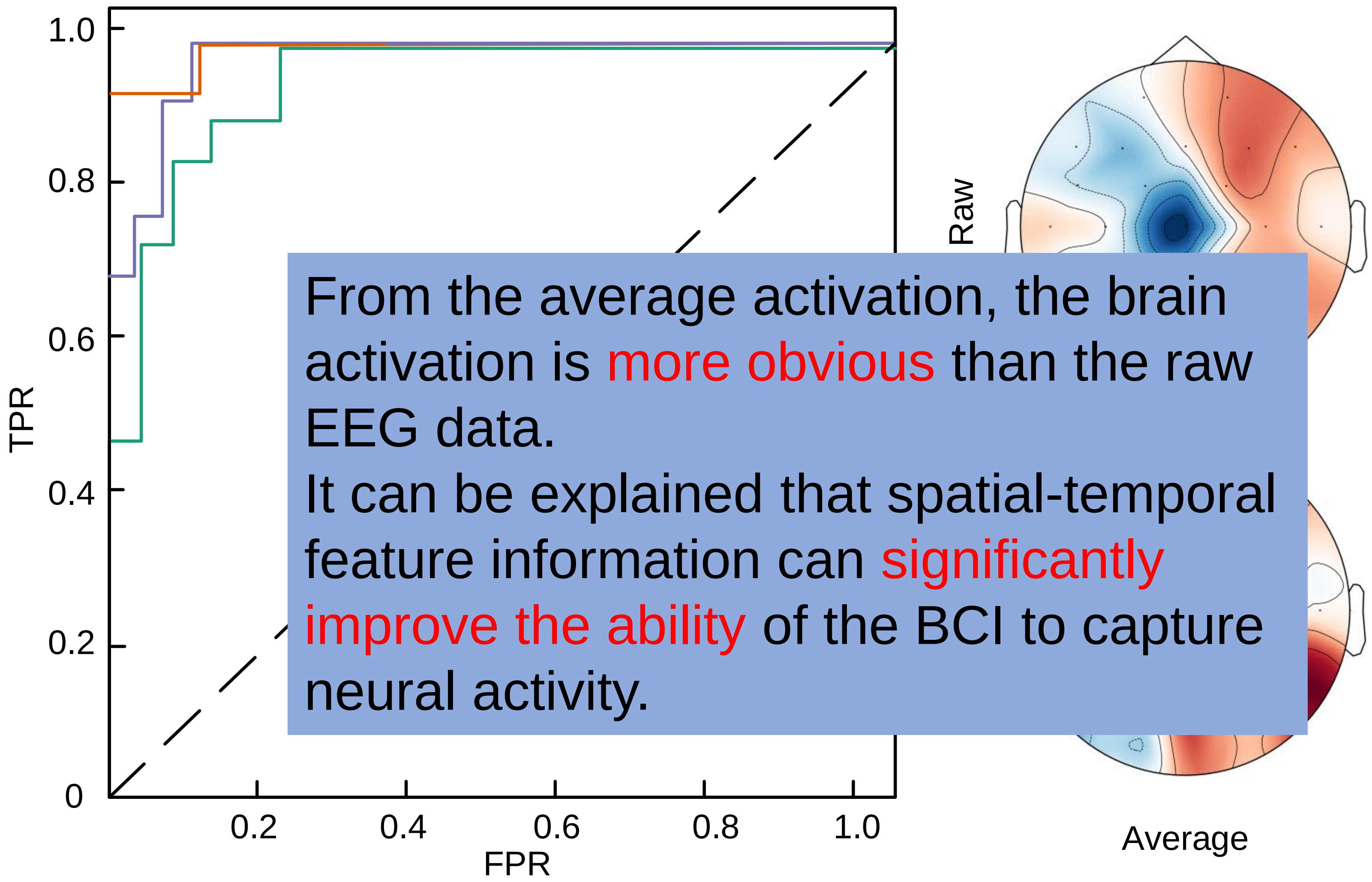
the above results show that STformer has significantly better performance and more stable data adaptability than baseline methods.

Experiments and results



(a) Classification results for the three clenching speeds. (b) Brain activation maps for raw data and trained data.

Experiments and results



From the average activation, the brain activation is more obvious than the raw EEG data.
It can be explained that spatial-temporal feature information can significantly improve the ability of the BCI to capture neural activity.

(a) Classification results for the three clenching speeds. (b) Brain activation maps for raw data and trained data.

Conclusion

- A Spontaneous speed Imagery Brain-Computer Interface paradigm is Proposed
- An end-to-end decoding method for EEG signals
- the spatial-temporal features from EEG signals using a LFG module and a GFG module

Thank you! Questions?