Attention-Based CNN Capturing EEG Recording's Average Voltage and Local Change

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Problem Identification

Most brain-machine interface research use convolutional neural network (CNN) as machine learning model

CNN is notorious for its black box nature,

i.e., lack of interpretability

Interpretability is important as it enables

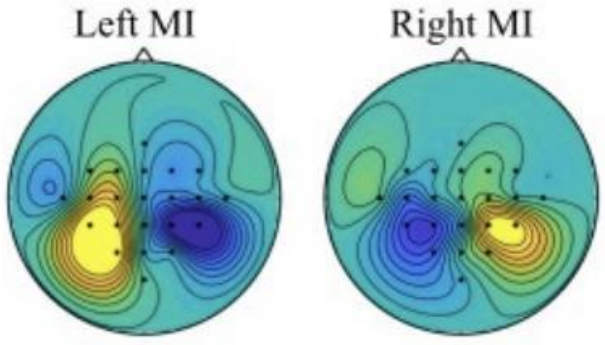
1. verify neural networks
2. discuss and improve neural networks
3. Improve our understanding and gain insight

Related Work

Fuzzy Inference Systems (Lotte et al. 2010)

Combined Layer-wise Relevance Propagation with CNN (Bang et al. 2021, Sturm et al. 2016)

Combined Gradient-weighted Class Activation Mapping with CNN (Kumar et al. 2022)



Locate the brain region and frequency band

Philosophy

- The attention mechanism (Bahdanau et al. 2015) assigns importance to each element within a collection based on relevance, is an arguably interpretable model

i.e. $\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$

Q: *L* **Q**ueries of size *d*, to attend for
K: *L* **K**eys of size *d*, to attend to
V: *L* **V**alues of size *d*

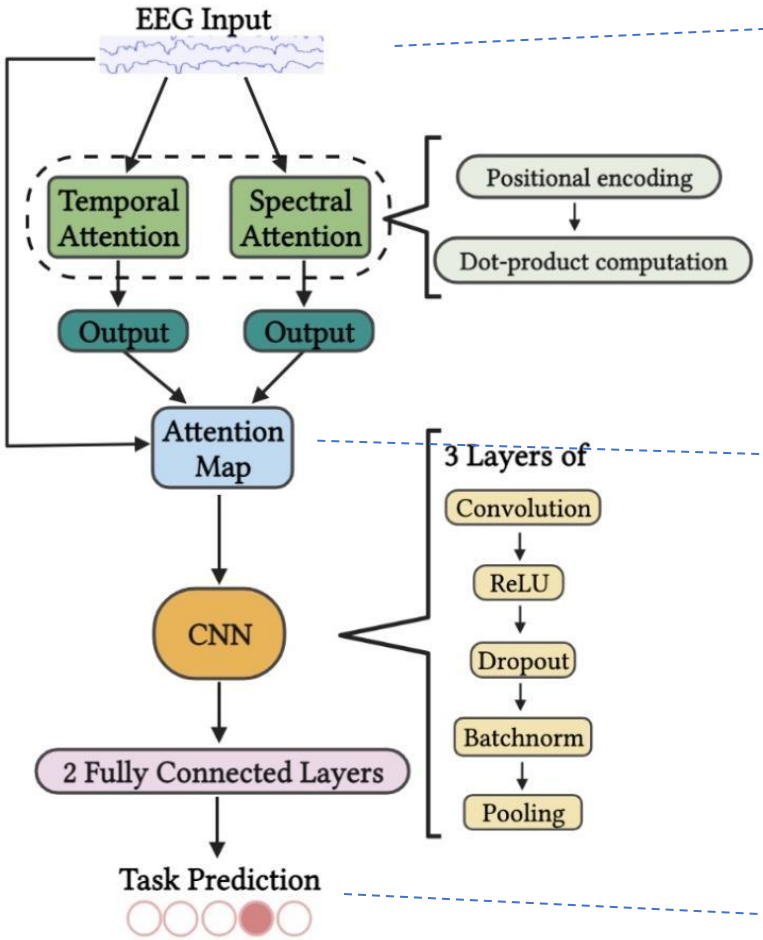
L: length of sequence
d: depth of attention

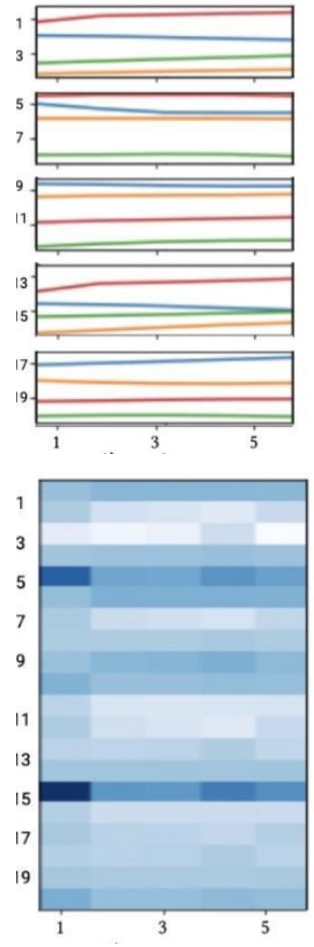
- Combines the attention mechanism with CNN to leverage the advantage of both models

- Zhang et al. (2021) states that CNN can work in complement with the attention mechanism and they suffice a general BMI framework.

- Locate the time point and frequency band for rather small datasets

Model Architecture





[left-hand movement, right-hand movement, word generation]

https://github.com/longyi1207/Attention_Based_CNN/blob/main/Attention_Based_CNN.py

Experiment

Experiment on two Datasets of EEG signals

Table 1: Summary of Datasets

	RWT	BCI III
Recording Signal	EEG	EEG
Category Of Task	Cognitive	Motor imagery
Number of Subjects	14	1
Recording Device	Muse Headband	Biosemi System
Artifact Removal	Muscle Movement	None
Signal Feature	BP	PSD
Data Size For Each Subject	10528×96	2022×20
Recording Length for each Input	500 ms	500ms

Experiment cont.

Training

- GPU provided by Google Colab
- 100 epochs
- Cross entropy loss
- Lr: 5e-4 to 5e-5

Result

Prediction Accuracy

BCI III (3 tasks): 79% (same as benchmark result)

RWT (5 tasks): 46% (set benchmark)

Comparison with Convolutional Block Attention Module (CBAM)

Table 3: Comparison with CBAM CNN

	Our Model	CBAM-based CNN
Performance on RWT (%)	46	46
Number of Parameters on RWT	5155	2532
Performance on BCI III (%)	79	78
Number of Parameters on BCI III	63011	53658

Result

Ablation experiment

	Accuracy on RWT (%)	Accuracy on BCI III (%)
Full Model	46	79
CNN	36	73
Temporal Attention	33	69
Spectral Attention	38	70
Temporal Attention + CNN	39	75
Spectral Attention + CNN	41	77

Observation

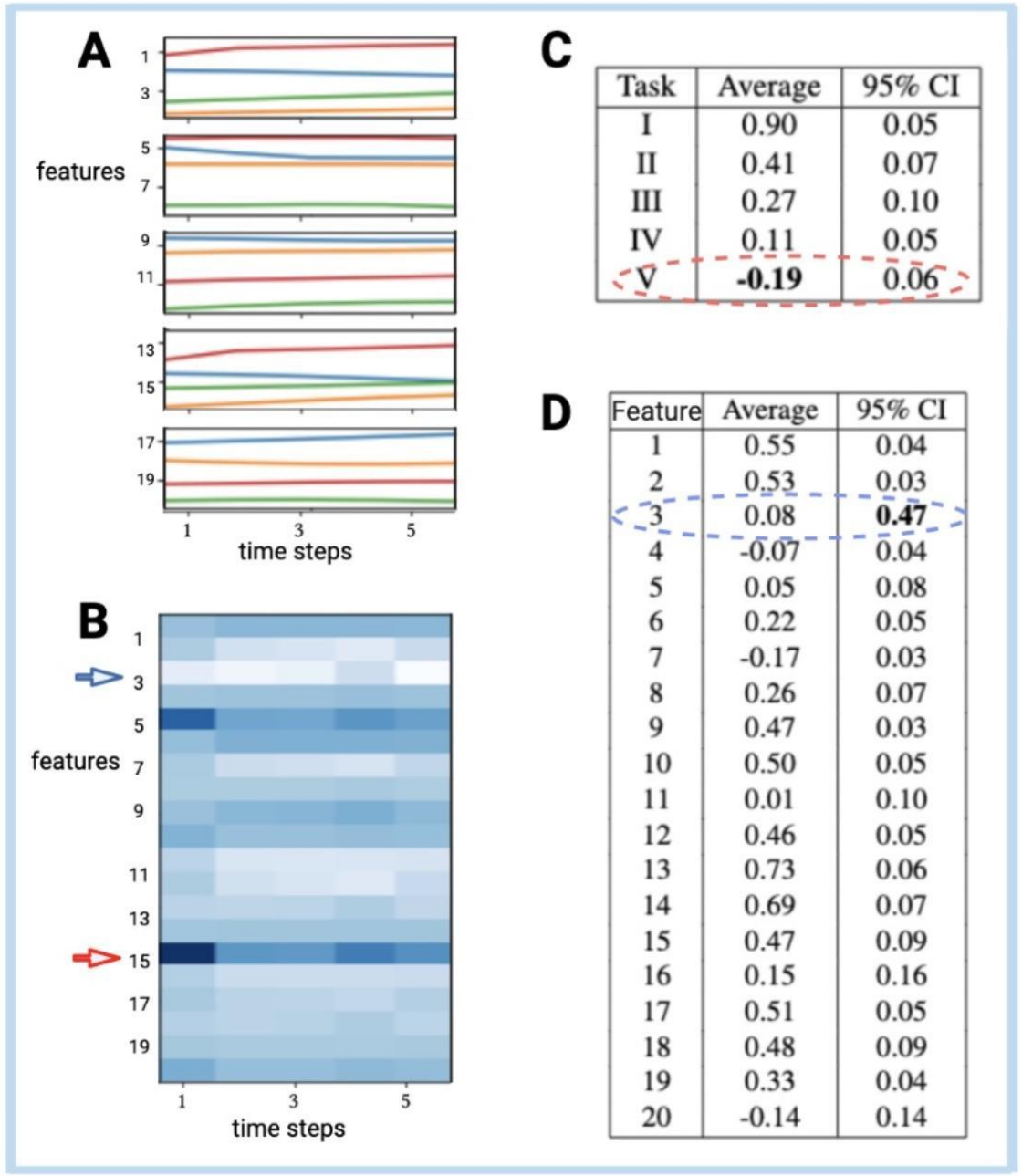
1. CNN alone performed better than either self- attention modules alone
2. the Spectral Attention performed better than the Temporal Attention
3. both self-attention modules and CNN gained in performance when being concatenated to each other.

Result cont.

Interpretability

On power domain

Channel 15 is assigned the highest attention, as it helps Differentiate task five with the four other tasks.
Channel 3 is assigned the lowest attention as it has the least indicative power



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Task	Average	95% CI
I	0.90	0.05
II	0.41	0.07
III	0.27	0.10
IV	0.11	0.05
V	**-0.19**	0.06

D

Feature	Average	95% CI
1	0.55	0.04
2	0.53	0.03
3	0.08	**0.47**
4	-0.07	0.04
5	0.05	0.08
6	0.22	0.05
7	-0.17	0.03
8	0.26	0.07
9	0.47	0.03
10	0.50	0.05
11	0.01	0.10
12	0.46	0.05
13	0.73	0.06
14	0.69	0.07
15	0.47	0.09
16	0.15	0.16
17	0.51	0.05
18	0.48	0.09
19	0.33	0.04
20	-0.14	0.14

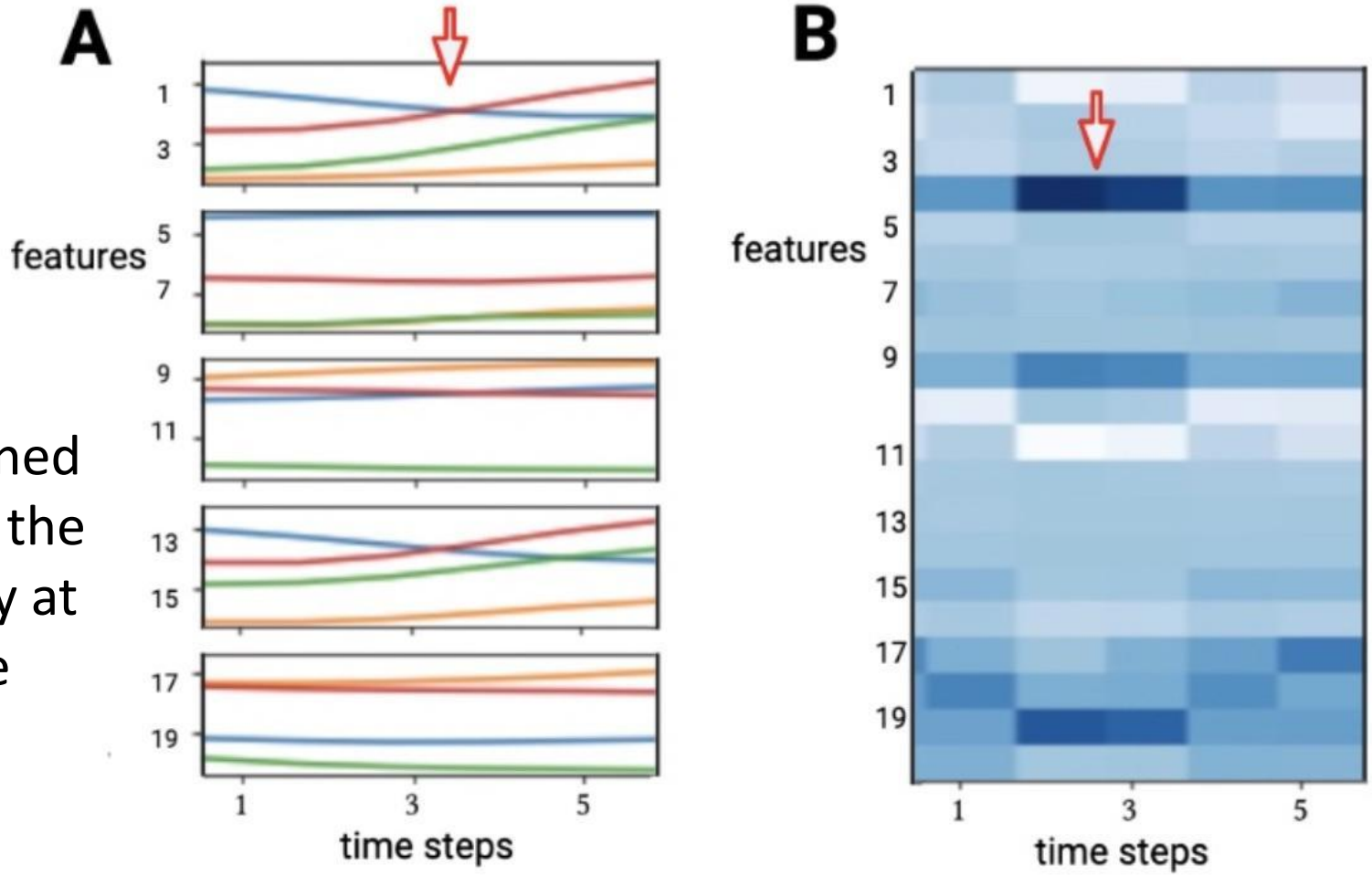
Instance data from RWT

Result cont.

Interpretability

On temporal domain

Time point there is assigned the highest attention, as the input fluctuates distinctly at that point, might provide useful information



Instance data from RWT

Discussion

- The ensemble of attention with CNN increases accuracy
- As well provides interpretability – the model learned average voltage of channels and instant temporal oscillation

Discussion cont.

- This model can be tested with more data, e.g. epilepsy
- Need more empirical data as well as conceptual understanding on the compatibility of CNN and attention
- Interpretable is as important as high-performance

Questions