Blending CNNs with Different Signal Lengths for Real-time EEG Classification Sensitive to the Changes

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Abstract— **Although a lot of BMI research has been performed, CNN's response to changes in the input EEG is too late to proceed in real-time. We propose a method to improve the real-time performance by blending multiple CNNs with different input lengths.**

I. Introduction

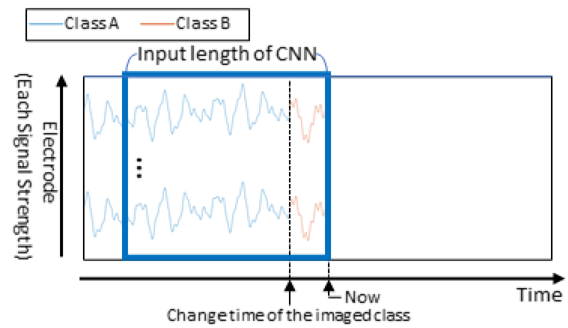
Brain Machine Interface (BMI) is a technology that uses brain information such as electroencephalogram (EEG) to connect a brain to machines. EEG is the electrical activity generated in the brain, and is recorded non-invasively. EEG measurement devices that are small, portable, and have temporal resolution are available. Therefore, a lot of research on brain machine interface using EEG has been actively conducted. Especially in recent years, there has been a lot of research on EEG classification using neural networks. For example, Schirmeister et al. showed that Convolutional Neural Network (CNN) can classify EEG with the same accuracy as Filter Bank Common Spatial Pattern (FBCSP)[1], a conventional EEG decoding technique[2]. Although CNN is highly accurate and selects features automatically, it requires a certain length of signal input in the time axis direction to improve accuracy. That will be a delay for real-time system. In this paper, we propose a new method to blend CNNs with different input signal lengths, and verified its usefulness.

II. Problems

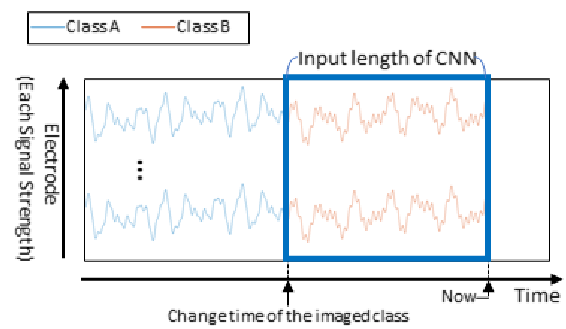
EEG classification by CNN involves inputting EEG intensity data on a two-dimensional plane with the horizontal axis being the time axis and the vertical axis being the electrode number into a CNN, and obtaining the output of the class with the highest estimated probability. When the input signal length to the CNN is long in the time axis, there is a disadvantage that the tracking of the change in the user's imaged class is delayed. In other words, right after the user's imaged class changes, the input to the CNN contains almost no EEG of post-change imaged class (Figure. 1-(a)), and the estimated probability of the pre-change imaged class (Class A) becomes high. When the EEG of the post-change imaged class becomes the majority of the input to the CNN (Figure. 1-(b)), the prediction probability of the post-change imaged class (Class B) becomes high for the first time. One of the CNN architectures used in research[2] had an input data of 522 samples in the time direction for a 250Hz sampling EEG. If this CNN is used for the real-time system, EEG of post-change imaged class occupies all of the input of the CNN, barely $522/255 \fallingdotseq 2.1$ seconds after the imaged class changes.

III. Proposed Method and Conclusion

We propose a method to blend CNNs with different input signal lengths in the time axis direction. By blending CNNs with different input signal lengths, classifier that is sensitive to EEG changes, and has high classification performance under normal conditions can be obtained. In other words, this method enables a classifier that combines the advantages of both CNNs with short input signal length and CNNs with long input signal length. In this study, we generated multiple CNN classifiers for three different input signal lengths using 256 Hz sampling EEG data, each with a different random seed. Then, we compared the blended CNNs with different input signal lengths (proposed method) with the blended CNNs with the same input signal length. The results showed that the proposed method outperformed the blended classifier with medium input signal length in terms of classification stability and response speed to changes in the imaged class. Its delay to the change in imaged class also decreased to 33% of the blended classifier with long input signal length, although it was inferior in terms of classification stability.



(a) Right after the change of imaged class



(b) When all input signals are in the post-change imaged class

Figure.1: Input signals after imaged class changes

IV. Acknowledgement

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References

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[2] Schirrmeister RT, et al.: Deep Learning With Convolutional Neural Networks for EEG Decoding and Visualization, Human Brain Mapping, Vol. 38, No. 11, pp. 5391–5420, 2017.