

Decoding Individual Finger Movements from Single Trial EEG of Motor Execution and Imagery Using CNN

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Abstract—This study aimed to decode motor imagery electroencephalography (EEG) of the finger movements. In this study, we used a convolutional neural network (CNN), which has been reported to have a high decoding accuracy for classifying time-series EEG signals. The performance was evaluated by decoding accuracy for nine healthy subjects while making four-finger movements with their right hand. The highest decoding accuracy for motor imagery was obtained with a simple two-layer CNN model, with a decoding accuracy of 53%.

I. INTRODUCTION

A brain-computer interface (BCI) is a technology that estimates intentions from brain activity and controls devices according to these intentions. To improve the controllability of grasping movements, research has been conducted to decode the EEG during the movements of different fingers within the same hand. Our research group has previously reported the decoding of MI EEG for the movements of different fingers within the same hand, we have not been able to decode it sufficiently [1]. Recent studies on BCI have used convolutional neural networks (CNNs) and long short-term memory (LSTM), and by examining the discriminators, it may be possible to decode finger movements. EEG of the movements of different fingers is decoded using two types of CNN models, Shallow ConvNet [2] and simple two-layer CNN [3], and the decoding accuracy was compared.

II. METHODS

The subjects comprised nine healthy right-handed male university students ranging in age from 21 to 28 years. Informed consent was obtained from all subjects to participate in the study. Some of the EEG signals were the same as in previous studies [1] and were measured using the same method. The subjects performed two types of tasks, motor execution (ME) task and motor imagery (MI) task. The subjects repeatedly flexed and extended each finger of the right hand (thumb, index, middle, and little fingers). To measure brain activity during the experiment, EEG signals were recorded using the ActiveTwo system (Biosemi, Amsterdam, Netherlands). We also measured finger joint angles using Cyber Glove (Virtual Technologies Inc., California, USA). Five-fold cross-validation was performed, and the decoding accuracy (DA) was calculated from the training data (80 %) and test data (20 %). Six pairs were compared: thumb

This work was partly supported by JSPS KAKENHI Grant Numbers 18H04109, 20H05464, 21H03287, 21H03480, KDDI foundation, and Nagaoka University of Technology Presidential Research Grant.

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TABLE I: Average decoding accuracy for all subjects. The star * indicates that the accuracy is beyond chance (53 %).

Methods	Decoding accuracy (%)	
	ME session	MI session
SVM	52	47
ShallowConvNet	54*	51
Simple two layer CNN	57*	53

vs. index finger, thumb vs. middle finger, thumb vs. little finger, index finger vs. middle finger, index finger vs. little finger, and middle finger vs. little finger. There are three types of methods used to classify the two classes: support vector machine (SVM), CNN-based Shallow ConvNet [2], and a simple two-layer CNN [3]. Shallow ConvNet has been reported to be suitable for time-series EEG analysis because it can learn the temporal structure of the power change of the band and is expected to be suitable for finger movements. A simple two-layer CNN have also been reported to be highly accurate.

III. RESULT

The average decoding accuracy for all subjects is shown in Table I. In both ME and MI sessions, Simple two layer CNNs had the highest accuracy, with the highest average accuracy of 57%. For the statistical analysis, a permutation test was performed and the precision by chance was 53%. In the ME session, the both CNN-based methods outperformed chance, while in the MI session they did not outperform 53%.

IV. DISCUSSION & CONCLUSIONS

We tried to decode the finger movements from the EEG during the motor execution and imagery of the finger flexion movement. It is found that the CNN-based classifier can decode this EEG data with higher accuracy than SVM. However, the decoding accuracy is not high. Therefore, further studies are needed.

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