Movement State Classification for Bimanual BCI from Non-Human Primate's epidural ECoG using Three-dimensional Convolutional Neural Network

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Abstract— **During bimanual movement, brain state is known to be different from the unimanual movement. Thus the conventional arm movement classifier for unimanual arm movement decoding method seems to be insufficient to decode bimanual movement. In this research, we suggested the convolutional neural network (CNN) for movement state classification to improve the decoding accuracy for bimanual movement estimation. We recorded the monkey's cortical signal while the bimanual task, and convert to spectrogram dataset for decoding. To evaluate the CNN, we stacked several layers for deep structure and figured out the best configuration. As a result, this method showed improved the arm movement state classification performance for bimanual tasks. This technique could be applied to arm movement brain computer interfaces (BCIs) in real world and the various neuro-prosthetics fields.**

Keywords- bimanual movement, movement state classification

I. INTRODUCTION

In past decades, numerous studies have demonstrated that the limb movement intention induces the change in brain rhythmic activity recorded over the brain cortex. This phenomenon used for brain computer interfaces (BCIs) and develop communication systems in which users explicitly manipulate subject's thought to control the computer. However, previous BCIs research mainly focused on single arm move restoration because the brain activities of bimanual movements are more complex than that of unimanual movements.

Bimanual movements were known to require substantive interhemispheric interactions to coordinate movements of the two limbs, as well as greater involvement of cortical regions rather than single arm movement. According to past studies, the brain does not encode bimanual movements simply by superimposing two independent single-limb representations Furthermore, the brain activity could be different according to behavioral conditions like stationary state (no movement), unimanual and bimanual movement. Considering these points, the cortical signal could be classified the brain state during bimanual movement. In our previous study, we tried the four-class classification using linear discriminant analysis, however the accuracy was not enough to apply in real life BCIs.

In this paper, we suggested the convolutional neural network (CNN) method for movement condition classification to improve the accuracy and reduce the classification error. The movement conditions were classified by four types: stationary state, left/right arm unimanual movement, and bimanual movement. Then we predicted the movement type using CNN. Finally, we reported the results of improved performance compared to the conventional methods and it might be effective in bimanual BCIs.

II. MATERIALS AND METHODS

A. Subject

Adult male rhesus monkey (Macaca mulatta, M24) was implanted with two ECoG electrodes patches in the epidural space of the left and right hemisphere covering arm movement related area. It covered the primary motor cortex (M1), supplementary motor area (SMA), premotor cortex (PMC), and primary somatosensory cortex (S1). All procedures were approved by the Seoul National University Hospital Animal Care and Use Committee (IACUC No. 13-0314)

B. Behavioral task

The monkey sat on the chair and executed 3 types of arm movement tasks – left arm unimanual task, right arm unimanual task, and bimanual-simultaneous task - during recording of the ECoG signal and arm movement trajectory. The cue buttons' light color, which represented the arm movement target (left arm-blue and right arm-red), was randomly lit by each task. Each session contained 200 trials, and the monkey performed 4 sessions per day for 4 months. (Figure 1)

C. Data acquisition and signal processing

The recording started three weeks after surgery. Cortical signals were recorded by EEG 1200 (Nihon Kohden, Japan) at a sampling rate of 1 kHz per channel. To record the arm trajectory, 6 wireless IMU (inertial measurement unit, XSENS, Netherlands) were used for motion tracking. The trackers were attached to both wrists, upper arms, and back of the monkey's shoulders and recorded with 20Hz sampling rate.

For preprocessing, we used MATLAB (Mathworks, USA) software. The ECoG data was band-pass filtered from 0.3 to 200 Hz, and notch filtered 60, 120, and 180 Hz to remove

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power noise. Then every 50ms, the data was transformed to 10~120Hz, 1sec width scalogram, which represented time-frequency power change, using wavelet transform.

To make input image data for CNN, we made topographic images, which called "topomap", from scalogram data which preserve the spatial and multi-spectral information. We transformed the scalograms into a 2D image to preserve the spatial structure and we used multiple color channels to represent the spectral dimension. Among 1 sec scalogram, the latest time bin (100 msec) was used for mapping. Frequency bins were averaged in three bands; alpha-like: 10-16Hz, beta: 17-30Hz, and gamma: 31-110Hz, which are represented in red, green, and blue, respectively. Then we also labeled what type of movement it is. (Figure 2)

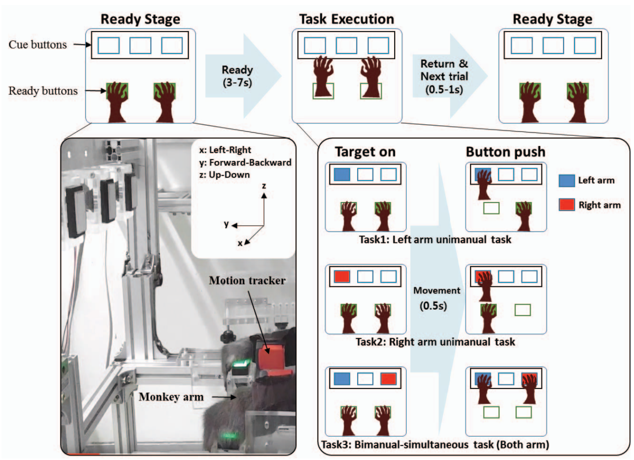

Figure 1. Button task paradigm

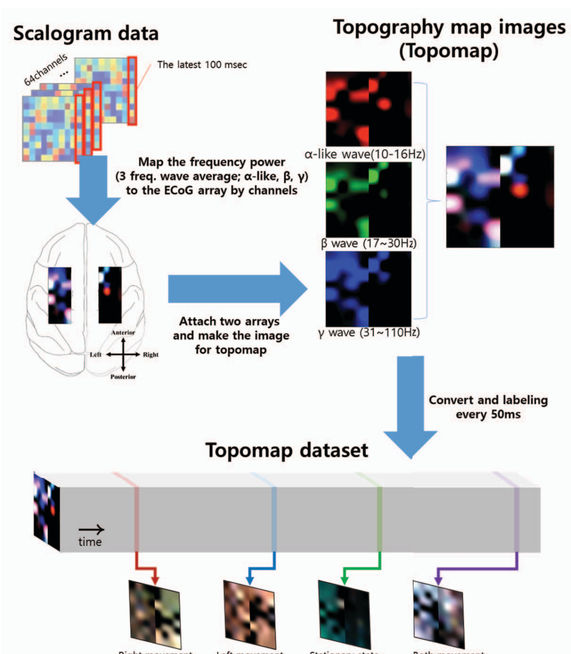

Figure 2. How to make input image data for CNN

D. *Convolutional Neural Network*

A	B	C	D	E
Input (trials, 10, 112, 112, 3)				
Convolution (64) Maxpooling	Convolution (64) Maxpooling	Convolution (64) Maxpooling	Convolution (64) Maxpooling	Convolution (64) Maxpooling
	Convolution (128) Maxpooling	Convolution (128) Maxpooling	Convolution (128) Maxpooling	Convolution (128) Maxpooling
		Convolution (256) Convolution (256) Maxpooling	Convolution (256) Convolution (256) Maxpooling	Convolution (256) Convolution (256) Maxpooling
			Convolution (512) Convolution (512) Maxpooling	Convolution (512) Convolution (512) Maxpooling
				Convolution (512) Convolution (512) Maxpooling
Fully-connected(4096) Batch normalization Dropout				
Fully-connected (Softmax)				

Figure 3. Evaluated CNN Configurations for Movement State Classification.

The CNN has been well known for great strength in image classification. To evaluated CNN configurations for classifier, we stacked several layers for deep structure and figure out the best configuration. (Figure 3) Then, we calculated the confusion matrix between true label and predicted label and receiver operating characteristic (ROC) curve.

III. RESULTS

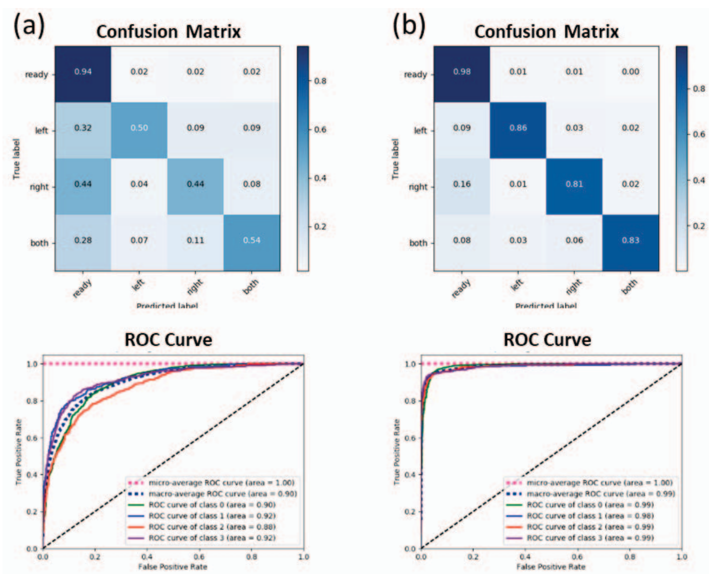

Figure 4. Confusion Matrix and ROC Curve: (a) Result of Configuration-C, (b) Result of Configuration-E from figure 3

The CNN method showed meaningful performance to classify the brain signals of arm movement. It is more accurate than the LDA method, and deeper structure more accurate. When we classified the bimanual movement using deep CNN structure, it significantly improved the accuracy and F1 score and reduced the classification error.

IV. DISCUSSION

The performance of the bimanual movement state classification using the deep CNN structure is much more accurate than the shallow one because the deep structure could allow for more sophisticated parameter updates. To our knowledge, this is the first study to apply the CNN to bimanual BCIs. In the future, we are going to identify the differences in the CNN features for each movement state, and interpret it with the physiological background.

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