Motor Trajectory Decoding based on fMRI-based BCI - a simulation study

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Abstract—Recent brain computer interface (BCI) studies using chronically implanted microelectrode array demonstrated that electro-physiological responses from primary motor cortex (M1) can be successfully used to control a robotic arm by reading subjects’ intention to move their arm [1]. In order to avoid the invasiveness of electrophysiological recording, more non-invasive approaches such as EEG or fMRI was likewise proposed. However, most non-invasive BCI studies suffer from the fact that they classify brain differential activity states, rather than deciphering the actual neural responses underlying the target behavior. In this simulation study, in order to decode the brain activity states underlying the target behavior from the fMRI signals, we found the directional tuning properties, a basic functional property of neural activity in M1, at the voxel level for motor trajectory decoding, and we performed a simulation to demonstrate that it is feasible to control the robotic arm in real time based on multi-voxel patterns.

Keywords—fMRI; invasive BCI; noninvasive BCI; directional tuning curve

I. INTRODUCTION

There have been two different traditions in the BCI research field. One of them is invasive BCI based on electrophysiological signals in the motor cortex. Invasive BCI studies have shown that it is possible to execute reaching, grasping, and force control in the robotic arm from neural spike trains. The other one is noninvasive BCI that primarily use electroencephalography (EEG). Because invasive methods have a surgical risk and EEG-based BCI signals from scalp electrodes are spatially blurred, we are interested in noninvasive BCI based on fMRI. However, most noninvasive methods using classification approaches have a limitation of classifying a few differential activity states of brain, which are not related to the intrinsic neural signals. In this simulation study, we tested noninvasive BCI based on fMRI to demonstrate the possibility of controlling the robotic arm by mimicking the subjects’ arm movement in two-dimensional space, and in order to decode the brain activity states using an intrinsic neuronal property from the fMRI signals, we used correlation tuning curves, which is estimated from correlation between multi-voxel patterns elicited by different directional movements.

II. METHODS

In order to test the feasibility of motor trajectory decoding using fMRI, we developed a forward model from neuronal activities in M1 to fMRI signals for this simulation study.

A. Directional tuned cells in M1

The single cells in M1 are directionally tuned to the direction of arm movement. The firing rate of directionally tuned cells is highest with arm movement in a preferred direction and decreases gradually with arm movements in directions farther away from the preferred one. This resulted in bell-shaped directional tuning curve. This directional tuning is a functional property of cell activity in M1 [2]. We generated the eight directional tuning curves for this simulation study.

B. Modeling of the primary motor cortex

The single cells with similar preferred directions are organized into functional modules consisting of several minicolumns [3]. Therefore, according to the previous study [4] to model the distribution map of preferred directions in M1, we assumed that a width of directional minicolumns, the basic unit in the distribution model of the motor cortex, is 30 um, and a width of the columnar structure clustered with similar preferred directions is 240 um. In addition, we assumed that there are 8 directional tuned minicolumns, and the cluster of minicolumns has same directional sensitivity to the direction of arm movement. The voxel size is 3 × 3 mm². The average size related to the arm area is around 36 voxels [5] (Fig. 1).

![Figure 1. Distribution map of preferred direction in M1](image)

The voxel size is 3 × 3 mm². The average size related to the arm area is around 36 voxels.
C. Forward modeling of BOLD fMRI signal

Each of minicolumns in M1 was activated according to direction of arm movements, and in order to represent the neural signal, we used the Poisson spike generation model. Because the fMRI responses are proportional to average firing rates [7], the spike trains of each minicolumns inside a voxel were averaged and then convolved with the hemodynamic response function (HRF) to generate the BOLD fMRI signal. The model of HRF peaked at around 6 seconds. After generating the synthetic BOLD fMRI signal, the signals were sampled at every second because we defined that the TR is 1 second.

D. Experiment

The experiment consists of two sessions. First, during the training session, fMRI signals generated by simulated arm movements from the center position toward the eight equidistant targets were analyzed using correlation analysis between multi-voxel spatial patterns in order to find the directional tuning properties at the voxel level. Then, during the test session, the trajectories of continuous arm movements toward random directions were predicted from the fMRI signals using the estimated directional tuning curves.

E. Motor decoding

We obtained the eight average correlation tuning curves predicted during the training session and the correlation coefficients calculated during the test session, we were able to predict and reconstruct the trajectories of arm movement from 0° to 360° (at 1° intervals).

III. RESULTS

Directional tuning properties can be found at the voxel level analyzed using correlation between multi-voxel patterns (Fig. 2). Furthermore, the result of motor decoding showed that the trajectories of arm movements can be predicted in two-dimensional space using the motor decoding method based on multi-voxel patterns, and the prediction performance is the best when time delay is 6 seconds (Fig 3). However, it takes a long time to control the robotic arm in real time. Therefore, the weighted average windowing method was applied to reduce the time delay for real time control system, and the result showed that the prediction performance can be increased when the delay time is faster than 6 seconds using the average windowing method (Fig. 4(A)). Fig. 4(B) showed the effect of the averaging windowing when the delay time is 3 seconds.

IV. DISCUSSION AND CONCLUSION

As a result of this simulation study, we demonstrated the feasibility to control the robotic arm in real time using fMRI-based BCI by finding the directional tuning property at the voxel level. Furthermore, this study provided that if we should find the directional sensitivity during motor imagery, it would be also possible to read the subject’s intention to move their arm and to control the robotic arm between the thought of the moving the arm and the movement of the robotic arm in real time. For the future work, we will perform the real fMRI experiment to control the robotic arm by mimicking and thinking the subject’s action.

REFERENCES


