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著者(和文)	陳超
Author(English)	chao chen
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Type(English)	Summary

（博士課程）
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論 文 要 旨

THESIS SUMMARY

専攻： Department of	物理情報システム　専攻	申請学位（専攻分野）： Academic Degree Requested	博士 Doctor of　（　学術　）
学生氏名： Student's Name	陳超	指導教員（主）： Academic Advisor(main)	小池康晴
		指導教員（副）： Academic Advisor(sub)	

要旨（英文 800 語程度）
Thesis Summary（approx.800 English Words ）

Over the past two decades, brain-machine interfaces (BMI) have been developed utilizing the growing understanding of brain function and the development of technology to measure brain activity. BMI employs neuron activities or brain signals to send messages to outside or control devices such as robot arm or neural prosthetic. This new communication pathway has not only the potential to help to disabled persons but also provide insight into the motor system of the brain. A number of methods have been developed to measure brain signals, such as multi-neuron activity, local field potentials, electroencephalography, and functional magnetic resonance imaging. BMIs are mainly categorized into two types, invasive and non-invasive BMIs, according to the signal source.

Invasive BMI, which measure activities form cortical neurons directly, has high spatial-temporal resolution and signal-to-noise rate. Kinematic information can be decoded in real time and used for self-feeding robot control. However, invasive BMI always penetrates the cortex and damage the brain. Thus, invasive BMI suffer from high clinical risk and poor long-term stability. On the other hand, no-invasive BMI can provide basic communication to people with severe disability. However, due to the low spatial or temporal resolution, compared with invasive signals, it is still difficult to realized real time control of three-dimensional robot arm or neural prosthetic by no-invasive BMI.

Since the limitation in both invasive and no-invasive BMI, as semi-invasive brain signals, electrocorticography (ECoG) has drawn attention as a new type of signal source for BMI. ECoG signals have higher signal-to-noise ratio and spatiotemporal resolution than non-invasive recording methods, because ECoG electrodes are laid on the surface of the cerebral cortex. In addition, long-term stability had been showed and the level of clinical risk is lower compared with invasive methods, because the electrodes do not penetrate the brain. Within about ten years following with this succeed, productive ECoG based BMI research were reported, including cursor control, classification of hand movement, and grasp types, detection of start time point of grasp, decoding of muscle activities, movement-related intracortical activity, hand trajectories and finger movement in human and monkey subjects.

The goal of this study is to develop a high performance ECoG-based upper limb brain machine interface, such as neural prosthetic. To complete a neural prosthetic with multi-degree of freedom, position in formation and control method for gripping is necessary. Thus, we intended to

decode hand trajectory and grasp force profile from ECoG signals. Two monkeys were trained to perform reaching and grasping task. The ECoG signals, 3D hand positions and grasp force were recorded simultaneously. Three dimensional hand trajectories and grasp force profile were predicted from ECoG signals in primates' sensorimotor cortex.

We proposed an algorithm to decode hand trajectory and grasp force from 15 and 32 channel ECoG signals recorded from primary motor cortex (M1) in two primates. To determine the most effective areas for prediction, we applied two electrode selection methods, one based on position relative to the central sulcus (CS) and another based on the electrodes' individual prediction performance. The best coefficients of determination for decoding hand trajectory in the two monkeys were 0.4815 ± 0.0167 and 0.7780 ± 0.0164. Performance results from individual ECoG electrodes showed that those with higher performance were concentrated at the lateral areas and areas close to the CS. The results of prediction according with different numbers of electrodes based on proposed methods were also shown and discussed. These results also suggest that superior decoding performance can be achieved from a group of effective ECoG signals rather than an entire ECoG array.

We also demonstrated that lateral grasp force profile can be decoded using a sparse linear regression from 15 and 16 channel ECoG signals recorded from sensorimotor cortex in two non-human primates. The best average correlation coefficients of prediction after 10-fold cross validation were 0.82 ± 0.09 and 0.79 ± 0.15 for our monkeys A and B, respectively. These results show that grasp force profile was successfully decoded from ECoG signals in reaching and grasping tasks and may potentially contribute to the development of more natural control methods for grasping in neural prosthetics.

In addition, the future directions of brain research and interface development were investigated. The major burns in current brain research and interface development were discussed. With the development of next generational ECoG electrode, ECoG signals may play an important role in future brain and interface research.

As future work, we want to complete real time robot control based on the result mentioned about. This work can be divided into three parts: the time point of reaching and grasping, target hand trajectory of robot arm, and control of gripper. In previous ECoG based study, the time point of reaching and grasping were decoded successfully. Using the same method, it is possible to achieve. For target hand trajectory of robot arm, we can calculate shoulder and elbow joint angle from the predicted hand trajectory and length of robot arm. For control of gripper, it is better to decode aperture, the distant between thumb and index finger, then control the gripper from aperture and grasp force profile.