Towards Multi-Dimensional Robotic Control via Noninvasive Brain-Computer Interface

Xuedong Chen and Ou Bai

Abstract— **Brain-computer interface (BCI) provides a new communication pathway for patients with neurological disorders who may not make voluntary muscle contraction. A potential BCI application is that patients may control a neuro-prosthetic robot directly from their brain so that they can achieve virtual interaction with environment. Therefore, a BCI supports multi-dimensional control is highly demanded for a multi-dimensional robot. We hypothesized that human intentions to move his right, left hand, leg and tongue can be detected by the somatotopic spatial activation patterns from single-trial MEG signal. Under reliable detection, human can intentionally control a two-dimensional robotic motion; right, left, up and down. The hypothesis was tested offline; the classification was performed on beta band activation (15-30Hz) of SAM virtual channels. Cross-validation results using linear discrimination provided high detection accuracy (70-90%) when considering a random level of 25%. We demonstrated that noninvasive BCI methods may support reliable multi-dimensional control of neuro-prosthetic robotics.**

I. Introduction

OPERATING machines just by thinking has been dream and a part of science fiction. Brain Computer Interface (BCI) is such a system. BCI is generally intended to be developed as a communication channel for patients with severe neuromuscular disease; it can also be used as a channel for man machine interface to gouge attention level, concentration and other emotional attributes [1]. BCI has been developed for people in locked-in or semi locked-in stage. Such a condition may happen due to cervical spinal cord injury, stroke or disease like amyotrophic lateral sclerosis (ALS). Such a condition may lead to severe motor paralysis. BCI opens a medium of communication and rehabilitation.

There are two broad ways of BCI; invasive and non-invasive. The invasive technique can capture intracortical action potentials of neurons and thus, provides high signal strength spatiotemporally, for example, prediction of movement trajectory [2]. But due to inherent difficulty and problems associated with such a method non-invasive techniques are generally used. In non-invasive technique Electroencephalogram (EEG) and Magnetoencephalogram (MEG) have emerged as viable options; both of them have time resolutions in milli seconds so we can study the dynamic activities of brain in contrast to imaging-based BCI [3]. Any activity in brain is accompanied by change in ionic concentrations in neuron leading to polarization and depolarization. Such an electrical activity is measured by EEG, while MEG measures the magnetic field associated with these currents. Electric and magnetic fields are oriented perpendicular to each other. MEG provides direct information about the dynamics of evoked and spontaneous neural activity. EEG has advantage that it is portable and cost effective but as magnetic fields suffer far less than the electric fields from the spatial blurring effect of the skull, MEG provides better spatial resolution so that we might accurately decode more brain information/minds [4], and eventually it might be possible to actually "read" human mind instead of indirect control of brain rhythmic activity [5] or slow cortical potential [6] in current EEG-based BCI.

Human has intention to move, and human movement intention is associated with at least two kinds of brain activity that can be observed in EEG/MEG; movement–related cortical potentials (MRCP) [7] and alpha (8-13Hz) and beta band (16-30Hz) event-related desynchronization (ERD) [8]. Functional study found that the corresponding motor areas are activated when human intends to move before the actual production of certain limb movement; for example, hand area is activated before the production of hand movement [9, 10]. According to human somatotopy, different motor areas will be activated when human intends to move their limbs. Therefore, we may discriminate human movement intentions before actual movement from spatial distribution of brain activities if the spatial resolution of the signal is high enough. Though it may be more difficult to identify movement intention from the spatial distribution of MRCP due to the small potential amplitude, the rhythmic activity of ERD can be more reliable for the discrimination, in particular, from single trial signal. As MEG signal provides better spatial resolution than EEG, we want to test our hypothesis to discriminate/predict multiple movement intentions from the ERD spatial distribution of single trial MEG. Upon the success of the prediction, it can be used as a robust BCI method supporting multi-dimensional control.

In this paper we propose a multi-dimensional BCI via reliably decoding human movement intentions. If the prediction/decoding of movement intentions to move right

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hand, left hand, leg and tongue before movements occur is reliable, the natural behavior of human intentions can be decoded to control a two-dimensional cursor for BCI purpose. Our BCI proposal is highly related to the reliable decoding intentions from spatial distribution of brain activity. We adopted synthetic aperture magnetometry (SAM) as the spatial filter for further improving the spatial resolution of MEG signal. We also compared with other spatial filter method, i.e., Laplasian derivation, that has been used in MEG signal processing for BCI purpose [11].

II. METHODS

A. *Subjects*

Eight healthy volunteers, 5 male and 3 female (age: 31±8 years) participated in the experiment. All subjects participating in this study were right-handed according to the Edinburgh inventory [12]. They were all naive subjects who hadn't received any BCI related training. The protocol was approved by the Institutional Review Board; all subjects gave their written informed consent for the study.

B. *Paradigm*

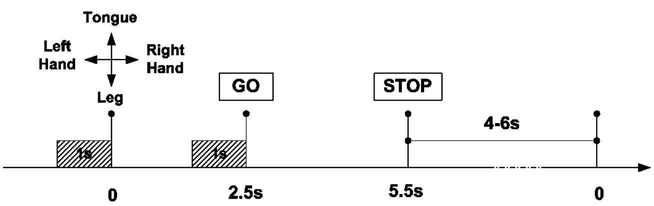

Fig. 1 Experimental paradigm. Activation period: -1 to 0 before 'GO' cue. Control period: -1 s to 0 before warning cue of 'Right', 'Left', 'Leg' and 'Tongue'. Both data of activation and control were used for SAM analysis, and virtual channel during the activation period was used for classification/prediction.

A visual warning cue randomly selected from a set of four activities; 'right" for right hand extension, 'left' for left hand extension, 'leg' for right foot toe curl, and 'tongue' press of the tongue on the roof of the mouth, was presented on a screen placed about 50cm before the subject (see Fig. 1). The subjects were instructed to urge the movement after the cue presentation. The duration of the visual cue was 0.5s. the subjects started thinking and urged themselves for the associated movement without physically moving. After 2.5 s a 'GO' signal was displayed at which the subject started physical movement as soon as possible. This continued for another 2.5 sec after which a stop signal was displayed and the subject stopped the motor task and relax. A 4-7 se rest period was provided after which the process was repeated. During the period of visual stimuli the subjects were asked to keep eyes open and reduce blinks as much as possible. The subjects were allowed to become familiar with the paradigm before data recording.

The experiment consisted of 6 sessions with each session of 30 movement tasks, i.e. about 45 trials for each of four movements. Subjects were asked keep head still to reduce head motion.

C. *Data Acquisition*

The MEG data were recorded at 600 Hz using a 275-channel CTF whole head MEG system in a shielded environment. The CTF MEG system was equipped with synthetic 3rd gradient balancing, an active noise cancellation technique that employed a set of reference channels to subtract background interference.

D. *Data Processing*

MEG analysis software developed at NIMH MEG core facility was used for epoching data, SAM analysis and MRI conversion. AFNI software developed at NIMH was used for group analysis.

The data was epoched according to the marker events for a period of 9 s starting 1 s before the event and continuing 8 s after it. All epoched data of same event were combined together to form grand dataset. Before doing SAM analysis, a multisphere head model was created for each subject (threshold value = 40%) based on anatomical images of each subject using MEG analysis software.

E. *SAM Analysis and Virtual Channel*

SAM was then used to analyze task related activity of brain. Frequency range was selected as 15 to 30 Hz. -1 se to cue onset was taken as active state and -1s to movement onset was set as control state for analysis. SAM calculates covariance between active state and control state and uses it to design an optimal spatial filter which creates a 3-d source image comparing the source strength for the two states. This image was superposed on MRI image and regions of high activity were selected for virtual channel analysis. The signal from the specified virtual channels were fed to a classification toolbox; BCI2VR [13].

We used movement signals as it is natural to the user; easy for the subjects to learn and control. The problem with most of the BCIs is that they rapidly fatigue and have high waiting and processing time. The proposed BCI associated with human natural motor control might be fast and easy to adapt to, and it needs low processing time. Synthetic aperture magnetometry (SAM) has been employed for signal processing. We adopted this method because it may provide better signal-to-noise ratio (SNR). The SAM processing is a semi-automatic analysis method. The users can apply SAM technique without expert knowledge. Only the time-frequency region of interest needs to determine. SAM estimates source location by focusing the array with linear weighting. It uses beamforming to obtain good data from the location of interest at the cost of bad data elsewhere. It interferometrically combines the SQUID sensor values.

When SAM results are combined with MRI it gives a visual image of regions of brain showing event-related Synchronization (ERS) and Event related desynchronization (ERD). BCI might work best with ERD/ERS due to the straightforward relationship between ERD/ERS and motor cortex activity.

According to the SAM image, we extracted virtual channel data from high spots in right hand, left hand, leg and tongue motor areas. Around 10-15 virtual channels were selected for further classification.

F. Feature Extraction and Classification

The power of all virtual channels signals during -1 s to ‘GO’ cue onset was calculated as the features for classification. For each subject, a total about 180 instances from single trial signal including roughly even four kinds of movement tasks were available for classification. We adopted 10-fold cross-validation; 180 instances were divided into 10 groups, and each time, 9 groups of instance were used for training/modeling and the residue group data was used for testing to guarantee the independence of training and testing. The training and testing procedures were repeated 10 times, and cross-validation accuracy was determined from the average of the 10 times independent testing.

We intended to predict/discriminate four movement intentions before actual movement from single trial virtual channel signals. We adopted decision-tree method for solving multi-class classification task in this study. In order to spatially discriminate four movement intentions, a large feature set including of all activities in the desired motor areas should be used. However, a certain feature subset, for example, virtual channel activity in leg motor area would be the best to discriminate intention to move leg whereas rather poorly for the discrimination of other movement intention. We employed multistage classification, i.e., decision tree, to discriminate one intention from others in each successive stage.

The order for classification was determined from the training dataset. We first calculated the Bhattacharyya distance of each feature for four of one-to-others tasks; right-hand-to-other-three, left-hand-to-other-three, leg-to-other-three and tongue-to-other-three. The Bhattacharyya distance of each feature quantified the feature’s impact; the larger the feature’s Bhattacharyya distance, the greater separability of the data by that feature [14]. The one-to-other task with the highest Bhattacharyya distance was the first stage of classification. For example, if the right-hand-to-other-three task had the highest Bhattacharyya distance, we would determine whether subject intended to move his right hand for each instance. The second classification stage was similar to the first stage, but the multi-classification task was reduced to three classes. The final stage was to discriminate binary classes. For the classification of each stage, we adopted linear classification method of Mahalanobis distance classifier (see detail method in [13]) . The number of feature was determined from cross-validation data; the one had best cross-validation accuracy by searching from feature number from 1 to 6.

We compared with classification accuracy performance using SAM as spatial filter with conventional Laplacian derivation methods [15] and direct sensor data classification without classification. Power spectral density was used as features for classification. The features extraction was implemented based on Bhattacharyya distance [13].

III. RESULTS

The SAM image associated with intention to move right hand, left hand, leg and tongue is illustrated in Fig. 2.

The comparison of classification performance on SAM spatially filtered signal, direct MEG sensor signal, and spatial Laplacian derived signal was performed. The classification results are show in Table I.

TABLE I PREDICTION OF INTENTION TO MOVEMENT RIGHT AND LEFT HAND USING DIFFERENT SPATIAL FILTERS (10-FOLD CROSS-VALIDATION ACCURACY)

Spatial Filter	SAM	None	Laplacian
Subject 1	**0.80**	0.58	0.61
Subject 2	**0.87**	0.58	0.58
Subject 3	**0.99**	0.54	0.57
Subject 4	**0.97**	0.62	0.65
Subject 5	**0.74**	0.57	0.58
Subject 6	**0.91**	0.57	0.61
Subject 7	**0.99**	0.56	0.62
Subject 8	**0.99**	0.41	0.56
Average±STD	**0.91±0.12**	0.56±0.06	0.60±0.03

Paired t-test on SAM results and channel classification results showed that the null hypothesis at 0.05 significance alpha level can be rejected because of the p-value <0.001.

TABLE II PREDICTION OF MULTIPLE MOVEMENT INTENTIONS WITH SAM FILTER (10-FOLD CROSS-VALIDATION ACCURACY)

	3-Classes*	4-Classes**
Subject # 1	0.65	0.65
Subject # 2	0.82	0.50
Subject # 3	0.57	0.71
Subject # 4	0.85	0.81
Subject # 5	0.67	0.55
Subject # 6	0.90	0.83
Subject # 7	0.64	0.77
Subject # 8	0.80	0.58
Average±STD	0.74±0.12	0.68±0.12

* Prediction of movement intention of left hand, right hand and leg.

** Prediction of movement intention of left hand, right hand, leg and tongue

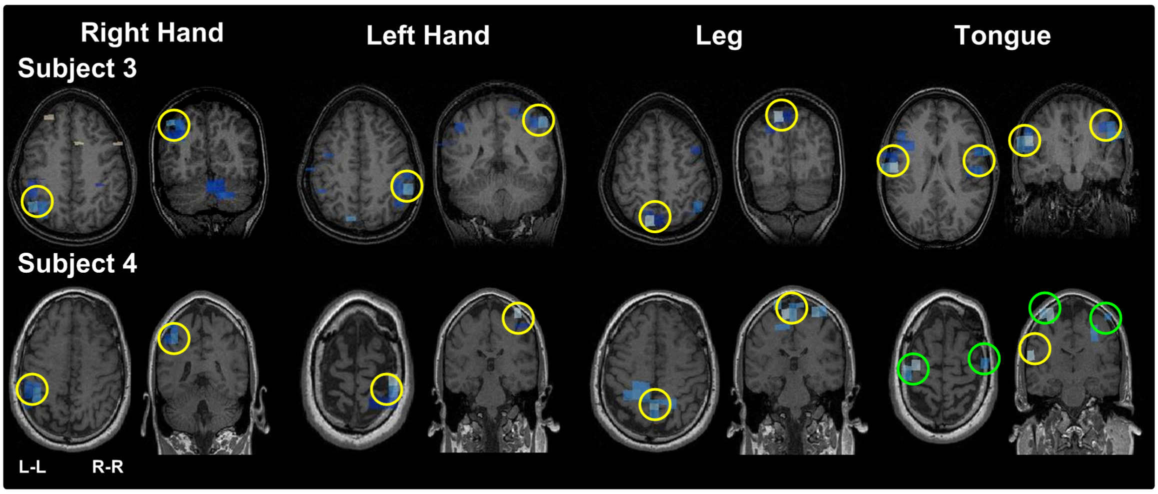

Fig. 2 SAM image: activation (marked in yellow) in the corresponding motor areas associated with the intention to move; right, left hand, leg and tongue. However, for subject 4, when intended to move tongue, bilateral hand areas were also activated.

Similarly paired t-test was done on SAM and Laplacian method results also showed that the null hypothesis at 0.05 significance alpha level can be rejected because of p-value <0.01.

The statistical results demonstrated SAM spatial filter significantly improves the classification performance for decoding human movement intentions.

IV. Discussions

All the subjects showed ERD before and during the movement, followed by ERS after the movement. ERD occurred in similar regions during intention/readiness and actual movement period. As expected, signals were more enhanced during movement than for movement intentions. Different movement intentions showed different regions of activity in the brain. However, some overlapping regions were also found.

The SAM image illustrated in Fig. 2 showed that human movement intention was predictable from MEG spatial and temporal patterns associated with different movements. All subjects showed activity mostly in beta band (15-30 Hz) associated with movement intentions. All the subjects showed different regions of activation for different movement intentions, but these regions varied from subject to subject. All the tasks showed bilateral activity, requiring co-ordination between both the hemispheres of brain, but generally one hemisphere dominates. All the four movement intentions produced spatially different regions of activity. For left hand movement, right motor cortex was activated; whereas for right hand movement, left motor cortex region showed greater activity. For leg movement, middle motor cortex was activated. Tongue activity showed lot of variation across the subjects activating regions of both the hemispheres. The tongue representation was relatively small and distributed across both the hemispheres. Hand area also was activated during tongue movement. This might be because tongue is difficult to move as compared to hand or foot, so that it involves large activations that may overlap with other motor regions.

The classification result showed SAM provided better classification than Laplacian and other channel based methods. T-test results showed that SAM was significantly better than other sensor-based techniques. Binary classification accuracy above 90% has been achieved by discriminating activities from virtual channels. Location of virtual channels for better classification varied among subjects. Strength and location of cortical activity were different for different subjects and motor tasks.

The reliable prediction in this study showed that MEG was much better than EEG for prediction multiple movement intentions [16]. MEG provides better resolution both spatial and temporal. If we employ appropriate technique for source imaging, we may obtain accurate and reliable prediction of movement intentions. The highly reliable prediction would provide strong support for a multi-dimensional robotic control.

The proposed BCI provided best results when differentiating between right hand and left hand movement intentions. We found that the prediction was worse when differentiating tongue movement from other movements. The possible reason is that the tongue somatotopy area is very close to hand somatotopy area. In order to improve the prediction accuracy, subjects may urge other alternative movements instead of tongue movement, for example, left foot.

In summary, the proposed BCI has the following advantages over other BCI methods: two dimensional controls; a natural control scheme; a system with high spatial resolution; acceptable time response; robust and reliable. The proposed highly reliable BCI could greatly impact the lives of patients suffering from ailments such as amyotrophic lateral sclerosis (ALS) or spinal cord injury. This may help in their speedy rehabilitation and provide a mechanism for mechanical control and communication device. This may also provide new features for entertainment industry especially gaming world: controlling cursors and remote devices may provide novel opportunities. However MEG-based BCI is costly currently and not portable, but if recording technique can be improved; the MEG may be a possible potential way for BCI control.

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