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Single Trial Detection of Human Movement Intentions from SAM-Filtered MEG Signals for a High Performance Two-Dimensional BCI

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***Abstract* - The objective of this research is to explore whether a two-dimensional BCI can be achieved by reliably decoding single-trial magneto-encephalography (MEG) signal associated with sustaining or ceasing right and left hand movements. Seven naïve subjects participated in the study. Signals were recorded from 275-channel MEG and synthetic aperture magnetometry (SAM) was employed. The multi-class classification for four-directional control was evaluated offline from 10-fold cross-validation using direct-decision tree classifier and genetic algorithm based Mahalanobis linear distance. Beta band (15-30Hz) event-related desynchronization and event related synchronization were observed in right and left hand movement related motor areas for physical movements as well as motor imagery. The cross-validation accuracy for the proposed four-direction classification from SAM- filtered MEG signal was as high as 95-97% for physical movements and 86-87% for motor imagery. The high classification accuracy suggests that a reliable high performance two-dimensional BCI can be achieved from single trial detection of human natural movement intentions from SAM-filtered MEG signals, where user may not need extensive training.**

I. INTRODUCTION

PATIENTS with degenerative diseases such as amyotrophic lateral sclerosis (ALS), cerebral palsy, muscular dystrophy and multiple sclerosis or from trauma such as brainstem stroke, brain or spinal cord injury suffer various movement disorders. Without voluntary muscle control, the patients become helpless and fail to communicate their needs to the environment. In the later stages of such diseases, though their cognitive ability is intact they are completely trapped in their own body or "locked-in". Brain-Computer interfaces (BCIs) can be an effective solution for patients with such diseases. BCIs are devices that allow for communicating intentions by analyzing mere brain activity, not involving the muscle movements [1]. The development of BCI technology is of immense importance to patients in the 'locked-in' or semi-'locked-in' stage, where BCI can be used as a communication and rehabilitation tool. The direct brain communication or control may offer patients the only possible way to interact with external world.

BCIs can be used for decoding brain signals and control applications based on these signals, invasively or non-invasively. A highly reliable and fast BCI for multi-dimensional control can be achieved using the invasive BCI applications; but they have inherent technical difficulties such as the need for chronic recordings and risks due to surgical implantation of electrode. Due to such difficulties non-invasive methods are generally used. Electro-encephalogram (EEG) and Magneto-encephalogram (MEG) have emerged as viable options in non-invasive techniques; both of them have time resolutions in milliseconds so we can study the dynamic activities of brain in contrast to imaging-based BCI [2]. EEG measures the electrical activity in the brain whereas MEG is an imaging technique used to measure the magnetic fields produced by the electrical activity in the brain. MEG is bulky and susceptible to urban and other magnetic noises. However, it provides direct information about the dynamics of evoked and spontaneous neural activity via the extremely sensitive super conducting quantum interference devices (SQUIDs). EEG has the advantage that it is portable and cost effective but magnetic fields suffer far less than the electric fields from the spatial blurring effect of the skull. Thus, MEG provides better spatial resolution and makes itself available for source localization so that we might accurately decode more brain information/minds [3], and eventually it might be possible to actually "read" human mind instead of indirect control of brain rhythmic activity [4] or slow cortical potential [5] in current EEG-based BCI.

Human natural voluntary movement is associated with at least two kinds of brain activity that can be observed in EEG/MEG; Event- related potentials or movement-related cortical potentials and the frequency changes occurring in the alpha (8-13Hz) as well as the beta band (15-30Hz) [6, 7]. There are two distinct power changes seen in both alpha and beta bands, the event-related desynchronization (ERD) or power decrease that occurs up to 2 s before movement and is sustained with continuous movement [8, 9] and the event-related synchronization or power increase, usually only seen in beta band, occurring after the end of movement [10]. According to human somatotopic studies, human limbs are controlled by contra-lateral brain hemispheres. The right and left hand movements activate contra-lateral motor areas in the brain. In light of these findings, we hypothesized that

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it may be possible to discriminate human movement intentions in a two-dimensional plane using intention to sustain right/left hand movements featured by ERD or to cease right/left hand movements featured by ERS. As the spatial distribution of post movement beta rebound (also termed as beta ERS) is more focal than ERD distribution, the detection of ERS might be potentially more reliable than ERD detection only [11]. Since the spatio-temporal resolution of MEG is better than EEG, it is more efficient for single trial studies and thus supports high speed communication/control. As a result, using MEG for the proposed method to discriminate spatial distribution of ERD and ERS might provide more accurate classification results and lead to a reliable and fast two-dimensional BCI.

II. METHODS AND DESIGN

A. Subjects

Seven healthy volunteers, 5 male and 2 female (age: 31±8 years) participated in the experiment. All subjects participating in this study were naïve to BCI and right-handed according to the Edinburgh inventory [12]. The protocol was approved by the Institutional Review Board. All subjects gave written informed consent for the study.

B. Experimental paradigm

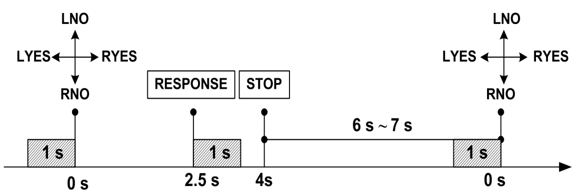

Fig. 1: Experimental paradigm. Activation period: 0s to 1s after RESPONSE cue, i.e. 2.5s – 3.5s. Control period: -1s to 0s before the cue of Right Yes RYES, Right No RNO, Left Yes LYE, or Left No LNO. Data from the activation and control windows were used for SAM analysis, with virtual channels during the activation period used for classification/prediction. Instruction cue (RYES, RNO, LYES, or LNO) period: 0s - 2.5s, RESPONSE cue period: 2.5s – 4s, STOP (Rest) cue period: 4s – 10s

A visual instruction cue randomly selected from a set of four cues: RYES for Right hand Yes, RNO for Right hand No, LYES for Left hand Yes, and LNO for Left hand No, was presented on a computer screen placed about 50cm before the subject (Fig. 1). The subjects were instructed to perform either physical or imaginary movements of their right or left hand after the initial cue presentation. They had to begin with repetitive wrist extensions of the right arm at the onset of the initial cue RYES or RNO. Similarly, for LYES or LNO, the same task had to be performed, except that the subjects had to use their left hand. After 2.5sec a Response signal was displayed at which time the subject, depending on the YES or NO cue for the right/left hand had to sustain (ERD) or cease (ERS) the hand movements respectively. At 4 seconds, a STOP cue was given, the response cue disappeared, after which the subject had to cease all movements and return to baseline rest. A 6-7 sec rest period was given 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. Subjects were asked to keep the head still during recording to reduce head motion.

C. Data acquisition and Data processing

MEG data was recorded at 600 Hz using a 275-channel CTF whole head MEG system (VSM MedTech Inc., Coquitlam BC, Canada) in a shielded environment. The CTF MEG system is equipped with synthetic 3rd gradient balancing, an active noise cancellation technique that uses a set of reference channels to subtract background interference. High-resolution structural MRI images were also acquired for co-registration for each subject using a magnetization-prepared rapid acquisition by gradient echo sequence (MP-RAGE) (TI/TE/TR/FA=725/2.928/7.6/6°, FOV=22 cm, partition thickness=1.2mm, 256 x 256, in-plane voxel size=0.859375). EMG was recorded using bipolar electrodes over the right and left wrist extensors. This allowed for the exclusion of any trial with movement prior to the instruction cue by monitoring for premature muscular activity. The physical movement data analysis for subject 7 was excluded due to performance glitches during data acquisition. For motor imagery, due to the lack of number of samples in individual events (RYES, RNO, LYES and LNO), for subjects 2 and 6, the data had to be excluded. Subject 1 did not participate in the motor imagery trial.

MEG analysis software developed at NIMH MEG core facility was used for epoching data, SAM analysis and MRI conversion. The data was epoched across a couple of sessions (2-3) according to the marker events for a period of 9 sec starting 1 sec before the event and continuing 8 sec after. All epoched data samples for a similar event were combined together to form a grand dataset. The cross validation was performed on the pooled single trial samples. Before SAM analysis, a multi-sphere head model was created for each subject (threshold value ~ 40%) based on anatomical images of each subject using MEG analysis software.

D. Synthetic Aperture Magnetometry (SAM) Analysis and Virtual Channel selection

Synthetic Aperture Magnetometry (SAM) [12] was used for source localization to improve the signal to noise ratio. SAM estimates the source location by focusing the array with linear weighting. It uses minimum variance beamforming [13] to interferometrically combine the SQUID sensor values from MEG. When SAM results are combined with MRI, an image of regions of brain showing ERD and ERS can be obtained. The proposed BCI will work best with ERD/ERS due to the straightforward relationship between ERD/ERS and human motor cortex activity. To analyze task related brain activity, the beta band frequency range (15 to 30 Hz) was fed into SAM. For Physical movements (see Fig. 1), the RESPONSE cue to 1 sec after cue onset was taken as active state (2.5s – 3.5s) and -1s to movement onset (instruction cue) was set as the control state (-1s – 0s) for SAM analysis. For Imaginary movements, the response of the subjects to RESPONSE cue was delayed and hence, a 0.5 sec delay was introduced for the active state (3s – 4s), the control state (-1s – 0s) remained unchanged. SAM calculates the covariance between an active and control state and uses it to design an optimal spatial filter which creates a 3D source image, comparing the source strength for the two states. This image was superposed on the MRI image and regions of high activity were selected for the virtual channel analysis (http://kurage.nimh.nih.gov/meglab/Meg/Meg). The signals from the specified virtual channels were fed into classification techniques developed in home-made MATLAB (MathWorks, Natick, MA) Toolbox: brain-computer interface to virtual reality or BCI2VR [14, 15] based on movement related signals which can reliably decode movement intentions spatially. From the SAM activation maps, we extracted virtual channel data from areas of peak activation corresponding to right and left hand sustained (ERD) and ceased (ERS) movement activity in contra-lateral motor areas. Around 20-30 virtual channels were selected for further classification. The virtual channel represents a weighted sum of the MEG channel signals using the SAM beamformer weights to isolate source activity from an area of interest.

E. Feature Extraction and classification

The power of all virtual channels signals during RESPONSE cue to 1 sec after cue onset was calculated as features for classification. 10-fold cross-validation (90% training set, 10% testing set) technique was adopted. It was intended to discriminate four movement intentions during and after movements from single trial virtual channel signals. It was of interest to study, whether the right hand physical and imaginary movements, ERD/ERS have been accurately distinguished from the left hand movements, ERD/ERS. In order to test if we have achieved a reliable two-dimensional BCI through the data analysis, advanced feature extraction and classification techniques were used.

For genetic algorithm-based Mahalanobis linear distance (GA-MLD) classifier, the optimal features were extracted using Genetic Algorithm and the selected features providing the best cross-validation accuracy were applied to Mahalanobis linear distance classifier (see detail method in [15]). Multistage classification, i.e., decision tree classifier (DTC), to discriminate one intention from others in each successive stage was also tested and compared. At each level of DTC, the features for one-to-others classification were ranked by Bhattacharya distance (see detail method in [15]) and the 4 features with higher rank were used for classification by MLD. The number of features for the subset for both GA based MLD and Direct-DTC was 4, which was determined from the cross-validation accuracy with feature numbers of 2, 4, 6, and 8.

III. Results And Discussion

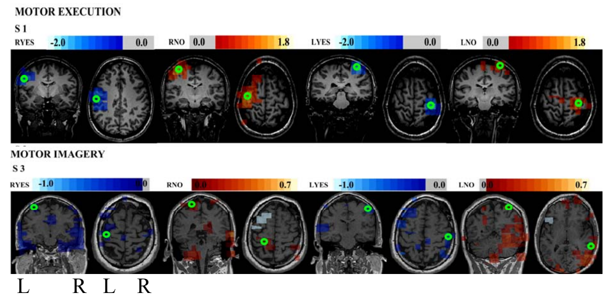

Fig. 2: SAM Image. The Coronal and Axial view of the head is shown for Subjects S1 and S3 for physical and imaginary movements respectively. Data from the activation and control windows were used to create SAM images. The threshold bar for power in ERD/ERS for corresponding movement activity is given above each head plot. Virtual channels corresponding to ERD (blue)/ERS (red) of contra-lateral motor area activation due to movement intentions were selected from areas marked (by green circle) for further classification.

From SAM analysis, it was seen that source localization of the intended natural motor behavior was successfully achieved. From the SAM image, the ERD and ERS patterns corresponding to the sustaining and stopping of right or left hand movements in the contra-lateral motor areas can be clearly distinguished for physical as well as imaginary movements (See Fig. 2). The ERD pattern was bilateral for most subjects, requiring co-ordination between both the hemispheres of the brain, but generally one lobe was seen to be dominant. Bilateral ERS was observed in some subjects during motor imagery. For all subjects, it was observed that the amplitudes of ERD/ERS were higher for physical movements than for imaginary movements (See Fig. 2). The reason for this deviation from the hypothesized fact might be because imaginary movements take more effort and training to achieve while physical movements are natural motor behavior. Movement-related signals were used for the proposed BCI because they are well defined, natural to the user and easy for subjects to learn and control. The problem with most BCIs is that subjects rapidly fatigue and there is a long training and processing time. Use of *natural human motor behavior* for the proposed BCI accounted for its reliability, short processing and training time and made it very easy to adapt to.

Virtual channels obtained from SAM analysis were selected from the corresponding ERD/ERS activation areas from dominant hemispheres as shown in Fig 2. Location of virtual channels for best results varied among subjects. Strength and location of cortical activity were different for different subjects and activity. Results from classification of these virtual channels as features for GA-MLD and direct-DTC classifiers are shown in Table 1 and Table 2. The number of samples used for each subject, obtained from the single-trial MEG, for feature extraction is also specified in the tables. The classification accuracy for the proposed SAM- filtered, MEG-based two dimensional BCI was as high as 96.5 ± 2.43% for physical movements and 89.7 ±3.34% for motor imagery using GA-MLD and 93.3± 5.71% for physical movements and 72.25 ± 5.8% for motor imagery using direct-DTC.

Table 1: Physical movements: 10-fold Cross-Validation Accuracy for different classifiers using SAM-virtual channel Analysis

Subject	SAM Virtual Sensor		Total no. of samples/ trials
	GA-MLD (%)	DTC (%)	
S 1	98.88 ± 0.71	97.38 ± 1.50	120
S 2	96.33 ± 1.05	87.25 ± 3.81	120
S 3	98.44 ± 1.09	98.44 ± 0.78	115
S 4	92.38 ± 1.20	85.63 ± 3.50	120
S 5	95.25 ± 1.54	92.75 ± 1.65	118
S 6	97.75 ± 1.42	98.25 ± 1.21	89
Average	96.51 ± 2.43	93.28 ± 5.71	114

Table 2: Imaginary movements: 10-fold Cross-Validation Accuracy for different classifiers using SAM- virtual channel Analysis

Subject	SAM Virtual Sensor		Total no. of samples/ trials
	GA-MLD (%)	DTC (%)	
S 3	94.63 ± 1.87	82.88 ± 2.95	116
S 4	88.25 ± 2.78	71.75 ± 2.65	120
S 5	87.25 ± 2.75	76.50 ± 2.93	87
S 7	88.63 ± 1.71	69.87 ± 3.51	114
Average	89.69 ± 3.34	75.25 ± 5.80	110

We also tested the decoding accuracy for four movement intentions directly from MEG sensor signal; 69.08 ± 3.58% for physical movement and 48.43 ± 11.26% for motor imagery using GA-MLD and 58.10 ± 5.79% for physical movement and 40.68 ± 12.48% for motor imagery using DTC. Our results show that SAM-filtered MEG yields very high classification accuracy to discriminate between the four movement intentions (RYES, RNO, LYES, and LNO). These intentions can be used to control four directions in a 2-D plane and thus achieve a reliable 2-D BCI.

MEG is expensive and immobile; at present shielded rooms are required for data acquisition. As technology progresses, there may be portable MEG devices, voiding the importance of shielded rooms for recording (see e.g. BabySquidw, Tristan Technologies). The whole process of SAM analysis in this study was offline. For real-time use, a calibration study may be performed to determine the source locations of the desired region of interest and using this model, the spatio-temporal activities of neural sources, i.e., virtual channels signal, can be estimated online. Future study is required to explore the robustness of online estimation of neural source activities from pre-determined source locations. However, the proposed SAM-filtered single-trial MEG based BCI may help tremendously in accelerating rehabilitation and provide a means for assistive device control or communication for patients with severe movement disorders.

This research has provided an insight on the advantages of using MEG as a potential means of interfacing for rehabilitation of patients suffering from the “locked in” syndrome. The results concur that MEG signals associated with human natural motor behavior provide a reliable and fast brain-computer interface (BCI) for 2-dimensional control. This is bound to reduce the long-term training for conventional BCI methods using rhythm control. This BCI could greatly impact the lives of patients suffering from ailments such as amyotrophic lateral sclerosis (ALS) or spinal cord injury. It may help in their speedy rehabilitation and provide a mechanism for mechanical control and communication device.

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