A High Performance MEG Based BCI Using Single Trial Detection of Human Movement Intention

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Additional information is available at the end of the chapter

1. Introduction

Human volitional movement is orchestrated by dynamic changes in brain activity that can be detected by noninvasive electrophysiological recording using electroencephalography (EEG) or magnetoencephalography (MEG). At least two kinds of movement-related brain activity can be observed: movement–related cortical potentials (MRCP) and event-related desynchronization/synchronization (ERD/ERS) in the alpha (8-13Hz) and beta frequency band (16-30Hz) as reviewed in [1-3]. Both have been observed prior to movement onset and represent the activation of widespread sensorimotor networks responsible for the preparation and intention to move. Although it may be more difficult to identify premovement activity from the spatial distribution of MRCP due to the small amplitude of the signal and the need for signal averaging to enhance the signal-to-noise ratio, changes in oscillatory activity may be detectable even on a single trial basis. Functional mapping studies using EEG and MEG have demonstrated that somatotopically restricted motor areas are activated before the actual production of certain limb movements. For example, as assessed by studying movement-related ERD in [4-6], the hand area is activated before the production of hand movements whereas the foot area is activated prior to foot movements. Furthermore, there is a consistent lateralization of activation with right hand movements activated by predominantly left sensorimotor cortex whereas left hand movements are activated by right sensorimotor cortex. If the spatial resolution of the signal is high enough, discrimination of different movement intentions from the spatiotemporal distribution of oscillatory brain activity should be possible on a single trial basis and could be harnessed as a flexible control signal for external devices in the design of brain computer interfaces (BCI).

Brain computer interfaces are neural signal driven systems developed as a means of communication for patients with severe neuromuscular impairment. Although BCI technology can

also be used to monitor human attention level or other higher level cognitive tasks such as decision making as detailed in [7,8], the predominant goal of current BCI efforts is the restoration of motor function. Due to neurologic conditions such as spinal cord injury, stroke or Amyotrophic Lateral Sclerosis (ALS), severe motor paralysis may develop and at the extreme, progress to a locked-in state, where there is complete inability to move but retained ability to think. By detecting brain activity associated with specific user intentions and translating thought into action, BCI provides a potential medium for communication and rehabilitation. By providing users with feedback control, BCI systems may be useful in promoting cortical plasticity after conditions including stroke or spinal cord injury.

There are two methodological approaches to BCI: invasive and non-invasive. The invasive approach utilizes intracortical neuronal population activity as detected with microelectrode arrays implanted directly into the brain with the advantage of high signal strength. Several groups in [9-11] have utilized this approach successfully for the prediction of movement trajectory, cursor control or use of a robotic arm. However, due to the inherent technical demands and risks of surgical implantation, non-invasive techniques are generally used. In the non-invasive approach, electroencephalography (EEG) and magnetoencephalography (MEG) have emerged as the most viable options. Any activity in the brain is accompanied by changes in ion concentrations in neurons leading to polarization and depolarization. Such neuronal population activity can be measured by EEG, whereas MEG measures the magnetic field associated with these currents. Both modalities have a time resolution on the order of milliseconds, allowing for the study of the highly dynamic activity of the brain in contrast to slower response time from imaging-based BCI using positron emission topography (PET), optical imaging using near infrared spectroscopy (NIRS) or functional MRI signals as in [12]. EEG is advantageous in that it is portable and cost effective but as magnetic fields suffer far less degradation than electric fields from the spatial blurring effect of the skull, MEG provides a better spatial resolution leading to more accurate decoding, as reviewed in [13]. The advantage of MEG is the more simplified reconstruction of signals into source space leading to reduction of noise and subsequent better feature separation. MEG may have a greater potential to interpret brain activity on a single trial basis instead of utilizing indirect control of brain rhythmic activity or slow cortical potentials as used in current EEG-based BCI and detailed in [14,15]. However, the lack of portability and the costs of MEG instrumentation are impractical for general BCI use.

Optimization of BCI involves the use of technology and design of signal processing algorithms with a fast response time, low error rate, and reduced training time. Due to the need for high temporal precision, electromagnetic signals are the most practical for widespread BCI use. Signal processing algorithms using a combination of spatial and temporal filters or signal averaging extract relevant features, enhance the signal-to-noise ratio and reduce classification error and are an active area of research reviewed in [16,17]. Ideally, BCI operation on a single trial basis is preferred due to the improved response speed and higher information transfer rate, but at the cost of a potentially noisier signal with higher error rate depending on the feature selected. In addition, identifying signal features that represent the activation of biologically realistic sources reduces the likelihood of misclassification from neurophysiologic

artifacts such as eye blinks, scalp muscle activity or cognitive activity unrelated to the task paradigm. Shorter training times reduce the likelihood of mental fatigue and improve the generalizability of use for diverse patient populations. A task paradigm based on movement direction or natural motor behavior may also reduce training time as it may be more intuitive.

In this chapter we present a multi-dimensional prediction based BCI that reliably decodes human movement intention. We previously demonstrated that ERD/ERS changes using a contingent negative variation based four class-paradigm can be reliably discriminated using EEG in [18]. In this study, subjects began to prepare for one of four movements after viewing an initial cue signal. After a period, they performed the movement, but the classification took place during the period of mental preparation. We also demonstrated that spatially distinct movement intentions using the right hand and left hand using an ERD/ERS paradigm can be reliably classified and differentiated with MEG signals in [19]. However, several potential BCI users may have brain injury specifically affecting the structural or functional integrity of the hand area, limiting the ability to generalize from this paradigm. If the prediction/decoding of movement intentions to move the right hand, left hand, leg and tongue before movements occur is robust, the natural behavior of human intentions to move different effectors can be decoded to control a two-dimensional cursor for BCI applications. Our BCI performance critically depends on the reliable decoding of intention from the spatial distribution of brain activity. We adopted synthetic aperture magnetometry (SAM) as a spatial filter for enhancing the spatial resolution of MEG signals. The robustness of the prediction suggests that spatially filtered MEG can be used as a robust BCI method supporting multi-dimensional control.

2. Spatiotemporal filtering in BCI

2.1. Optimizing BCI signals for classification

In order to extract a robust control signal for classification from multichannel EEG or MEG data, various signal processing methods are available. The selection of a simple task paradigm associated with a reliable neurophysiological signal is an important first step prior to data processing and classification. As ERD is a fundamental physiological signal associated with natural movements, it is a logical choice for analysis. Spatial and temporal filters reduce the data load and improve discrimination and classification. As many potential signals including ERD are spatially restricted to the sources of activation from somatotopic representation and lateralization, algorithms that enhance the spatial signal may improve the distinctness of spatial patterns. Restricting the analysis to a subset of electrodes or sensors over areas of interest (i.e., C3 and C4 EEG electrodes over sensorimotor cortical regions) is a simple method of spatial filtering. Computational data-driven spatial filters that have been used in EEG-based BCI include independent component analysis (ICA), common spatial patterns (CSP), surface Laplacian derivation (SLD), and principal component analysis (PCA) in [20-23]. These methods are similar in their ability to enhance the spatial resolution of the feature in order to enhance discrimination. In the temporal domain, frequency filters may be used to reduce dimension-ality as different cognitive tasks may be associated with dynamic changes in specific frequency

bands. Furthermore, there may be subject-specific dominant frequency band changes associated with the same task, making optimization and selection of temporal filters an adaptive process. Temporal filters that are used include finite impulse response (FIR) filtering, power spectral density (PSD) estimation and discrete wavelet transformation (DWT). Signal averaging is also a commonly used method in the P300 and visual evoked potential (VEP) based BCI systems in [24,25] to enhance signal quality although this may slow down the response time.

The exact choice or combination of signal processing methods may depend on the task paradigm utilized or the subject population studied. Comparison of the combination of various methods including spatial and temporal filtering, feature extraction and pattern classification have been explored by several groups in decoding single trial EEG signals associated with movement in [26,27]. These studies demonstrate the critical point that the selection of computational methods can affect the speed and accuracy of BCI performance.

2.2 Synthetic Aperture Magnetometry (SAM) and Source Space BCI

Synthetic aperture magnetometry (SAM) is a powerful adaptive beamforming approach used in MEG. Beamforming is a technique used in radar or sonar technology that involves estimating the contribution of a single source to a group of sensors by excluding activity from all other sources. SAM is a minimum variance beamformer technique that is designed to pass the signal from a small region of interest with unit gain while blocking signals from outside that area as detailed in [28]. Data from single trials are used to estimate sensor weight matrices which then applied to raw MEG data from sensors yield source images. The number of sources does not need to be specified using this method. SAM takes advantage of the spatial and temporal correlation of MEG sensor arrays and acts as a spatial filter to map three dimensional source power. The spatial distribution of event-related changes in cortical rhythm within a specified frequency range and time window relative to the event can be estimated. Furthermore, using the sensor weight covariance matrices, virtual sensor time series can be generated and used for source based estimates of changes in activation or connectivity. This technique has been demonstrated to be effective in localizing source activation associated with various cognitive tasks including speech, motor and sensory processing in [29-31]. It has been used effectively in various clinical settings including preoperative localization of motor cortex for tumor resection, identification of epileptogenic foci and mapping language areas as demonstrated in [32-35].

Source space analysis methods are a relatively novel avenue in BCI research. Compared with sensor based signals, source based signals should be less noisy and provide better features for classification. High-resolution EEG techniques including source reconstruction have been proposed as a useful method in [36] to improve BCI accuracy. Several EEG studies have used source reconstruction methods in classifying movement related signals in [37-40]. A prior study utilized beamforming techniques as a spatial filter in BCI design using EEG data in [37]. Regions of interest were preselected and beamforming was used to suppress source activity outside of the regions of interest. Results showed better classification accuracy compared to surface Laplacian and comparable to common spatial pattern (CSP) filtering in the setting of

large artifacts. Another EEG study used a source reconstruction method with a spherical head model and simple source distribution to demonstrate better classification rate compared to electrodes studying movement related ERD and MRCP in [38]. These studies provide evidence that source localization may help refine accuracy of classification using EEG. However, source localization including beamforming using EEG may be limited by sparse electrode sampling in typical EEG-based BCI compared to the dense whole head sensor coverage with MEG, limiting the ability to estimate sources accurately. Furthermore, the signal-to-noise ratio of EEG signals on a single trial basis is low, making source localization more difficult. The Laplacian spatial filter is commonly used for EEG signals to improve the signal-to-noise ratio. However, due to the more intricate geometry of magnetic fields compared to electric fields, it is not possible to find a general spatial filter that improves the signal-to-noise ratio analogous to Laplacian filtering. For MEG signals, the position and orientation of the sources of interest must be taken into account as well.

Due to the more robust source localization methods with MEG, source space MEG BCI analysis may be a powerful paradigm to enhance signal strength for improving feature classification. Prior MEG based BCI studies have been conducted based on the sensor domain, focusing mainly on the source identification problem [41-43]. In [44], a source based MEG analysis was proposed using a novel blind source separation method called functional source separation (FSS) to identify sources of activation and source time courses for potential BCI use. There are few beamformer based MEG BCI studies despite the robustness of these techniques in mapping movement-related desynchronization as demonstrated in prior studies. As movement-related ERD can be somatotopically restricted as well as lateralized, we hypothesized that using SAM as a spatial filter would give rise to improved separation of spatially distinct patterns for classification.

3. Methods

3.1. 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 in [45]. All subjects had not received prior BCI-related training. The protocol was approved by the Institutional Review Board. All subjects gave written informed consent for the study.

3.2. Experimental paradigm

A visual warning cue randomly selected from a set of four cues: 'right" for right hand extension, 'left' for left hand extension, 'leg' for left foot extension, and 'tongue' for pressing the tongue against the roof of the mouth, was presented on a computer screen placed about 50 cm in front of the subject (see Figure 1). The subjects were instructed to prepare for the movement without physically moving after the initial cue presentation. The duration of the visual cue was 0.5 s. After 2.5sec a 'GO' signal was displayed at which time the subject started

physically moving as soon as possible. This continued for another 2.5 sec after which a stop signal was displayed at which time the subject stopped moving and returned to baseline rest. A 4-7 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. The experiment consisted of 6-7 sessions with each session consisting of 30 movement tasks, i.e. about 45 trials for each of four movements. Subjects were asked to keep the head still during recording to reduce head motion. Trials contaminated with EMG activities before the 'GO' cue were excluded both for the classification and analysis.
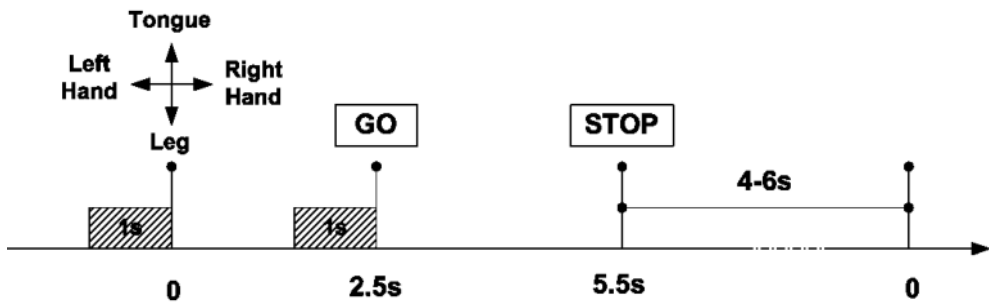

Figure 1. Experimental paradigm. Activation period: -1 second to 0 before 'GO' cue. Control period: -1 second to 0 before warning cue of 'Right Hand', 'Left Hand', 'Foot' and 'Tongue'. At the "GO" cue, subjects began repeated extensions of the right hand, left hand or left foot or tongue movements as per the initial instruction cue. Subjects continued the movements until the "STOP" cue. Data from the activation and control windows were used for SAM analysis, with virtual channels during the activation period used for classification/prediction.

3.3. Data acquisition

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 (extensor digitorum communis), and left ankle dorsiflexors (tibialis anterior). This allowed for the exclusion of any trial with movement prior to the 'GO' cue by monitoring for premature muscular activity. Premature motor execution was monitored by the experimenter by EMG and trials with early activation were excluded from the analysis.

3.4. SAM analysis

Synthetic Aperture Magnetometry (SAM) was used for source localization of MEG signals. "Source localization" implies simplification of the complex activity of a very large numbers of neurons to a few parameters that help describe that activity, as in [46]. During SAM analysis, the SAM images were created for active state vs. control state, i.e. it extracted a dominant modulated source from a background of less pronounced modulation and noise.

MEG analysis software developed at NIMH MEG core facility was used for epoching data, SAM analysis and MRI conversion. For all measurements, fiducial skin markers were placed on subjects' nasion and bilateral preauricular points. The data was epoched according to the marker events for a period of 9 sec starting 1 sec before the instruction cue and continuing 8 sec after. For SAM analysis, all epoched data for each event ('right', 'left', 'leg', or 'tongue') were pooled together to form a grand dataset. Before SAM analysis, a multisphere head model was created for each subject (threshold value about 40% to determine the boundary of shells) based on anatomical images of each subject using MEG analysis software.

For SAM Analysis, single-trial event-related MEG data from the grand datasets were used to compute covariance matrices for each dataset corresponding to each event. The frequency range of interest was the beta band (15-30 Hz). The active state was defined 1 sec before 'GO' cue to 'GO' cue onset (1.5 s – 2.5 s); -1 s to instruction cue onset was set as the control state (-1 s – 0 s) (see Figure 1). These parameters were fed in to compute the covariance between the active and the control state. For ERD analysis a statistical parametric image was computed, on a voxel- by-voxel basis, from the difference in cortical power for the two states, relative to their noise variance. Only voxels displaying statistically significant power changes were displayed in color scale on the individual MRI. Thus an optimal spatial filter was designed which created a 3D source image comparing the source strength for the two states. This image was super-posed on the MRI image of the subjects to obtain the source- signal-to-noise ratio image corresponding to each event for all the subjects.

3.5 Virtual channel selection

A *virtual channel* is tuned to a particular source or target. In SAM analysis as described above, a beamformer was calculated for each voxel of the image, and the beamformer was used to calculate a source power estimate. The same beamformer was used to determine coefficients or weights for each channel, and a virtual channel was obtained from a weighted sum of all the MEG channels with those weights. The target location for the present study was the motor cortex area. As previously described, human limb movements are controlled predominantly by the contralateral sensorimotor areas. The source-signal-to-noise ratio image obtained through SAM analysis would have high activity regions in these areas. Consistent with expected somatotopic representations, virtual channels were selected from regions showing strong ERD in the left and right hand, leg and tongue areas respectively. Around 20-30 virtual channels were selected for each subject.

3.6. Time–course analysis of MEG sensor and virtual channel data

The digital MEG signal was sent to a DELL PC workstation and was offline processed using a home-made MATLAB (Math Works, Natick, MA) Toolbox: brain-computer interface to virtual reality or BCI2VR [27,47]. This was used for time-course analysis, feature extraction and classification for MEG-Sensor domain as well as Virtual channel data.

3.6.1. Time–frequency analysis of MEG sensor data

Time-Frequency analysis was performed on the MEG sensor data (See Figure 2) to observe the power (ERD) patterns for each event. The region of interest was selected in the motor cortex areas associated with human movement intention as detailed in [48-50]. The MEG channels constrained to the central MEG sensors associated with the right hand, left hand, leg, or tongue area depending on the event were used for the analysis. It was intended to analyze the power in the beta band, i.e. the ERD patterns with respect to the time-course of the motor tasks. Power in the frequency range 0- 60 Hz, for four movements was calculated using the Welch method described in [51], which was applied with the use of a Hamming window to reduce side-lobe effect and estimation variance. A baseline correction was introduced from -1 s to 0 s. The length of the sliding window was 1 s with a slide increment of 0.1 s. The segment length was 0.25 s with frequency resolution of 4 Hz and there was no overlapping between consecutive segments.

3.6.2. Time–course of event-related power for virtual channel data

An event related power analysis was performed on the virtual channel data obtained through SAM analysis. We intended to observe the ERD patterns over time for each event. The time-course of event-related power was obtained from the variance of virtual channel signal in a sliding window with length of 1s and a slide increment of 0.1 s. These virtual channels were already filtered from the beta band. A baseline correction was introduced from -1 s to 0.5 s. Event related power analysis was performed to verify whether ERD was a dominant pattern for virtual channels selected when subjects were intending to perform the four different movements.

3.7. Feature extraction and classification

The data pool consisted of about 180 trials with 45 samples for each of four classes. The offline performance of multi-class classification was evaluated from 10-fold cross-validation; 90% of data pool was used for training, and the other 10% was used for testing so that the testing dataset was independent from the training dataset. For classification methods using feature evaluation for feature selection, those parameters or features were also determined by training data set only.

3.7.1. Feature extraction for MEG sensors and virtual channels

For MEG -Sensor based classification, the MEG channels were constrained through empirical channel reduction; this covered the entire motor cortex area. Thus the central 52 MEG chan-
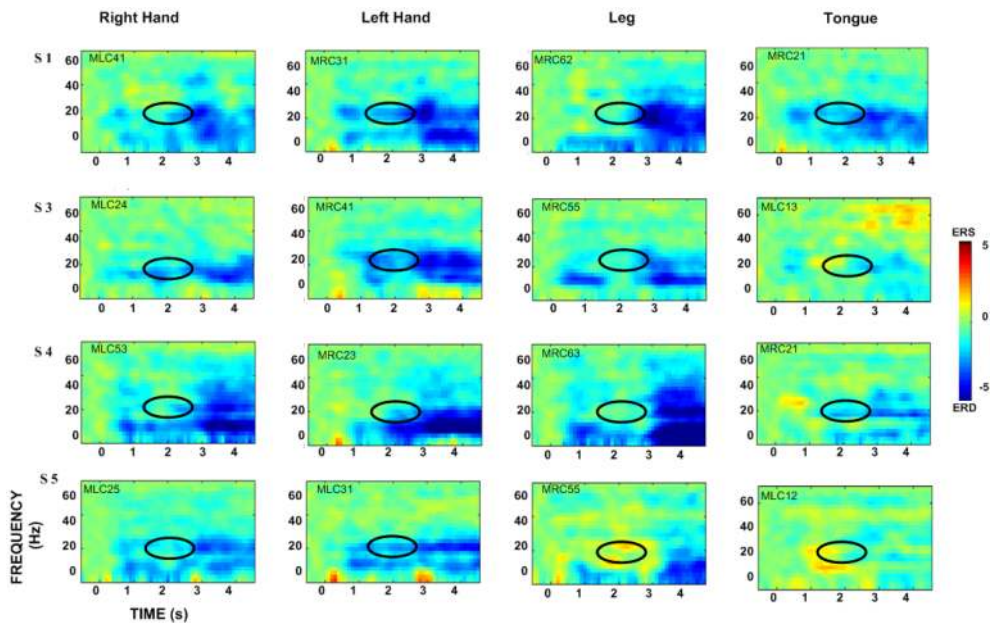
Figure 2. Time-frequency analysis in the sensor domain. Time-frequency map for movements of the right hand, left hand, leg and tongue for subjects S1, S3, S4 and S5 are plotted from the MEG raw sensor domain (left corner of each map, M – MEG, R – right, L – left, and C – central). Power is symbolized by blue for ERD and red for ERS. The region of interest corresponding to the active state period corresponding to movement intention is marked by the black ellipse.

nels were used for sensor based classification (The layout can be found in http://kur-age.nimh.nih.gov/meglab/Meg/Meg). For SAM-filtered virtual channel based classification of movement intensions from MEG data, channel reduction was achieved through the selection of virtual channels. Also, the selection of beta band (15- 30 Hz) to study ERD served as an important parameter for feature reduction. In the MEG-Sensor domain, the power samples were calculated in the beta band (15- 30 Hz) for the active state period when subjects were intending or urging to move (1.5 s – 2.5 s), the segment length was 0.25 s with no overlapping between consecutive segments. For Virtual channels, the beta band power samples were calculated as the variance of the data samples from the active state period before movement occurred.

The SAM-filtered MEG virtual channel signals or MEG sensor domain signals provided high-dimensional features; for example, 25 virtual channels with 16 frequency bins produced 400 features. A subset of features determined by feature selection was determined for classification.

3.7.2. Feature selection and classification

The feature selection was achieved by either Bhattacharyya distance or genetic algorithm.

Bhattacharyya distance: The Bhattacharyya distance is the square of mean difference between two task conditions divided by the averaged variance of the samples in two task conditions

so that a larger Bhattacharyya distance will lead to better classification accuracy as described in [52]. The empirically extracted features were ranked by Bhattacharya distance for further classification.

Genetic Algorithm (GA): Genetic algorithms are computational models inspired by evolution as described in [53]. It is a stochastic search in the feature space guided by the concept of inheriting, where at each search step, good properties of the parent subsets found in previous steps are inherited. 10-fold cross-validation was used with a Mahalanobis linear distance (MLD) classifier for feature evaluation as in [54]. The population size used was 20, the number of generations was 100, the crossover probability was 0.8, the mutation probability was 0.01, and the stall generation was 20.

The classification techniques were developed in a home-made MATLAB (Math Works, Natick, MA) Toolbox: brain-computer interface to virtual reality or BCI2VR described in [27,47]. It was intended to use these classification techniques to reliably decode human movement intentions spatially for the four classes. The classifiers selected were based on their performance in previous computational comparison studies in [27,54-56].

GA-based Mahalanobis Linear Distance Classifier (GA-MLD): The Mahalanobis Distance Classifier had proved effective for classification in previous studies [27,57]. It was further optimized using GA-based feature extraction method. The optimal feature subset was selected by GA, and the selected features providing the best cross-validation accuracy were applied to a Mahalanobis Linear Distance Classifier (MLD) as in [52]. The number of features for the subset was 4, which was determined from the 10-fold cross-validation accuracy with feature numbers of 2, 4, 6, and 8.

Direct Decision Tree Classifier (DTC): A Decision tree is a classifier which uses symbolic treelike representations of finite sets of if-then-else questions that are natural, intuitive and interpretable as in [58]. For example, a certain feature subset of channels over the left motor cortex area are associated with right hand movement as shown in [59-61]. Then, these would be the best to discriminate intention to move the right hand, whereas they might operate rather poorly for the discrimination of other movement intentions. We used multistage classification, i.e., decision tree classifier (DTC), to discriminate one intention from others in each successive stage. At each level of DTC, the features for one-to-others classification were ranked by Bhattacharya distance (see detailed method in [27]) and the 4 features with higher rank were used for classification by MLD. The number of the feature for classification was determined from preliminary comparison (through 10-fold cross validation accuracy) with numbers of 2, 4, 6 and 8.

4. Results

4.1. Sensor–based ERD/ERS visualization

ERD/ERS visualizations for 4 subjects are included from MEG sensor data to demonstrate characteristic power changes located over motor cortical regions (Figure 2). Power changes

were notable for a sustained decrease in the 8-30 Hz range beginning 1-1.5 second before S2 and continuing through the time of execution of movement. From the ERD images, it was observed that ERD signals were enhanced during the period of motor execution compared with the movement intention period.

4.2. SAM–based spatial visualization of ERD activation

Spatially filtered ERD activity was visualized using SAM. Figure 3 demonstrates SAM images from 4 subjects demonstrating activation of motor areas corresponding to the intention to move under the four different conditions. Virtual channels were derived from the areas of peak ERD activation for power analysis, feature extraction and classification.
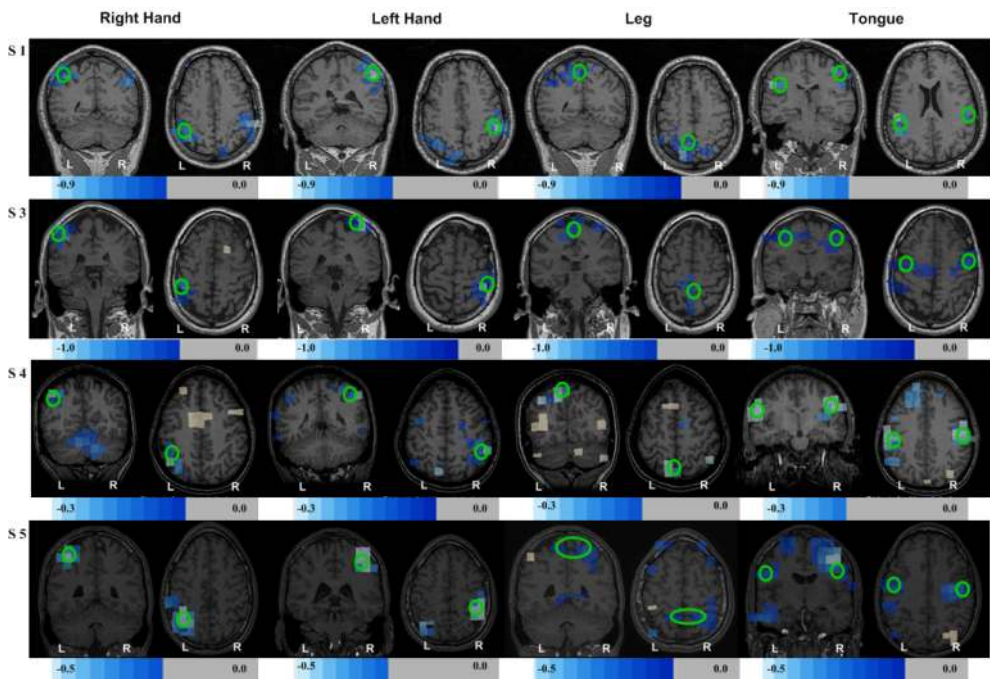

Figure 3. SAM image. Coronal and axial views of the head are shown for subjects S1, S3, S4 and S5. Virtual channels corresponding to the ERD (Blue) over areas of activation corresponding to movement intention were chosen from areas marked by the green circle for further classification.

4.3. Virtual channel power analysis

Time-frequency analysis was performed on single-trial MEG virtual sensor data. The time course of ERD/ERS changes from virtual channels demonstrates consistent patterns of desynchronization associated with the time period chosen for prediction (Figure 4).
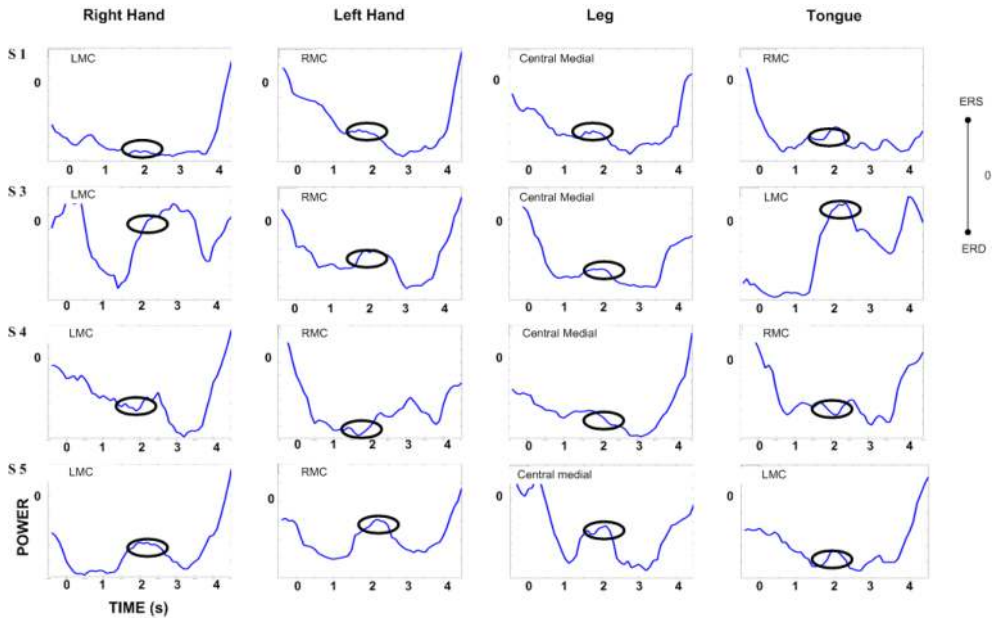
Figure 4. Time course of event-related power change for SAM-Virtual channel signal. Time-power maps for events Right hand, Left Hand, Leg and Tongue for the single-trial MEG data for subjects S1, S3, S4 and S5 are plotted for corresponding SAM-Virtual channels over regions of interest (LMC – left motor cortex, Central medial cortex, RMC – right motor cortex). The region of interest corresponding to the active state period for movement intention is marked by the black ellipse.

4.4. Classification

To compare the advantage of using SAM, results from virtual channel classification were compared with MEG sensor based classification. Classification of signals using 2 different classification methods (GA-MLD and DTC) were higher using MEG virtual sensors compared to raw sensors (Table 1). The virtual channel-based classification accuracy for four classes using GA-MLD was on average 88.90% with standard deviation of 7.74%. Similarly, virtual channel based classification using direct DTC was 73.34% with standard deviation of 16.71%.

Classification with MEG sensors was much less accurate. MEG sensor based classification accuracy using GA-MLD was 42.41% with standard deviation of 7.26%. Using direct DTC, accuracy was 30.13% with standard deviation 5.56%.

Subject	SAM Virtual Sensor		MEG Sensor Domain		Total no. of
	GA-MLD (%)	DTC (%)	GA-MLD (%)	DTC (%)	samples/trials
S 1	96 ± 0.44	85.19 ± 4.14	40.78 ± 2.11	30.44 ± 3.01	191
S 2	87.31 ± 1.32	61.75 ± 2.04	33.57 ± 2.32	26.14 ± 3.56	219

Subject	SAM Virtual Sensor		MEG Sensor Domain		Total no. of
	GA-MLD (%)	DTC (%)	GA-MLD (%)	DTC (%)	samples/trials
S 3	89.17 ± 1.62	85.75 ±1.86	44 ± 1.36	31.37 ± 2.97	181
S 4	84.25 ± 1.55	73.37 ±1.86	51.11 ± 2.16	29.5 ± 2.53	200
S 5	99.14 ± 0.19	97.16 ± 0.85	53.15 ± 1.66	41.90 ± 0.66	202
S 6	79.69 ± 2.36	42.68 ± 3.12	44.56 ± 1.57	32 ± 2.79	202
S7	96.58 ± 0.97	71.25 ± 3.61	38.18 ± 2.91	25.55 ± 3.33	177
S8	79.08 ± 2.06	69.58 ± 4.52	33.94 ± 2.07	24.17 ± 2.77	173

Table 1. SAM-Virtual channel signal vs. MEG-Sensor signal Classification

5. Discussion

In this study, a prediction based BCI was designed using spatially filtered MEG signals associated with four different movement intentions. Successful classification of discrete movement intentions was achieved with a high degree of accuracy. The results from this study demonstrate that the spatiotemporal activity associated with human movement intention is predictable and can be spatially separated and used for classification. These movement intentions can be potentially used as control mechanisms. Previously, we reported our results in [16] classifying movement based intentions from MEG using ERD/ERS patterns generated from right and left hand movement. The limitations of the previous paradigm are the reliance on the integrity of hand movement, which is often compromised in BCI user populations such as those with unilateral stroke or motor neuron disease. The ability to differentiate effector specific movement intentions from a range of body parts allows for a greater flexibility of our BCI approach.

All subjects demonstrated ERD before and during the movement, followed by ERS after the movement. ERD occurred in similar regions for the intention and movement execution period. As expected, desynchronization signals were stronger during actual movement than during movement intention. Distinct movement intentions led to distinctly different regions of activity in the brain, although some overlapping regions were also found. ERD activation was seen bilaterally suggesting coordination between both the hemispheres, although generally one side would dominate. For left hand movement, right motor cortex was predominantly activated whereas for right hand movement left motor cortex region showed greater activity. For leg movement, mesial motor cortex was activated. Tongue activity showed a great deal of variation across the subjects activating regions of both hemispheres. Global activation of motor networks have been reported for movements of the foot and tongue in [62], potentially making the distinction between classes more difficult due to overlap of activation. The tongue representation is relatively small and distributed across both hemispheres. The hand area also was activated during tongue movement. This may occur because the tongue is more difficult

to move as compared to hand or foot, leading to a broader region of activation overlap as detailed in [62,63]

All subjects showed dynamic activity mostly in the beta band (15-30 Hz). This is consistent with previous studies demonstrating the important role of beta band activity in motor control [3]. All eight subjects showed different regions of activation for different movement intentions, but these regions varied from subject to subject. Each individual subject had particular pairs of movement intentions which produced better results than the rest, but the trends were not consistent across the subjects. This variability may be related to inherent differences in terms of individual motor learning and movement strategy. More research in this area may explain this trend. More generally, such research could lead to a better understanding of different neural activity involved in the learning of a motor task.

Previous studies have demonstrated the feasibility of using MEG signals for BCI purposes in [64-67]. In [65], a MEG study exploring the decoding of movement directions, a reasonable detection accuracy was achieved from signals associated with the motor execution of physical movement. Although it seems more intuitive for BCI users to control directional movement, practical application of BCI substitutes more reliable control for the intuitiveness of the approach. Comparing the premovement data to the results in that study, our BCI provided much better classification accuracy. The best detection accuracy was found to be after movement onset, which may not be useful in subject populations who can not physically move. Furthermore, the approach utilized in that study was performed on the sensor domain level. The conclusions from this study suggest that spatial filtering may lead to improved performance using their paradigm. Another study in [66] used MEG and sensorimotor mu rhythm control with successful results in 6 out of 8 patient, but their approach required extensive training over several weeks. In contrast, our BCI requires less extensive training and a faster response time due to the natural motor task performed.

Our method showed that MEG provides high resolution both spatially and temporally. If optimized techniques are used for source imaging, robust results can be obtained for suitable multi dimensional BCI control. By applying SAM filter, the classification accuracy was significantly improved with the average classification accuracy 91±12%. These results demonstrate that SAM spatial filter may effectively improve MEG signal spatial resolution to achieve an accurate classification of movement intentions. Four-class classification in this study using spatial filtering was highly accurate despite the visualized overlap of activation across different body parts. BCI results using this method may be further improved by replacing tongue movement with an alternative movement, such as the right foot. With better classification technique it may be possible to classify even finger movements, which may help in complex higher level control.

6. Conclusion

A high performance BCI was designed using spatially filtered MEG signals to decode movement intentions on a single trial basis. The combination of a natural motor task paradigm, SAM

spatial filtering and event-related desynchronization analysis at the source level was able to discriminate four different movement intentions with a high level of accuracy. Although the computational analysis was performed offline, the robust performance suggests that online implementation using this paradigm would be effective in the setting of real-time feedback and user adaptation. Overall, this BCI has the following advantages over other BCIs: two-dimensional control, a more natural control scheme, less training time, high spatial resolution, and robust performance.

Due to the lack of portability and higher costs, MEG is less practical for BCI use compared with EEG. However, the advantages of MEG include high spatiotemporal resolution and robust spatial filtering methods facilitating reduced computational load and improved decoding and classification accuracy. The high level of multidimensional control attainable through the use of MEG signals as demonstrated in this study has great potential for future BCI applications. Such a MEG-based system could be used for patients to monitor and enhance ERD sensori-motor rhythms to facilitate motor rehabilitation or to practice in improving the efficiency of motor intention or imagery for BCI purposes using less costly technology such as EEG.

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