Published in final edited form as:

Clin Neurophysiol. 2009 November ; 120(11): 1978–1987. doi:10.1016/j.clinph.2009.08.017.

Spatial detection of multiple movement intentions from SAM-filtered single-trial MEG signals

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Abstract

Objective—To test whether human intentions to sustain or cease movements in right and left hands can be decoded reliably from spatially filtered single-trial magnetoencephalographic (MEG) signals for motor execution and motor imagery.

Methods—Seven healthy volunteers, naïve to BCI technology, participated in this study. Signals were recorded from 275-channel MEG, and synthetic aperture magnetometry (SAM) was employed as the spatial filter. The four-class classification was performed offline. Genetic algorithm based Mahalanobis linear distance (GA-MLD) and direct-decision tree classifier (DTC) techniques were adopted for the classification through 10-fold cross-validation.

Results—Through SAM imaging, strong and distinct event-related desynchronization (ERD) associated with sustaining, and event-related synchronization (ERS) patterns associated with ceasing of right and left hand movements were observed in the beta band (15–30 Hz) on the contralateral hemispheres for motor execution and motor imagery sessions. Virtual channels were selected from these areas of high activity for the corresponding events as per the paradigm of the study. Through a statistical comparison between SAM-filtered virtual channels from single-trial MEG signals and basic MEG sensors, it was found that SAM-filtered virtual channels significantly increased the classification accuracy for motor execution (GA-MLD: $96.51 \pm 2.43\%$) as well as motor imagery sessions (GA-MLD: $89.69 \pm 3.34\%$).

Conclusion—Multiple movement intentions can be reliably detected from SAM-based spatially filtered single-trial MEG signals.

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Significance—MEG signals associated with natural motor behavior may be utilized for a reliable high-performance brain–computer interface (BCI) and may reduce long-term training compared with conventional BCI methods using rhythm control.

Keywords

Magnetoencephalography (MEG); Synthetic aperture magnetometry (SAM); Virtual channels; Event-related desynchronization/synchronization (ERD/ERS); Brain–computer interface (BCI); Movement intention; Motor control

1. Introduction

Patients with degenerative diseases such as amyotrophic lateral sclerosis (ALS) may progress to the locked-in syndrome. In the later stages of this disease, the patients are awake and conscious but have no ability to produce speech, limb or facial movements. Other patients with severe conditions of muscular dystrophy, traumatic brain or spinal cord injury also suffer from minimal or no useful motor functions (Dobkin, 2007). Without voluntary muscle control, these patients are unable to effectively communicate their needs to the environment. Brain–computer interfaces (BCIs) are devices that allow for communicating intentions by analyzing brain activity (Wolpaw et al., 2002). The patients who can formulate and command movements, but not physically enact their intentions, could benefit from a BCI (Dobkin, 2007). BCIs may provide an effective solution for patients with such diseases to improve their quality of life. The development of BCI technology can thus prove to be advantageous to patients in the ‘locked-in’ or semi-‘locked-in’ stage, where it can be used as a communication and rehabilitation tool.

BCIs can be used for decoding brain signals and controlling applications based on brain signals, invasively or non-invasively. A highly reliable and fast BCI for multi-dimensional control can be achieved using invasive methods, but they have inherent technical difficulties such as the need for chronic implantable recording and risks due to surgical implantation of electrodes. Due to such difficulties non-invasive methods are generally used. Electroencephalogram (EEG) and magnetoencephalogram (MEG) have emerged as viable non-invasive options. Both have time resolutions in milliseconds so we can study the dynamic activities of brain in contrast to imaging-based BCI (Laconte et al., 2007).

Human natural voluntary movement can be associated with frequency changes occurring in the alpha (8–14 Hz) and beta (15–30 Hz) bands. There are two distinct power changes seen in EEG 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 (Toro et al., 1994; Bai et al., 2005) and the event-related synchronization or power increase, usually only seen in beta band, occurring after the end of movement (Pfurtscheller, 1988). The beta frequency band has been implicated as important in various motor control processes including sensorimotor integration and motor learning (Andres and Gerloff, 1999). Human limbs are largely controlled by the contralateral sensorimotor areas of the brain hemispheres. However, the source localization of ERD/ERS with EEG is poor due to limited spatial resolution. This is partially due to the return volume currents generated due to the convolution of the cortex by numerous sulci and gyri (Vrba and Robinson, 2001). MEG

measures the magnetic fields produced by the electrical activity in the brain. It provides direct information about the dynamics of evoked and spontaneous neural activity via the extremely sensitive super conducting quantum interference devices (SQUIDs). It is least affected by the spatial blurring effects of the skull (Salmelin et al., 1995) produced by the return volume currents. It thus obtains a better signal-to-noise ratio (SNR) as compared to EEG. Particularly for single trial studies, MEG can prove very advantageous due to the high SNR property and consequently its ability for source localization. Accordingly, it is superior in studies related to movement related beta-ERD/ERS recordings.

Previously, most MEG data analysis focused on the average evoked potential paradigm (Hillebrand et al., 2005). However, with the advent of large MEG sensor arrays with whole-head coverage, it was found that the evoked response mapped by a large whole-head array was almost identical to that detected by serial multiple placement and measurement by single-channel MEG sensor at the same sites. Signal averaging did not make use of information available from large MEG sensor arrays. In contrast to this, the unaveraged or single-trial MEG signals seemed to exhibit spatial and temporal correlations which could be used for better signal-to-noise ratio (SNR) and source localization of the activity (Vrba and Robinson, 2001). Synthetic aperture magnetometry (SAM) is a novel spatial filtering technique which achieves three-dimensional source estimation during task performance (Wolpaw et al., 2000). It uses the spatial and temporal correlation of the MEG sensor array. It is based on the nonlinear constrained minimum variance beamformer. It thus provides excellent spatial resolution and can image a high signal-to-noise ratio (SNR) of the unaveraged or single-trial MEG signals.

In the present study, we employed SAM as a spatial filter for single-trial MEG signals. It was intended to classify four human movement intentions, i.e., to sustain right/left hand motor execution or motor imagery featured by ERD or to cease right/left hand motor execution or motor imagery featured by ERS. The results were compared to MEG sensor based classification to verify the effectiveness of SAM-Source domain. We hypothesized that the SAM-filtered single-trial MEG signals would provide better signal-to-noise ratio and facilitate a fast and reliable detection/classification of motor activities. MEG may be inconvenient for conventional BCI applications due to the size and cost of the device. However, when human intentions can be reliably decoded from single trial signals as tested in this study, the convenience and communication speed can be highly improved, which can broaden the BCI application. Also, a real-time single trial analysis may support other applications, for example, a monitoring tool for human motor activity for motor training purposes (Dobkin, 2007).

2. Methods

2.1. 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-type studies and right-handed according to the Edinburgh inventory (Oldfield, 1971). The protocol was approved by the Institutional Review Board. All subjects gave written informed consent for the study.

2.2. Experimental paradigm

A visual instruction cue randomly selected from a set of four cues (RYES, LYES, RNO, and LNO) was presented on a computer screen placed about 50 cm before the subject (see Fig. 1). Subjects were tested during two different sessions to examine performance of the paradigm using motor execution and motor imagery separately. They were seated with the forearms semi-flexed and had to perform repetitive wrist extensions (~2 extensions/s) of the right or left hand depending on the initial instruction cue. They were asked to keep all muscles relaxed, except for those in the performing arms. The task for the motor imagery was similar to that of the physical movements. The subjects were asked to imagine the movements with the same rate, speed, and strength as they performed the physical movements. During motor imagery, the investigator monitored the EMG activity continuously. Subjects were reminded to relax the muscle when EMG activity was observed, and trials with EMG activity were excluded both for the classification and analysis. After 2.5 s a second, non-specific RESPONSE cue was displayed at which time the subject, depending on the YES or NO letters of the initial cue, either sustained or stopped the hand movements. At 4 s, a STOP cue was given, after which the subject had to cease all movements and return to baseline rest. A 6–7 s 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, avoid body adjustments, swallowing or other movements as much as possible. They were also asked to keep their head still during recording to reduce head motion. The subjects were allowed to become familiar with the paradigm before data recording.

2.3. 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 third 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 = 1.2 mm, 256 × 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, not following the experimental paradigm for actual right/left hand movements and also the exclusion of any trial with movement prior to the instruction cue by monitoring for premature muscular activity. For Subject S7, the motor execution session contained excessive movement artifacts and was excluded due to these performance glitches during data recording. The motor imagery sessions for Subjects S2 and S6 were excluded from the analyses due to the lack of adequate number of samples of the individual events (RYES, RNO, LYES, and LNO). Subject S1 did not participate in the motor imagery session.

2.4. 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 (Robinson, 2004). SAM is a minimum variance beamformer technique. A beamformer is designed to pass the signal from a small region of interest with unit gain while blocking signals from outside that area (Keefer et al., 2008). Thus, the small area signal would be an estimate of the activity in that area. SAM has thus been used to image source power or source signal-to-noise ratio from MEG (Robinson, 2004). It characterizes the spatial distribution of event-related changes in cortical rhythm within a specified frequency range and time window, relative to the events (Robinson, 2004).

2.4.1. SAM imaging—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 s starting 1 s before the instruction cue and continuing 8 s after. For SAM analysis, all epoched data for each event (RYES, RNO, LYES, or LNO) were pooled together to form a grand dataset. Before SAM analysis, a multisphere head model was created for each subject (threshold value $\approx$ 40%) 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). For Physical movements (see Fig. 1), the active state was defined between the RESPONSE cue to 1 s after cue onset (2.5–3.5 s); –1 s to movement onset (instruction cue) was set as the control state (–1 to 0 s). For Imaginary movements, the response of the subjects to RESPONSE cue was delayed and hence, a 0.5-s delay was introduced for the active state (3–4 s, see Fig. 1); the control state (–1 to 0 s, see Fig. 1) remained unchanged. These parameters were fed in to compute the covariance between the active and the control state. For ERD/ERS 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 superposed on the MRI image of the subjects to obtain the source signal-to-noise ratio image corresponding to each event for all the subjects.

2.4.2. Virtual channel selection—A *virtual channel* is similar to a regular MEG channel, except that it is tuned to a particular source or target. For regular SAM analysis as described above, a beamformer is calculated for each voxel of the image, and the beamformer is used to calculate a source power estimate. To calculate the virtual channel, the same beamformer was used, but in a different way. A beamformer is just a set of coefficients, or weights, one for each channel, and a virtual channel is just a weighted sum of all the MEG channels with those weights (<http://kurage.nimh.nih.gov/meglab/Meg/Meg>).

The target location for the present study was the motor cortex area. As previously described, human limb movements are controlled by the contralateral sensorimotor areas. It was of interest to study the activity associated with right and left hand movements in the beta band. The source signal-to-noise ratio image obtained through SAM analysis had high activity regions in these areas. For the right and left hand physical movements as well as motor imagery, for the YES (sustain movement) case, virtual channels were selected from regions showing strong ERD in the left and right motor cortex area, respectively (see Fig. 2). Similarly for the NO (cease movement) case, virtual channels were selected from regions showing strong ERS in the respective motor areas (see Fig. 2). Around 20–30 virtual channels were selected for each subject.

2.5. 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 (Bai et al., 2007, 2008). This was used for time-course analysis, feature extraction and classification for MEG-Sensor domain as well as virtual channel data.

2.5.1. Time–frequency analysis of MEG sensor data—Time–frequency analysis was performed on the MEG sensor data (see Fig. 3) to observe the power (ERD/ERS) patterns for each event. Since it was intended to study movement intention associated cortical activities, the region of interest for the present study was assumed to be the motor cortex area (Pfurtscheller and Berghold, 1989a; Toro et al., 1994; Muller-Gerking et al., 1999). The MEG channels constrained to the central MEG sensors associated with the right or left motor cortex 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/ERS patterns with respect to the time-course of the motor execution as well as motor imagery tasks.

Power in the frequency range 0–60 Hz, for right and left hand movements was calculated using the Welch method, which was applied with the use of a Hamming window to reduce side-lobe effect and estimation variance (Welch, 1967). A baseline correction was introduced from –1 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.

2.5.2. 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 (see Fig. 4). We intended to observe the ERD/ERS 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 1 s 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 to 0.5 s.

Event-related power analysis was mainly done to verify whether ERD was a dominant pattern for virtual channels selected from the sustaining movement related events (RYES, LYES) and whether ERS was dominant for virtual channels selected from the stopping of

movement related events (RNO, LNO). This was performed for both physical and motor imagery virtual channel data.

2.6. Feature extraction and classification

For either motor execution or motor imagery, there were about 120 trials making the data pool of 120 samples with 30 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.

2.6.1. 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 channels were used for sensor based classification (for review see: SensLayout-275, <http://kurage.nimh.nih.gov/meglab/Meg/Meg>). For SAM-filtered virtual channel based classification of movement intentions from MEG data, channel reduction was achieved through selection of virtual channels. Also, the selection of beta band (15–30 Hz) to study ERD/ERS 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 during motor execution (2.5–3.5 s) and motor imagery (3–4 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 for motor execution and motor imagery.

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.

2.6.2. Feature selection and classification

2.6.2.1. Feature selection. 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 (Marques, 2001). The empirically extracted features were ranked by Bhattacharyya distance for further classification.

Genetic algorithm (GA): Genetic algorithms are computational models inspired by evolution (Whitley, 1994). 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. Ten-fold cross-validation was used with a Mahalanobis linear distance (MLD) classifier for feature evaluation (Li and Doi, 2006). 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.

2.6.2.2. Classification methods: The classification techniques were developed in a home-made MATLAB (Math Works, Natick, MA) Toolbox: brain-computer interface to virtual reality or BCI2VR (Bai et al., 2007, 2008). 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 (Babiloni et al., 2003; Li and Doi, 2006; Bai et al., 2007; Huang et al., 2009).

GA-based Mahalanobis linear distance classifier (GA-MLD): The Mahalanobis distance classifier had proved effective for classification in previous studies (Babiloni et al., 2001; Bai et al., 2007). 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) (Marques, 2001). 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 (Duda et al., 2001). For example, a certain feature subset of channels over the left motor cortex area are associated with right hand movement (Kawashima et al., 1993; Volkman et al., 1998; Jung et al., 2003). 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 Bhattacharyya distance (see detail method in Bai et al. (2007)) and the four 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.

3. Results

3.1. Neurophysiological analysis of ERD and ERS in SAM domain

In this study we intended to discriminate the ERD, associated with sustained motor execution or motor imagery, from ERS associated with ceasing motor tasks in the beta band from single-trial MEG signals. To give an impression of SAM images and virtual channel selection, the source signal-to-noise images obtained from SAM analysis are shown in Fig. 2. Data from the active and control states were used for the analysis (see Fig. 1). The regions of high activity, displaying ERD and ERS for motor execution tasks were clearly seen for the active state between 2.5 and 3.5 s. For motor imagery, they were observed for the active states between 3 and 4 s. Virtual channels were selected from these regions of high activity, for power analysis, feature extraction, and classification. From the SAM images obtained for both motor execution and motor imagery, it was observed that ERD/ERS signals were more enhanced during motor execution than for motor imagery.

3.2. Time–frequency analysis in sensor domain

Time–frequency analysis was performed on the single-trial MEG sensor-channel data to observe the beta band ERD/ERS patterns over these channels for each event (see Fig. 3). The MEG channels constrained to the central MEG sensors associated with the motor cortex area were used for the analysis. These central MEG sensors covered both the right and the left motor cortex area. When an MEG sensor-channel selected from the left motor cortex area was analyzed for the event RNO with the active state period for that event in the beta band, a strong, distinguishable ERS pattern was observed for almost all the subjects. Similar was the case for event LNO, for which the MEG sensor was selected from the right motor cortex area. When an MEG sensor-channel selected from the left motor cortex area was analyzed for the event RYES with the active state period for that event in the frequency band of 15–30 Hz, a distinguishable ERD pattern was observed for almost all the subjects. The same was the case with event LYES, for which the MEG sensor-channel was selected from the right motor cortex area. In all the subjects, ERS was more enhanced than the ERD. The power analysis showed very weak ERD/ERS patterns for motor imagery in Subject S3 (see Fig. 3) and Subject S7. The delay in response to visual cues during motor imagery was again established from this power analysis and can be seen in Fig. 3.

3.3. Event-related power analysis for virtual channel data

The source signals obtained from the virtual channels were used for power analysis with respect to time (see Fig. 4). As described earlier, event-related power analysis was mainly performed to verify whether ERD was a dominant pattern for virtual channels selected from the sustaining movement related events (RYES, LYES) and ERS was dominant for virtual channels selected from the stopping of movement related events (RNO, LNO). This was done for both motor execution and motor imagery. When the source signal from a virtual channel for the event RNO was plotted with respect to all other events (RYES, LYES, and LNO), a strong ERS was observed for the active state period for that event. Same was the case for event LNO with respect to events RYES, LYES, and RNO. Similarly, when the source signal from a virtual channel for the event RYES was plotted with respect to all other events (LYES, RNO, and LNO), ERD was observed as a distinguishable pattern for the active state period for that event. This was also seen for the event LYES with respect to events RYES, RNO, and LNO for its active state period. The trend observed, as also seen in Fig. 4, was that the events featuring ERS were more distinguishable than the events featuring ERD.

3.4. Classification

It was intended to discriminate four events (RYES, RNO, LYES, and LNO); while sustaining and ceasing hand movements for the motor execution and motor imagery tasks from single-trial MEG virtual channel signals obtained through SAM analysis. To verify the effectiveness of SAM, the results of virtual channel classification were compared to MEG-Sensor based classification. Classification results carried out using GA-MLD and DTC techniques can be found in Tables 1 and 2.

From the results, it is clear that SAM-Virtual channels were successful in classifying the four events at high performance. The virtual channel-based classification accuracy for motor

execution using GA-MLD was on average 96.51% with standard deviation of 2.43%, and for motor imagery, the results for GA-MLD classification was on average 89.69% with standard deviation of 3.34%. Similarly, the SAM-Virtual channel based classification accuracy for motor execution using direct DTC was 93.28% with standard deviation of 5.71%, and for motor imagery, the results for direct DTC classification was 75.25% with standard deviation of 3.34%.

The MEG-Sensor based classification was performed in order to compare its results with SAM-Virtual channels. The MEG-Sensor based classification accuracy for motor execution using GA-MLD was 69.08% with standard deviation of 3.58%, and, for motor imagery, the results for GA-MLD was 48.43% with standard deviation of 11.26%. Similarly, the SAM-Virtual channel classification accuracy using direct DTC, for motor execution was 58.10% with standard deviation of 5.79%, and, for motor imagery, the result was 40.68% with standard deviation of 12.48%. For motor imagery tasks, the classification accuracy for Subjects S3 and S7 were found to be relatively low. It was observed by time–frequency analysis in the sensor domain, that ERS and ERD both were very weak for these subjects. ERD was hardly detected. Hence feature extraction and classification was difficult for these subjects.

3.5. Statistical analysis

To study the statistical significance of the results established through classification accuracies between SAM-Virtual channels and Sensor domains, a statistical analysis was done on the results obtained through GA-MLD classification technique. The significance level was chosen to be 0.05. It was of interest to know the statistical claim on two points, the first being, whether the classification accuracy obtained from SAM-Virtual channel analysis was better than that obtained through Sensor-based classification for motor execution. The second point was to determine whether the classification accuracy obtained from SAM-Virtual channel analysis was better than that obtained through sensor-based classification for motor imagery.

Using a paired t -test, there was clear evidence for increased classification accuracy ($t = 13.3$, $df = 5$, p -value < 0.0001) through SAM-filtered virtual channel analysis for motor execution. There was a significant improvement in the accuracy to classify the events RYES, RNO, LYES, and LNO through this analysis (point estimate of +27.43%; 95% confidence interval between 22.13% and 32.73%) as compared to the sensor domain results.

For motor imagery, a paired t -test was again conducted and a statistically significant increase in classification accuracy ($t = 6.03$, $df = 3$, p -value < 0.0046) through SAM-filtered virtual channel analysis was observed. When compared with sensor-based classification, a significant improvement in classification of events RYES, RNO, LYES, and LNO was seen with SAM-filtered virtual channel based classification (point estimate of +41.25%; 95% confidence interval between 19.47% and 63.04%).

4. Discussion

4.1. ERD/ERS analysis for human natural motor behavior vs. motor imagery

The analysis of movement related activities was made extremely sensitive due to the unique paradigm used. The asymmetric hemispheric activity during motor tasks as well as the features of ERD and ERS seen while sustaining and ceasing natural upper limb movements explicitly helped in enhancing classification accuracy. Since the spatial distribution of post movement beta rebound (ERS) is more focal than ERD distribution, the detection of ERS might be potentially more reliable than ERD detection to classify the four natural tasks. Using natural motor behavior for the paradigm was easier and motivating for the subjects to perform both motor execution and motor imagery tasks. This minimized training period and, consequently, fatigue, which is a common issue during data acquisition. The performance of a previously reported MEG-based BCI (Mellinger et al., 2007) presented results similar to a state-of-the-art EEG-based mu rhythm BCI (Guger et al., 2003) with large number of participants. The MEG-based BCI used voluntary amplitude modulation of sensorimotor mu and beta rhythms. The results of the present study indicate that the use of natural motor behavior for single-trial MEG-based SAM-Virtual channels gives better classification results when compared to methods using amplitude modulation of sensorimotor rhythms with either EEG or MEG signals. A recent study to decode human motor activity from EEG single trials for a discrete two-dimensional cursor control has been reported (Huang et al., 2009). The classification results from spatially filtered single-trial EEG signals were comparable with the results from direct sensor domain MEG single-trial signals. However, the classification on spatially filtered MEG single-trial signal (source domain) provided much better accuracy than classification from EEG signals, which suggests that MEG signals may support a BCI with higher performance.

For SAM analysis, for all the subjects, the ERD pattern was seen during the planning and execution of movements whereas the ERS pattern was seen after movement. This has been demonstrated in previous studies (Pfurtscheller, 1988; Toro et al., 1994; Bai et al., 2005). The areas of activation associated with right/left hand movement were asymmetrical over the two hemispheres as shown in Fig. 2. It was also observed that the left sensorimotor cortex is activated during dominant right hand movement, whereas sensorimotor cortices of both right and left hemispheres are activated during non-dominant left hand movement. This also has been reported previously with EEG studies (Kawashima et al., 1993; Volkmann et al., 1998; Jung et al., 2003). In this study, we selected the virtual channels from regions of high activity from the ERD/ERS patterns corresponding to different events present in the study without constraint over the primary motor cortex, because the activation regions associated with hand movement may also occur in other areas, for example, the premotor areas (Gaetz and Cheyne, 2006).

The classification accuracy results for motor execution were observed to be better than motor imagery. Studies show that the performance of motor imagery was associated with the ERD and ERS in the beta band similar to that of motor execution (Neuper et al., 2005). However, for the present study, during motor imagery this pattern was not always seen. Although a bilateral ERD was seen for most subjects mentioned in previous studies as the

“spill over” of cortical activation (Dhamala et al., 2003), it was interesting to see bilateral ERS for Subjects S3 and S4 for motor imagery (see Fig. 2). There was a variation of bilateral ERS in Subject S3 and mid-line ERS in Subject S2 for motor execution (see Fig. 2). This could result to a lower classification accuracy due to poor feature detection. However, the ERS pattern was found to be stronger in the left motor cortex area for RNO and right motor cortex area for LNO and the virtual channels for feature selection and classification were thus selected from these dominant lobes. Since natural motor behavior, i.e., right and left physical hand movement, was used for the motor execution tasks, the ERD/ERS patterns were strong and well defined. However, the ERD/ERS patterns for motor imagery were more bilateral and weak. Hence the feature extraction and classification of virtual channel data was difficult for motor imagery which led to lower classification accuracy for the events RYES, RNO, LYES, and LNO. This can be explained by the fact that the subjects need more control over their movement intentions to achieve accuracy for motor imagery tasks. Improved discrimination might be achieved through more effort and longer training periods. Considering the fact that the subjects who participated in this study were naïve to BCI and this was a single trial study, more accurate motor imagery classification could potentially be obtained through a short BCI training period.

4.2. SAM-Virtual channel signal

The neurophysiological mechanisms for voluntary movement have been extensively studied with EEG and also with MEG (Vaughan et al., 1968; Deecke et al., 1969; Pfurtscheller and Berghold, 1989b; Taniguchi et al., 2000; Bai et al., 2005, 2008). MEG has the advantage of superior spatial resolution and can identify the anatomical location of cortical activity with enhanced accuracy. Sensor-based processing is a basic method which only minimally uses the source localization ability of MEG for further classification of event related voluntary movements. A couple of prior MEG studies have been conducted based on the sensor domain, focusing mainly on the source identification problems (Lee et al., 2003; Barbati et al., 2006; Kauhanen et al., 2006). The Laplacian spatial filter is generally used for EEG signals to improve their signal-to-noise ratio. However, due to the more intricate geometry of magnetic fields vs. electric fields, it is not possible to find a general spatial filter that improves the signal-to-noise ratio in analogy to Laplacian filtering. For MEG signals, the position and orientation of the sources of interest must be taken into account. Knowing the pattern associated with a source of interest, it is possible to improve the signal-to-noise ratio (Mellinger et al., 2007). 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. To experimentally test this point, we performed a preliminary pilot study to classify the right and left hand movement intentions using Laplacian spatial filter with MEG. A significant improvement was not observed using the Laplacian spatial filter, and the results were consistent with Mellinger’s study.

SAM, when compared to Laplacian or Sensor-based processing, is a spatially selective beamformer, which filters out the background brain noise from other brain regions to obtain meaningful signals from the arbitrary target regions. SAM transforms neuro-magnetic signals into units of dipole moment on a per-voxel basis; this enables one to display simultaneously active multiple sources, provided that these sources are not perfectly

synchronized (Taniguchi et al., 2000). For the present study, further application of statistical imaging technique was applied to obtain statistical difference in the power of the selected beta frequency band which was evaluated between the active and the control states for events RYES, RNO, LYES, and LNO. Those areas with statistical difference were displayed on the individual MRI (see Fig. 2) in a tomographic manner (Ishii et al., 1999). Virtual channels were selected from these images. Thus, SAM-based virtual channels facilitates feature reduction while selecting the features from the cortical areas, from the source of activation. SAM-filtered virtual channels improve the signal-to-noise ratio (SNR) of the MEG single trial signals and also helps reduce the computational load. In the present study, the original data from 275 MEG sensors for each subject was reduced to mere 25–30 virtual channels, with high SNR from SAM-filtered virtual channel analysis. The SAM-based spatially filtered single-trial MEG signals use the virtual channels in the source domain for analysis of natural motor activity. Hence it is more advantageous in classification of the four movement intentions used in the study, as compared to other spatial filtering techniques ex. Laplacian or direct sensor domain based classification. Classification of these features related to the sustaining and ceasing voluntary movements RYES, LYES, RNO, and LNO, while analyzing single-trial, spatially filtered MEG signals may facilitate a high-performance BCI.

4.3. Event-related power analysis for virtual channels and MEG-Sensors

From the power analysis in the SAM domain, it is evident that among the four events for each virtual channel selected, the events featured by ERS were better detected for the single-trial MEG signals than those featured by ERD, during the active state period (see Fig. 4). The same can be observed in Fig. 3, from power analysis in the MEG-Sensor domain. Studies have reported this phenomenon previously (Pfurtscheller and Solis-Escalante, 2009). Variability in this phenomenon was seen in the MEG-Sensor domain in Subject S3, for whom ERS was not detected during the active state period in the beta band for the respective events for motor imagery trial. This suggests that, since the power samples for feature selection were calculated using the active state time window and ERS was not distinguishable for the events RNO and LNO during this time window, the classification accuracy for Subject S3 was low. This was the case with Subject S7 for the motor imagery trial in the sensor domain (see Table 2). For virtual channel analysis, since SAM further enhances the spatial resolution for the detection of both ERD and ERS, the selection of these features to classify the four events RYES, RNO, LYES, and LNO proved highly efficient to achieve the proposed high-performance BCI.

For the present study to verify the effectiveness of SAM-filtered virtual channel signals to classify natural human movement intentions, the performance of GA-MLD classifier was observed to be better than DTC. Hence GA-MLD based classification was used for the statistical analysis to compare SAM-filtered virtual channel signal vs. the MEG-Sensor signals.

4.4. Implications for BCI application

According to the statistical analysis performed on this study, the four events RYES, LYES, RNO, and LNO associated with sustained and ceased natural human motor control were efficiently classified with high accuracy by the SAM-filtered, single-trial MEG signals. The

results for GA-MLD based classification were on average, 96.51% with standard deviation of 2.43%. The results for motor execution can be advantageous for disabled motor disorder patients, even with very limited physical limb movement.

For motor imagery, the results for GA-MLD classification were 89.69% with standard deviation of 3.34%. Once the basic mechanism of converting event related movement intentions to computerized action is perfected, there would be many potential uses for this BCI technology. This can be achieved through introduction of a short training session for motor imagery trial for the proposed BCI.

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. Also, the paradigm used in the study used an external sync signal for improving the decoding rate. The performance of the system in a self paced mode may be tested in future studies.

Due to the high costs and lack of portability (shielded rooms for data acquisition), MEG is a less practical modality for BCI use compared with EEG. However, the advantages of MEG include high spatial and temporal resolution and moreover the ability to use SAM for the selection of virtual channels, which further enhances the source signal-to-noise ratio of MEG signals and also reduces the computational load for analyses. As technology progresses, there may be portable MEG devices voiding the importance of magnetically shielded rooms (see, e.g., BabySQUID, Tristan Technologies).

Overall, this BCI would have the following advantages: a natural control scheme, high spatial resolution, acceptable response time, robustness and reliability. Thus, a SAM-filtered single-trial MEG-based BCI may help in accelerating rehabilitation and provide a means for assistive device control or communication for patients with severe movement disorders. On the other hand, as the proposed paradigm is associated with human motor control, it can be used effectively for motor training and rehabilitation of patients with movement disorders to improve neural plasticity to restore upper limbs movement related brain functions.

Acknowledgments

This research was partly supported by the Intramural Research Program of the NIH, National Institute of Neurological Disorders and Stroke.

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Fig. 1.

Experimental paradigm. Activation period: 0–1 s after RESPONSE cue, i.e., 2.5–3.5 s. Control period: –1 to 0 s before the initial instruction cue of Right Yes RYES, Left Yes LYES, Right No RNO or Left No LNO. The subjects began repeated wrist extensions of either the right or left hand as per the initial instruction cue. At the RESPONSE cue, for RYES/LYES, the subjects continued wrist extensions, for RNO/LNO the wrist extensions were ceased till the STOP cue. From the STOP cue, there was a rest period of 6–7 s. Data from the activation and control windows were used for SAM analysis, with virtual channels during the activation period with respect to the control period used for classification/prediction. Initial instruction cue (RYES, RNO, LYES, or LNO) period: 0–2.5 s, RESPONSE cue period: 2.5–4 s, STOP (Rest) cue period: 6–7 s. The same paradigm was used for motor execution and motor imagery.

Fig. 2.

SAM image. The coronal and axial view of the head is shown for Subjects S1, S2, S3, and S4. Physical movements: SAM image head plots for Subject S1, Subject S2, and Subject S3 are given. Imaginary movements: SAM image head plots for Subject S3 and Subject S4 are given. Data from the active and control windows (see Fig. 1) were used for SAM analysis. For motor imagery a 0.5-s delay was observed in the response, hence active state was 3–4 s. Band-width: 15–30 Hz (beta band). 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 contralateral motor area activation due to movement intentions were selected from areas marked (by green circle) for further classification. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Fig. 3.

Time–frequency analysis in sensor domain. Time–frequency maps for events RYES, LYES, RNO, and LNO for the single-trial MEG data for Subjects S1, S2, S3, and S4 are plotted for corresponding MEG sensor-channels (left corner of each map, M – MEG, R – right, L – left, and C – central) are plotted according to hemispheric asymmetry. The power is symbolized by blue for ERD and red for ERS. The region of interest, i.e., the active state period corresponding to motor execution and motor imagery showing ERD for events RYES, LYES, and ERS for events RNO and LNO, is marked by the black ellipse. (For interpretation of color mentioned in this figure the reader is referred to the web version of the article.)

Fig. 4.

Time-course of event-related power analysis for SAM-Virtual channel signal. Time–power maps for events RYES, LYES, RNO, and LNO for the single-trial MEG data for Subjects S1, S2, S3, and S4 are plotted for corresponding SAM-Virtual channels (left corner of each map, RMC – right motor cortex, LMC – left motor cortex, VC – virtual channel) according to hemispheric asymmetry. The region of interest, i.e., the corresponding ERD/ERS pattern is marked by the black ellipse during the active state period for motor execution and motor imagery of each event. Legend and the power scale are provided on the right corner of the figure.

Table 1

SAM-Virtual channel signal vs. MEG-Sensor signal classification for motor execution (ME).

Subject	SAM-Virtual sensor		MEG-Sensor domain		Total No. of samples/trials
	GA-MLD (%)	DTC (%)	GA-MLD (%)	DTC (%)	
S1	98.88 ± 0.71	97.38 ± 1.50	63.90 ± 4.46	53.50 ± 4.03	120
S2	96.33 ± 1.05	87.25 ± 3.81	71.10 ± 2.28	62.50 ± 2.92	120
S3	98.44 ± 1.09	98.44 ± 0.78	72.56 ± 2.46	67.11 ± 3.28	115
S4	92.38 ± 1.20	85.63 ± 3.50	70.00 ± 4.22	58.11 ± 4.89	120
S5	95.25 ± 1.54	92.75 ± 1.65	71.50 ± 3.75	55.60 ± 2.80	118
S6	97.75 ± 1.42	98.25 ± 1.21	65.40 ± 3.90	51.80 ± 5.20	89
Average	96.51 ± 2.43	93.28 ± 5.71	69.08 ± 3.58	58.10 ± 5.79	114

SAM-Virtual channel signal vs. MEG-Sensor signal classification for motor imagery (MI).

Table 2

Subject	SAM-Virtual sensor		MEG-Sensor domain		Total No. of samples/trials
	GA-MLD (%)	DTC (%)	GA-MLD (%)	DTC (%)	
S3	94.63 ± 1.87	82.88 ± 2.95	39.20 ± 2.10	31.5 ± 3.34	116
S4	88.25 ± 2.78	71.75 ± 2.65	56.40 ± 3.47	48.20 ± 2.57	120
S5	87.25 ± 2.75	76.50 ± 2.93	59.82 ± 2.38	54.27 ± 2.43	87
S7	88.63 ± 1.71	69.87 ± 3.51	38.33 ± 2.93	28.78 ± 3.80	114
Average	89.69 ± 3.34	75.25 ± 5.80	48.43 ± 11.26	40.68 ± 12.48	110