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Stability of MEG for Real-Time Neurofeedback

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Abstract—**Movement-related field potentials can be extracted and processed in real-time with magnetoencephalography (MEG) and used for brain machine interfacing (BMI). However, due to its immense sensitivity to magnetic fields, MEG is prone to a low signal to noise ratio. It is therefore important to collect enough initial data to appropriately characterize motor-related activity and to ensure that decoders can be built to adequately translate brain activity into BMI-device commands. This is of particular importance for therapeutic BMI applications where less time spent collecting initial open-loop data means more time for performing neurofeedback training which could potentially promote cortical plasticity and rehabilitation. This study evaluated the amount of hand-grasp movement and rest data needed to characterize sensorimotor modulation depth and build classifier functions to decode brain states in real-time. It was determined that with only five minutes of initial open-loop MEG data, decoders can be built to classify brain activity as grasp or rest in real-time with an accuracy of 84±6%.**

I. Introduction

MAGNETOENCEPHALOGRAPHY(MEG) can be used to detect motor-related field potentials and provide real-time feedback [1,2]. In addition to being non-invasive, MEG also has the added benefit of high temporal and relatively high spatial resolution. While MEG is not practical for a portable Brain Machine Interfacing (BMI) system, it has great potential for non-invasive brain-mapping and neurorehabilitation [3,4]. However, the small magnetic fields generated by neural activity and recorded with MEG can lead to a poor signal to noise ratio. To combat the poor signal to noise ratio, traditionally MEG studies average signals across many repetitions of open-loop recording, where the subject has no feedback of their brain states. Despite the poor signal to noise ratio, MEG has recently been used to provide real-time (i.e. faster than 100 ms) neurofeedback to subjects [1,2].

One valuable application of real-time MEG is to aid in upper-extremity rehabilitation. Current rehabilitation methods strive to improve hand and arm functionality using strategies that rely on residual motor function. However, when there is little or no residual movement (e.g. stroke and incomplete spinal cord injury) a therapy using motor control signals collected directly from the brain may be a better option.

The attempted and imagined movements of body parts elicit stereotyped changes in cortical activity [5-8]. Some of these changes can be recorded and used to provide real-time feedback to individuals on their own brain states which could in turn promote neural plasticity and improve limb use. In particular, field potential changes in the mu (8-12 Hz) and beta (18-28 Hz) frequencies are associated with movement and can be readily accessed with electrodes on the scalp, on the dura, or on the cortex surface. These sensorimotor rhythms (SMR) have been used to control assistive devices as part of various BMI systems [4,6,9-11].

Many BMI systems use mathematical decoders to translate the power spectrum of the field potentials into device commands. These decoders typically require some initial open-loop data that is representative of the movement-related commands that will be used for the closed-loop control. To create appropriate decoders, sufficient amounts of open-loop data are needed. However, the more time spent collecting open-loop data the less time will be available for the closed-loop rehabilitation tasks. Therefore it is important to know how much open-loop data is needed for building appropriate decoders and also to provide a stable measure of brain activity to determine if any significant brain changes have occurred due to training.

II. Methods

A. Experimental design and setup

Four right-handed, able-bodied individuals were evaluated in this study. All procedures were approved by the institutional review board at the University of Pittsburgh. MEG and forearm EMG were collected while subjects made cued overt right hand grasps or rested their hand. A black screen with a green cross was shown to direct a subject to begin a grasp. After 3 s the image changed to a blank screen indicating to the subject to relax their hand. Subjects were instructed to perform grasps solely with their hand, keeping their arm at rest. To minimize eye movements, subjects were also instructed to fixate their eyes in the center of the screen throughout each trial. A separate rest period was indicated

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by a blank screen and lasted 2 s. 120 pairs of grasping and resting trials (i.e. blocks) were recorded for each subject. MEG was recorded with a 306-channel whole-head system (ElektaNeuromag®). This system has 102 sensor-triplets, each of which contains a magnetometer, a longitudinal gradiometer, and a latitudinal gradiometer. MEG and EMG signals were band-pass filtered between 0.1 Hz and 330 Hz and then sampled at 1000 Hz. For this study, the MEG and EMG data were resampled offline at 333.33 Hz. No preprocessing was required for noise removal.

B. Calculating modulation depth

Field potentials over the motor and sensory cortices decrease in power during movement relative to during rest [5]. Comparing the depth, or magnitude, of this power difference is a useful measure for determining the effect of a neurofeedback intervention [3, 12]. For the SMR, a more negative modulation depth indicates stronger modulation. To assess the sensorimotor related brain activity, only the channels over the contralateral motor area were used for calculating SMR modulation depth (figure 1 shows the channel locations). In addition, the magnetometers were not included in the analysis due to the poor signal to noise ratio [13]. The modulation depth was specifically defined as the percent change in power between 8 and 28 Hz over the contralateral sensorimotor area during grasp periods versus the power during rest periods. The modulation depth was calculated for each move and rest trial and averaged across multiple repetitions of each trial type. The power spectral density for each trial was calculated using a fast Fourier transform (128-point FFT) using the data between 500 ms and 1500 ms after cue onset to account for reaction time delays.

To evaluate the amount of data needed for an appropriate calculation of modulation depth, the modulation depth was computed using different numbers of blocks (i.e. move/rest trial pairs). The particular blocks used were randomized to remove any effects of non-stationary in the MEG signals and for a more rigorous evaluation. For each number of blocks evaluated (1-120) the block order was randomized 60 times.

C. Decoding in pseudo-real-time

Classifiers were calculated that could translate multi-channel brain recordings into a one dimensional command signal in real-time. To generate classifier functions that could be applied in real-time, the power spectrum was calculated every 48 ms for each channel in the contralateral sensorimotor area using a fast Fourier transform (128-point FFT) applied to a 382 ms sliding bin of data (2.6 Hz wide bands from 8 to 28 Hz). Linear discriminant analysis (LDA) was used to generate classifiers that distinguished the brain activity associated with hand grasp from hand rest. In a real-time application, the predicted hand state (i.e. rest or grasp) at every evaluation point (i.e. every 48 ms) could be used to incrementally increase or decrease the aperture of a hand orthosis or a virtual hand. For this offline study, each evaluation time-point was assessed as being correctly classified as grasp or rest. A percent accuracy measurement was calculated as the total number of correct classifications over the number of total possible classifications where the EMG data was used to define data as move or rest. By definition, the level of chance was 50%.

To evaluate the amount of data needed to build appropriate classifiers, a 10-fold cross-validation was performed. The cross-validation evaluation set aside a random 1/10th of the blocks (i.e. 12 move and rest trial pairs lasting 60 s total) for independent testing of the classifier functions. The various amounts of the remaining data were then used to build classifiers. For the training and testing sets, the number of rest and grasp data samples within each set were forced to be equal to prevent building biased classifiers or having biased testing. EMG data was used to calculate reaction in test data (see details below). However, because the target population will have limited muscle activity due to paralysis, using the EMG data to account for reaction time will not be possible. Therefore, in the training data, the first 500 ms after cue onset of each trial was removed to account for reaction time delays. This cross-validation process was repeated for each 1/10th of the data being used for testing and then the block-order is re-randomized 5 times, resulting in 50 accuracy measurements. In addition, different amounts of data (i.e. 10-108 blocks) were used to train the classifiers in order to assess the amount of data needed for appropriate decoding.

If the task cues were used to judge the decoding performance during the grasp trials, there would be an unfair penalizing of the results during reaction time delays. Instead, EMG data was used to determine when the participant was actively grasping within the testing trials. The change in the EMG signal was rectified and low pass filtered to 5 Hz. Every time point where this processed EMG signal passed a given threshold was marked as muscle activity. Thresholds were chosen which resulted in the best relationship between the discrete, thresholded EMG signal and the task cue as defined by classification accuracy. With the optimal threshold values, an EMG classification accuracy of 90±5% (mean±s.d.) was found across subjects. Note that this method did not take into consideration any delays due to reaction time, therefore perfect accuracy was not possible. This simple classification process was used to estimate the time when the grasp had started in each grasp trial. Because brain activity precedes movement onset, the start of a grasp trial was defined as 100 ms before EMG onset in the testing data. No EMG information was used in training the decoders.

III. Results

A. Modulation depth

Figure 1 displays the SMR modulation depth on all 204 gradiometers from all trials, averaged across all four subjects. A strong negative modulation, indicating a decrease in power during movement, was found on both gradiometer types in the expected hand area of the contralateral sensorimotor cortices. As expected, little or no modulation was observed in other cortical areas.

The total modulation depth of the sensorimotor rhythms (8-28 Hz) was computed across the 36 contralateral

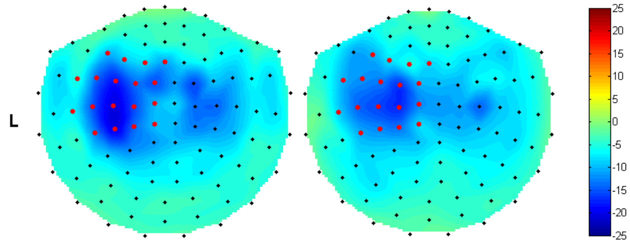

Figure 1: Modulation depth of the sensorimotor rhythms (8-28 Hz) from all trials averaged across all four subjects during right-handed grasping from the longitudinal and latitudinal gradiometers (left and right respectively). Modulation depth was calculated as the percent change in power during grasping relative to the power during hand rest. Shown in red are the channels over the contralateral sensorimotor area used in this study.

sensorimotor sensors (locations indicated on figure 1). This modulation depth is shown in figure 2 when different amounts of data were used for the calculation. As expected, the more data used, the less the variability observed in the calculation of modulation depth. Table 1 shows the mean modulation depth for each subject across all 120 blocks.

To determine how much data was needed for a stable and appropriate calculation of modulation depth, the data from each subject was assessed in the order it was collected. As more data was used to calculate the depth of modulation, the mean modulation depth approached the mean modulation depth found across all 120 blocks (as seen in figure 2a). The point at which the mean modulation depth was within 10 percent of the mean across all 120 blocks of data was marked as the minimum amount of data needed to have a stable modulation depth calculation. The minimum numbers of blocks found this way are shown in table 1 which resulted in an 8±2% change in modulation depth from the 'true' mean modulation depth calculated using all blocks across all subjects. In addition, using as little as 40 blocks results in a 5±4% change from the 'true' mean modulation depth across all subjects.

B. Pseudo-real-time decoding accuracy

The classification accuracies found from the 5x10-fold cross-validation are shown in figure 3 and table 1. The mean (±s.d.) of the accuracies found was 85±5% when using the maximum allowed data for training (i.e. 108 blocks), and still 81±6% when using only a quarter as much data for training (i.e. 27 blocks). As expected, the more data used for training, the better the decoding.

The minimum amount of data needed for real-time decoding was determined by comparing the accuracies found using different amounts of training data during the 5x10-fold cross-validation with the accuracies found using the maximum allotted training data (i.e. 108 blocks). A paired t-test was used to determine the minimum number of blocks that resulted in accuracies that were not significantly different from the accuracies using 108 blocks ($p>0.01$). Table 1 shows the minimum number of blocks calculated in this way for each subject. Using this minimum number of blocks for each subject, there was on average only a 2±1 classification accuracy decrease compared to using all 108 blocks.

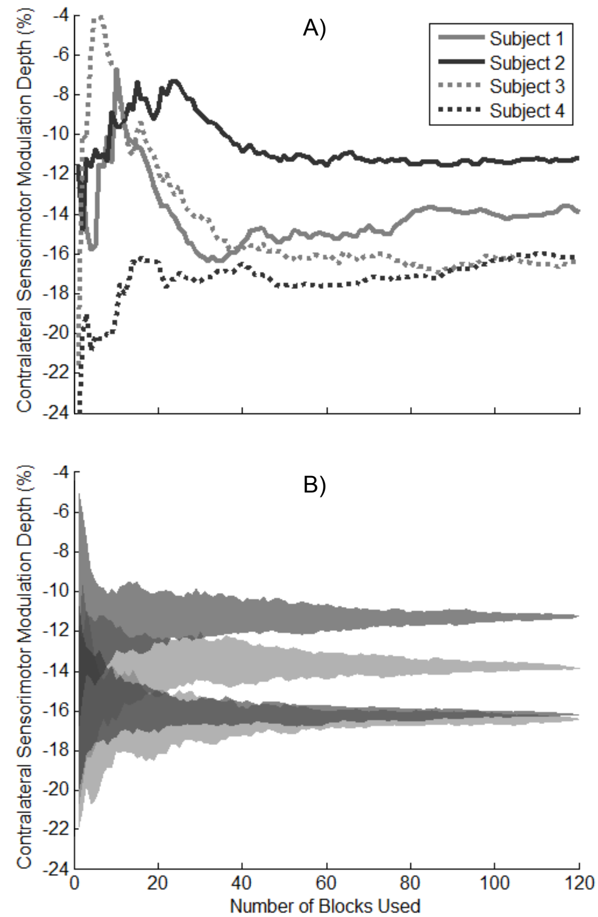

Figure 2: The stability of calculating SMR modulation depth over the contralateral sensorimotor cortex in four subjects using different amounts of data. A) Mean modulation depth found using a given number of blocks in the order they were origianally collected. B) The interquartile ranges of the modulation depth found using a given number of blocks when block order was randomized 60 times. The lines are in subject order from top to bottom: 2 1 4 3.

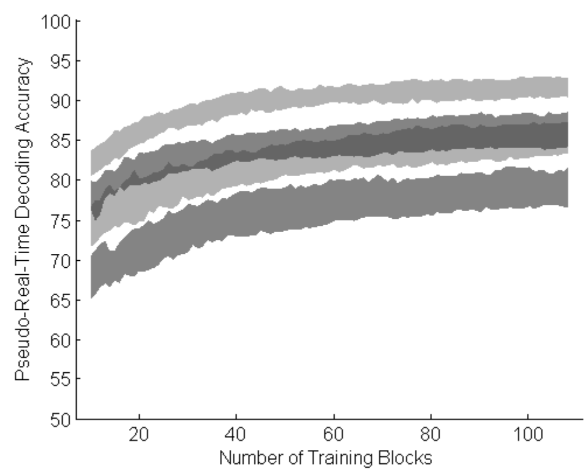

Figure 3: The stability of the pseudo-real-time decoding of grasp for four subjects using different amounts of training data. Different amounts of randomized MEG blocks were used to build decoders that classified the sensorimotor rhythms every 48 ms as a grasp or rest state. The interquartile range is shown for each subject where an accuracy of 50% is chance. The lines are in subject order from top to bottom: 4 3 1 2.

Table 1: Number of blocks needed for calculating sensorimotor modulation and for pseudo-real-time classification of grasp. Also shown are the modulation depth and decoding accuracy for each subject using all possible blocks.

Subject	Modulation Depth	Decoding Accuracy	Number of Blocks	
			For Modulation	For Decoding
1	-13.89%	85±3%	64	63
2	-11.25%	79±4%	37	60
3	-16.43%	86±3%	33	57
4	-16.21%	91±2%	13	55

IV. DISCUSSION

This study demonstrated that hand-related SMRs can be successfully decoded from MEG for real-time neurofeedback and the amount of initial data needed for decoder training and to assess changes in modulation after an intervention is practical. Unlike other BMI studies that use multiple sessions of subject training or extensive open-loop data collection [1,4,6,9] prior to close-loop device control, this study demonstrated that less than five minutes of open-loop data is needed to achieve one-dimensional device control from naïve subjects. Furthermore, it is predicted that for these four subjects, an 84±6% real-time classification accuracy of grasp could be achieved with only 5 minutes of open-loop data collection (i.e. 60 blocks). With this fast initial data collection, more time and effort can be placed on neurofeedback tasks to encourage rehabilitation.

This study classified each time point during single grasps and during rest periods. Often other studies require subjects to perform repetitive hand activity instead of single movements because it can elicit stronger modulations. Stronger modulations may mean that less data is required to build an effective decoder. However, we have shown that using single cued movements, less than 5 minutes of data is needed to build a one degree-of-freedom decoder that can detect single movement-intents in real-time. Having individuals control a single movement of an orthosis or virtual hand using a single attempted movement could be particularly useful for encouraging plasticity and improving rehabilitation.

The majority of BMI applications target individuals with motor impairments and it is possible that the amount of data required for estimating a stable depth of modulation and decoder would be different than observed in this study. However, BMI studies have demonstrated that though individuals with spinal cord injuries or strokes have less movement-related modulation than some able-bodied individuals, they are still capable of using their non-invasive field potentials to command simple devices [4,10,11].

One of the major factors influencing decoder performance is the number and independence of the features used in classification. Here, 9 frequency bins on each of 36 sensor signals (at 18 locations with two gradiometer types) were used; a total of 324 features. Commonly BMI studies use only a few hand-selected features and channels to decrease the amount of needed training data [1,6,9]. For this study, choosing more specific frequency bins, choosing less channel locations, or simply choosing a single type of gradiometer could decrease the amount of training data needed. However, this feature reduction could possibly decrease the decoder performance and would require additional experimenter involvement.

One of the major advantages of MEG over other field potential measurement techniques is the high spatial resolution over the whole head which can be used to perform source imaging techniques. Source localization and spatial filtering methods can be applied in real-time to further improve decoding of movement information. However, most complex source imaging methods require substantial amounts of data for adequate modeling of the sources. The tradeoff between collecting open-loop data to improve decoding performance and performing close-loop trials for neurofeedback will always need to be considered.

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