EEG and MEG Brain–Computer Interface for Tetraplegic Patients

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***Abstract*—We characterized features of magnetoencephalographic (MEG) and electroencephalographic (EEG) signals generated in the sensorimotor cortex of three tetraplegics attempting index finger movements. Single MEG and EEG trials were classified offline into two classes using two different classifiers, a batch trained classifier and a dynamic classifier. Classification accuracies obtained with dynamic classifier were better, at 75%, 89%, and 91% in different subjects, when features were in the 0.5–3.0-Hz frequency band. Classification accuracies of EEG and MEG did not differ.**

***Index Terms*—Brain–computer interface (BCI), dynamic classification, electroencephalographic (EEG), MEG, tetraplegia.**

I. Introduction

BRAIN–COMPUTER interface (BCI) research has been conducted in the Helsinki University of Technology since 1998. We were partners in an EU-funded project *Adaptive Brain Interfaces* from 1998 to 2001. The Academy of Finland funded the project *On-line Adaptive Brain-Computer Interface* from 2003 to 2005. We are a partner in an EU-funded project called *Non Invasive Brain Interaction with Robots—Mental Augmentation through Determination of Intended Action*. Currently, our team consists of two senior researchers, three Ph.D. students, and two undergraduate students. Our tetraplegic subjects are undergoing rehabilitation at the Käpylä Rehabilitation Centre, Helsinki, Finland.

We have developed a MATLAB-based BCI system that can be used for both offline and online research [1]. It has a graphical user interface for fast and easy handling of subject information, recordings, and model building. A program that transfers electroencephalographic (EEG) data to MATLAB in near real time has been developed. We have tested functionality of the design in an online experiment in which four healthy subjects performed cued finger extensions every 2 s. Mean classification accuracy was 73.5% [2].

In our EEG-based BCI, artificial neural networks are used to recognize and classify brain activation patterns associated with real and attempted movements. We have also examined the use of magnetoencephalographic (MEG) signals, which are more localized than EEG signals. The 306-channel MEG device used allows simultaneous measurements of EEG. We have examined offline classification of single MEG trials of data from five subjects [3]. Classification accuracy of the left versus right finger movements was 80%–94%, quite similar as obtained in previous comparable EEG studies.

When BCIs are developed for motor-disabled persons, it is natural to use signals generated in the sensorimotor cortex to control, e.g., cursor movements on a computer screen. The 10- and 20-Hz components of the mu rhythm detected over the sensorimotor cortex have been previously used to distinguish between different movements in healthy subjects. This rhythm is suppressed contralaterally by movement execution [4], [5]. The movement-related suppression is followed by a contralaterally dominant fast recovery and rebound of the mu rhythm [5], [6]. Left versus right hand movements have also be separated in healthy subjects by the lateralized readiness potential (LRP), also called Bereitschaftspotential, which precedes voluntary initiation of movement [7]–[9].

Even though tetraplegic patients cannot move their extremities, their sensorimotor cortices are activated during attempted movements. An fMRI study of five tetraplegic patients showed sensorimotor activation during attempted hand and foot movements [10]. Such activation to attempted big-toe movements was also found in nine paraplegic patients [11]. The activation patterns resembled those of the healthy control group during real movements. Contralateral motor cortex activation during attempted finger movements was also found in a recent EEG study with 24 tetraplegic patients [12].

There are only a few studies that have examined tetraplegics using BCIs (see, e.g., [13] and [14]). Tetraplegics often need several weeks or even months to learn to operate the BCI. Our aim was to test whether good classification accuracy is possible after only 15 min of training. Motor-cortex activity during attempted finger movements was measured with both MEG and EEG. We compare the classification accuracies of both the MEG and EEG single trials. Part of the MEG data has been presented in a preliminary form [15].

We compared the classification accuracy of a batch-trained classifier and a dynamic classifier. In batch training, a classifier is trained with a set of previously collected samples and remains

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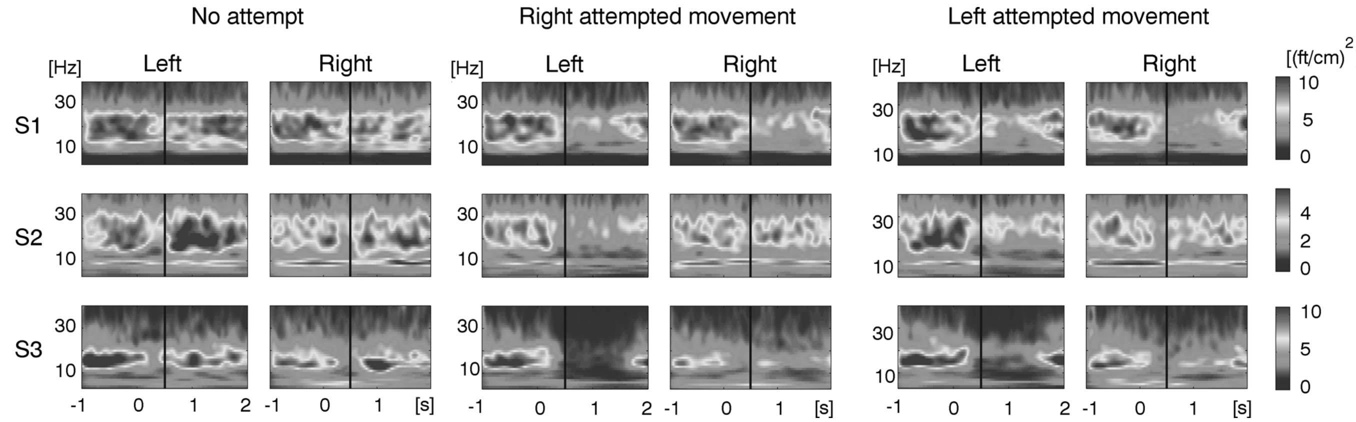

Fig. 1. TFPs (averages of about 80 trials) of MEG signals of three tetraplegic patients from sensors over left and right motor cortex. TFRs are shown during no movement (left) and attempted right (middle) and left (right) finger movement. Onset of movement attempt is indicated with black vertical line.

constant in the testing phase. Batch training is used in most BCI experiments (for a review, see [16]). However, brain activity is not stationary and the feature space changes over time. Dynamic classification enables the classifier to follow the changes in feature space. Dynamic classification with particle filters has been used in an offline study to successfully distinguish between left and right finger movements in healthy subjects, based on the movement-related rebound of the 20-Hz activity [17].

II. Material and Methods

Subjects were three right-handed male tetraplegics (S1-S3). The level of injury was C4-C5 and time since the injury was from four months to five years. None of them had previous experience of BCIs. All patients had a complete spinal cord injury. One of four visual stimuli (duration 0.5 s, once in 3 s) instructed the subject to attempt to lift the left (←) index finger, the right (→) index finger, both (↔) fingers, or not (□) to attempt finger movements. The subjects attempted to perform a quick movement after the stimulus disappeared. The experiment consisted of two 16-min sessions with 80 repetitions of each task. No data were rejected, e.g., due to eye movement artefacts.

Recordings were made in a magnetically shielded room using a 306-channel whole-head MEG device. This device measures neuromagnetic signals from 102 locations with triple sensor units. Each unit consists of one magnetometer and two orthogonal planar gradiometers. A 58-channel EEG was recorded simultaneously, with a reference electrode at nose. Signals from six EEG electrodes (F3, F4, C3, C4, P3, P4) and 24 MEG gradiometers from 12 locations (each location has two orthogonal gradiometers) over the sensorimotor cortices were used in classification.

MEG and EEG signals were filtered with a zero-phase FIR bandpass filter with passbands of 0.5–3 Hz and 3–7 Hz. In EEG analysis, the difference of the filtered signals from the channels C3-C4, F3-F4, and P3-P4 was calculated. In MEG analysis, signals from six parallel gradiometers over the left and six over the right hemisphere were averaged to form two time series per hemisphere. For each channel, six amplitude values were downsampled from a 200-ms time segment starting from the time point when the cue arrow disappeared. In total, there were three channles $\times$ 6 timepoints $=18$ EEG features and 4 channels $\times$ 6 timepoints $= 24$ MEG features.

EEG and MEG trials were classified using a batch classifier and a dynamic classifier. In both cases, the classifier function was a linear combination of the features [18]. Particle filters were used for dynamic classification. They are sequential Monte Carlo algorithms used for online Bayesian inference [19]. They sequentially update the parameters of the classifier function, without the knowledge of the "true" class labels. The used particle filtering algorithm was sampling-importance resampling (SIR) [19] with model augmentation as in [20].

Both batch and the dynamic classifiers were initially trained using data from the first 16-min session and tested with data from the second session. Because the SIR algorithm is stochastic, the results are calculated over 20 runs.

III. Results

A. Characterization of Features

The left side of Fig. 1 shows averaged time-frequency representations (TFRs) of MEG signals recorded over the left and right sensorimotor cortices of all subjects when they were relaxed and did not attempt to move their fingers. The cue was presented at zero and it disappeared after 0.5 s.

The 20-Hz MEG activity was suppressed bilaterally during attempted finger extensions (Fig. 1). Suppression started before the attempted movement was supposed to begin (cue vanished). EEG signals (not shown) were noisier than the MEG signals, but similar patterns were evident. Desynchronization was not followed by a typical contralateral "rebound" (resynchronization) as seen in healthy subjects' data (see, e.g., [3]). Because of their symmetric distributions during attempted movements, we did not try to classify single trials on the basis of 10- or 20-Hz band activities.

Fig. 2 demonstrates slow movement-related responses during attempted movements in both MEG and EEG. These responses were dominant on the side contralateral to the attempted movement.

Based on these lateralized slow responses, we tested two feature sets in classification of single MEG and EEG trials. The first feature set was derived from the 0.5–3 Hz frequency band,

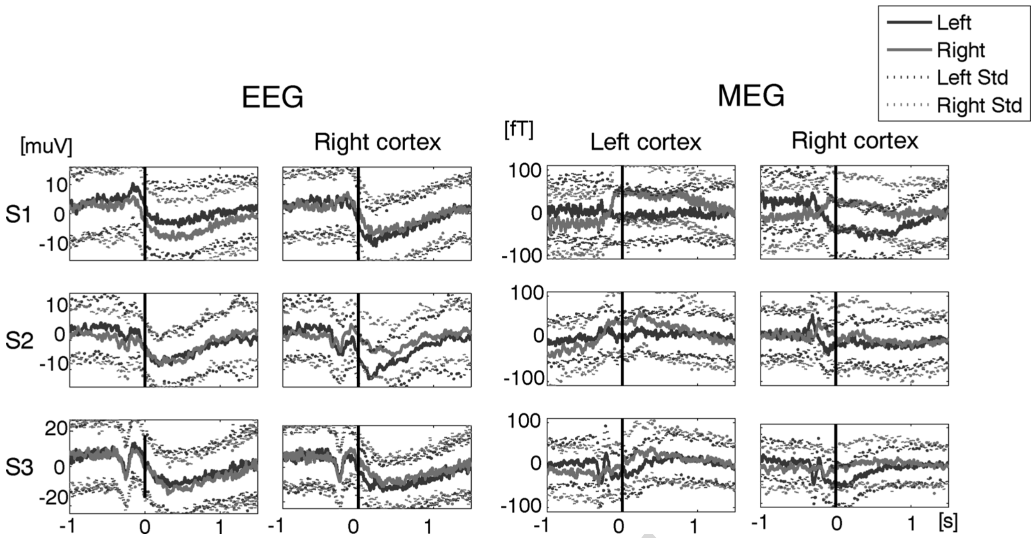

Fig. 2. Movement related activity (averages of about 80 trials) from one sensor over left and one sensor over right side of cortex when subjects were attempting right and left finger lifts. Onset of movement attempt is indicated with black vertical line.

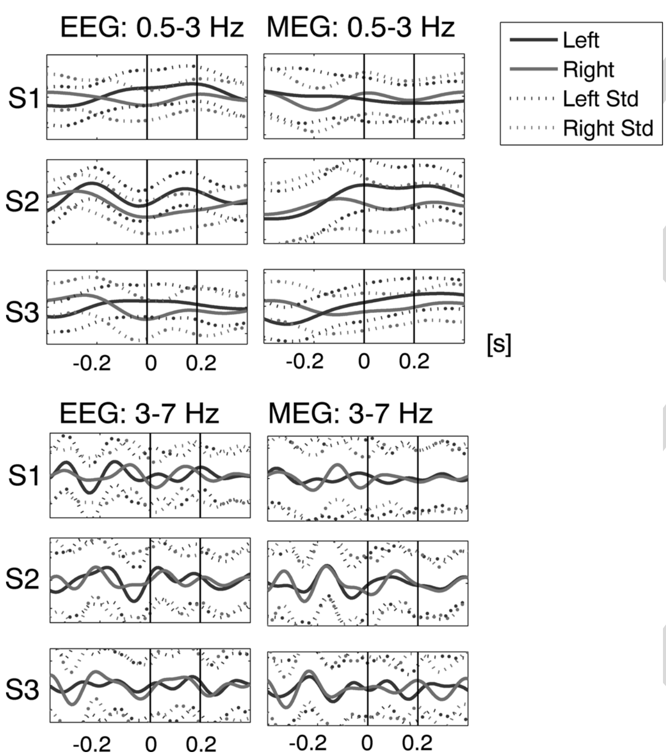

Fig. 3. Left: Filtered EEG difference signals (C3-C4; averages of about 80 trials) during right and left finger lift. Right: Filtered MEG signals averaged from six gradiometers measured over left sensorimotor cortices. Onset of movement attempt is indicated with first black vertical line. Feature used for classification was determined 0–200 ms after movement onset (indicated with black lines). Standard deviations of signals are shown with dotted lines.

corresponding to the frequency band of the LRP seen in EEG preceding voluntary finger movements in healthy subjects. The upper left part of Fig. 3 shows the EEG difference signals (C3-C4) of each subject. The upper right part shows MEG signals from one set of six averaged parallel gradiometers measured over the left sensorimotor cortex.

TABLE I
CLASSIFICATION ACCURACIES OF BATCH TRAINED CLASSIFIER

	Feature	S1	S2	S3	**Mean**
EEG	0.5-3 Hz	87	85	69	**80**
	3-7 Hz	67	66	63	**65**
MEG	0.5-3 Hz	81	79	79	**80**
	3-7 Hz	77	75	80	**77**

TABLE II
CLASSIFICATION ACCURACIES OF DYNAMICALLY TRAINED CLASSIFIER

	Feature	S1	S2	S3	**Mean**
EEG	0.5-3 Hz	91 ± 0.8	89 ± 0.6	75 ± 1.3	**85**
	3-7 Hz	70 ± 1.6	72 ± 2.1	69 ± 3.0	**70**
MEG	0.5-3 Hz	81 ± 1.3	83 ± 0.5	81 ± 0.8	**82**
	3-7 Hz	80 ± 1.1	75 ± 1.1	84 ± 0.5	**80**

The second feature set was derived from the theta frequency band (3–7 Hz, see [21] and [22]). The lower part of Fig. 3 shows the averaged theta band signals. The differences between the signals related to the left and right attempted movements are not as clear as in 0.5–3 Hz band.

B. Classification

Table I shows the classification accuracies of the batch classifier using the 0.5–3.0- and 3–7-Hz features for all subjects. Classification accuracy was quite similar for EEG and MEG and slightly better for the lower frequency band.

Table II shows the classification accuracies and variances (20 trials) obtained with the dynamic classifier using both the 0.5–3- and 3–7-Hz features for all subjects. Classification accuracy was better than that obtained with a batch classifier. The best classification accuracies were 91%, 89%, and 75%, using EEG signals in 0.5-3-Hz band. Again, the accuracies were quite similar for EEG and MEG.

IV. DISCUSSION

Our data showed that 10- and 20-Hz rhythmic activity, recorded over the sensorimotor cortex with both MEG and

EEG, was suppressed when tetraplegics attempted to move their fingers. Suppression was symmetric and was not followed by the contralateral rebound found in healthy control subjects, suggesting that these frequency bands are not useful for tetraplegic BCI users. However, more extensive training might enhance the hemispheric differences. For example, Pfurtscheller *et al.* [13] showed that when one tetraplegic patient learned to control a hand orthosis by controlling his sensorimotor EEG by imagining a foot movement, mu rhythm increased in amplitude over the 5 months training period.

The slow cortical activity during attempted movements was larger contralaterally and was used as a feature for classification of single trials. After only a short training period, the classification accuracies obtained with this feature was remarkable high.

Currently, EEG is the best option for practical noninvasive BCIs because EEG technology is inexpensive and mobile. MEG devices are expensive, immobile, and vulnerable to urban magnetic noise which can be six orders of magnitude larger than the measured magnetic fields. At the moment, these features certainly limit the online use of MEG in BCIs. Nonetheless, as technology progresses, we may even have portable MEG devices (see, e.g., BabySquid, Tristan Technologies).

Good classification accuracy was achieved using both MEG and EEG. The electric potentials measured by EEG are distorted by the inhomogeneities of the extracerebral tissues, whereas the magnetic fields are not affected as long as the electric inhomogeneities are concentric [23]. Therefore, MEG signals are more local than the corresponding EEG signals. Because no reference is needed, MEG signals are easier to interpret than EEG. This is especially the case with gradiometers, which pick up the biggest signal just above the current source in the brain [23]. However, in our present data and with the present analysis methods, MEG and EEG classification accuracies are quite similar. The good spatial resolution of MEG probably will probably be advantageous in multicategory classification when multiple tasks involve activity in distinct brain areas.

0.5–3-Hz features yielded better classification results than the 3–7-Hz features. In addition, the dynamical classifier performed better than the more traditional batch trained classifier.

We examined different signal features, imaging methods, and classifiers with tetraplegic patients. When developing BCIs for actual use, the methods should be tested with potential users as was done here. Methods developed and tested with healthy subjects do not necessarily work with motor-disabled patients. We showed that tetraplegic subjects could control a two-command BCI after a short training period. However, because of the small number of subjects, present findings are tentative and need to be verified in future experiments with more subjects and in online experiments.

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