

# ON THE DEVELOPMENT OF A BRAIN-COMPUTER INTERFACE SYSTEM USING HIGH-DENSITY MAGNETOENCEPHALOGRAPH SIGNALS FOR REAL-TIME CONTROL OF A ROBOT ARM

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## Abstract

This work describes a brain-computer interface (BCI) system using multi-channel magnetoencephalogram (MEG) signals for real-time control of a computer game and a robot arm in a motor imagery paradigm. Computationally efficient spatial filtering and time-frequency decomposition facilitate the extraction and classification of neurophysiologically meaningful and task-relevant signal components from all of the 275 channels comprising the high-density sensor array. To our knowledge, this is the first report of an MEG-based BCI system capable of real-time signal processing and control using the whole sensor array. The robust and reliable performance of this system was demonstrated several times in front of a large public audience at an open day celebrating the 5<sup>th</sup> anniversary of the F.C. Donders Centre for Cognitive Neuroimaging at Radboud University Nijmegen.

## 1 Introduction

A brain-computer interface (BCI) translates complex patterns of brain activity into commands that can be used to control a computer and other electronic devices. Thus, a BCI can provide a communication and control channel, which by-passes conventional neuromuscular pathways involved in speaking or making movements to manipulate objects [1]. BCI systems are anticipated to play an important role in the development of assistive and therapeutic technologies for paralyzed patients, for prosthesis or orthosis control, and in movement rehabilitation, e.g., after stroke or spinal cord injury [2,3].

Many BCI systems are based on the electroencephalogram (EEG), which provides a noninvasive measure of electrophysiological brain activity. There has also been growing interest BCI systems using magnetoencephalogram (MEG) signals [4-6], which have a higher spatial resolution compared with EEG. Notwithstanding the fact that MEG systems are not portable, MEG signals could be useful for providing enhanced feedback during training for EEG-based systems and for non-ambulatory BCI applications.

So far, the only working implementation of an MEG-based BCI system, which provides users with online neurofeedback has been developed by the Tübingen group [7]. Their BCI system, like many others, exploits the well-known neurophysiological phenomenon, e.g., [8], that both overt and imagined movement engage the primary sensorimotor areas of the brain in a similar fashion; i.e., by causing an amplitude reduction of spontaneous oscillatory neuronal activity in the  $\mu$  (8-14 Hz) and  $\beta$  (15-30 Hz) frequency bands during movement/imagery, followed by a “rebound” of  $\beta$ -band power on the contralateral side. The feedback in [7] relates to  $\mu$  or  $\beta$  power – computed from a small selection of sensors overlying the sensorimotor areas – which is visualized as a cursor on a computer screen, whose vertical position is computed using the method introduced in [9]. No special measures were taken to remove artifacts.

This work describes a somewhat different type of BCI system which processes information from 275 MEG channels at once in order to control a computer game and a robot arm in real-time. The system uses a multi-channel signal processing approach where the MEG (or EEG) signals measured at each sensor are considered to be linear mixtures of a set of underlying (unobserved) source signals that are associated with brain activity and various interfering artifacts. Only a small number of brain source signals reflect task-related brain states or subject intentions, which can be distinguished by the characteristic time-frequency signatures of each source.

Thus the approach here is to find a spatial and time-frequency decomposition of the multi-channel MEG data in order to identify task-related sources. These are then extracted during online signal processing using spatial filters that operate on all 275 MEG channels and suppress interference from other sources, thereby obviating the need for artifact detection and removal. Instead of direct position control, we use a control scheme – analogous to pressing buttons – where a 3-category classifier determines whether, and in which direction, a fixed-magnitude relative change in position should occur.

## 2 Materials and Methods

### 2.1 Experimental Setup

**Participants:** Three healthy volunteers (2 male, 1 female, age range 25-37) took part in an initial screening task, and one subject (male) whose data could best be classified (and is reported here) was selected for subsequent online training for a live BCI demonstration, which was held at an open day (on 28.10.2007) celebrating the 5<sup>th</sup> anniversary of the F.C. Donders Centre for Cognitive Neuroimaging.

**Task and Protocol:** Subjects were asked to play several rounds of the computer game Pong, which involves 1-D control of the vertical position of a bat (cursor) on a screen in order to hit a ball. The game was implemented in Presentation® (Neurobehavioral Systems, Inc., Albany, CA, USA) and controlled via the serial port, receiving input either from a response device or from the BCI. With MEG being recorded, subjects began by controlling the game through the response device using overt movements of their left (=up) and right (=down) index fingers. After the classifier had been trained, the game was controlled via the BCI system, initially using overt and then imagined finger movements. Finally, the BCI system was used to control a robot arm constructed using fischertechnik® components (fischertechnik GmbH, Waldachtal, Germany). The subject saw the robot via a video link and was immediately able to achieve control using imagined movement.

**Response Device:** Movements of the left and right index fingers were registered using a custom-built response device based on force transducers that operated as touch-sensitive switches (buttons). The device was controlled using LabVIEW (v8.2, National Instruments Corp., Austin, TX, USA) and configured to produce a trigger signal indicating whether or not the finger was resting on the touch-pad. A response consisted of a brief lift of the finger. The triggers were set to Presentation® and the MEG system.

**MEG Signal Acquisition:** Electromagnetic brain activity was recorded using a CTF MEG™ System (VSM MedTech Ltd., Coquitlam, British Columbia, Canada) installed at the F.C. Donders Centre for Cognitive Neuroimaging, Nijmegen, the Netherlands. The system comprises 275 DC SQUID axial gradiometers that provide whole-head coverage. Additional bipolar channels were used to record the vertical and horizontal electrooculogram (EOG), the electrocardiogram (ECG), and the surface electromyogram (EMG) from sites overlying the extensor muscles (*m. ext. indicis*) on the left and right forearm. The biomagnetic and electrophysiological signals, and the triggers from the response device were co-registered and sampled continuously at 600 Hz.

### 2.2 Offline Data Analysis

**Data Segmentation:** Using the triggers from the response device, the MEG signals were segmented into 2 second epochs which contained either left or right movement on- or offsets, or no movement; these were then assigned to one of three classes: left, right, nothing. Epochs from two separate gaming sessions formed training and test sets.

**Spatial and Time-Frequency Decomposition:** The MEG signals were decomposed into spatial and time-frequency elements using a blind source separation (BSS) approach based on the discrete wavelet transform (DWT), see [10]. The method uses non-orthogonal joint approximate diagonalization [11] of a set of DWT sub-band cross-covariance matrices – computed over 400 ms sub-intervals and averaged over epochs for each class – to find a linear (spatial) projection of the MEG signals into the space of temporally uncorrelated sources with maximally disjoint DWT amplitude spectra. This (supervised) approach is well suited for separating sources with unique activity profiles in different conditions [12].

**Classifier Construction:** Features for classification were extracted from the DWT of all signal segments as follows. We took the logarithm of the sum of the absolute DWT coefficients in the four sub-bands from 4-75 Hz over two 400 ms sub-intervals around the centre of each epoch, and concatenated the values to form an 8-element feature vector.

Separate probabilistic network classifiers were trained for each source. The hidden layer consisted of a Gaussian mixture model (GMM) [13] that was trained on all features combined over classes and where the number mixture components was chosen with reference to the Bayesian Information Criterion (unsupervised). The mixture component activations were mapped onto the output (classes) using a linear combination, whose weights were determined by regression onto the class labels (supervised), and scaled to reflect the class posterior probabilities. The classifiers (sources) were ranked according to their performance on training data and then cumulatively combined using a voting scheme in which the class posteriors are multiplied (the product rule). The best classifier “ensemble” – reflecting movement-related sources – was selected by peak classification rate.

### 2.3 Online Data Analysis

**MEG Data Streaming:** The CTF MEG™ acquisition software (Acq) runs on a Linux platform which allows simultaneous read and write file access by different processes. We therefore configured Acq to write data in 250 ms blocks and “streamed” the data to the BCI system by reading each new block as it became available, using the FieldTrip Matlab toolbox [14].

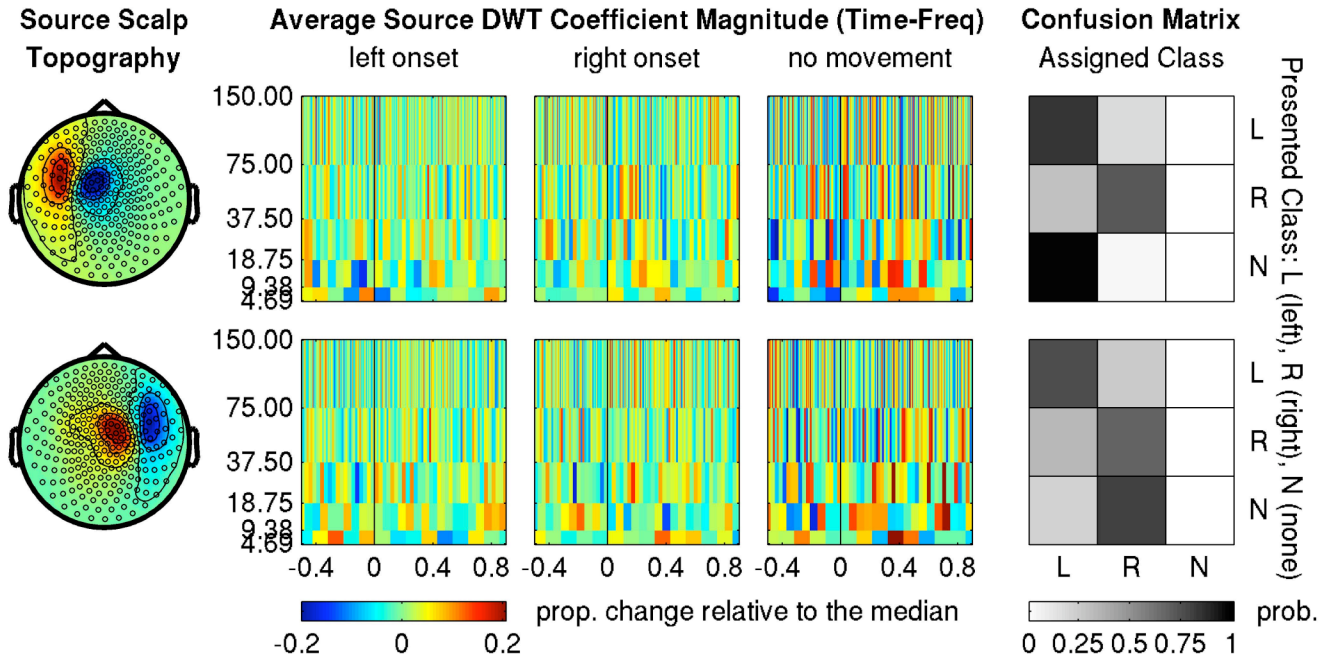


Figure 1: Shown for each of the two movement-related sources (rows, left to right) are their scalp topographies, their average DWT amplitude spectra for left, right and no movement, expressed as a proportion relative to the median of the epoch, and the confusion matrices for their individual classification of the training data.

**Feature Extraction:** Each new block of MEG data was added to a ring buffer that stored the last 2 s of data. The time-course for each source of interest was extracted (estimated) using a fixed spatial filter whose coefficients corresponded to the relevant row of the spatial decomposition (un-mixing) matrix obtained using the wavelet BSS method. The DWT of each source signal was computed – using efficient and fast sparse matrix multiplication – and features were extracted from the latest 800 ms as described.

**Classification:** Features extracted from the sources of interest were classified using the ensemble classification approach described above. For online classification we introduced additional weights to a) equalize classifier biases due to imbalances in the number of training samples for each class, and to b) increase the likelihood of no movement eightfold. Finally, BCI commands for “up” and “down” were generated only from segments where the posterior probability for “left” or “right” was greater than 0.6.

### 3 Results

#### 3.1 Offline Analysis

The wavelet BSS method applied to 275-channel MEG data produces 275 source signals, the majority of which are not task-related. Identifying the small

subset of “relevant” sources, i.e., those sources most clearly reflecting the differences between classes, is a difficult problem, to which the ensemble classifier approach here offers a solution. For the MEG data from the pong game only two sources were required to distinguish left from right from no movement. These are shown in Figure 1, where it is clear from the scalp topographies of the sensor projections that these sources reflect the primary sensorimotor areas of the left and right hemispheres. Moreover, the time-frequency representation of the source signal shows amplitude modulation in DWT sub-bands spanning the  $\mu$ - and  $\beta$ -bands (as well as higher frequency ranges) before, during and after left and right finger movement. The classification rates for the individual and ensemble classifiers on training and test data are plotted in Figure 2.

#### 3.2 Online Analysis

To validate the online processing and classification of the MEG-based BCI system the subject first tried – successfully – to play the pong game (against the experimenter) using overt finger movements but with the response device removed. Subsequently, over a period of about 20 min, the subject learned to play using only imagined movement. Finally, the BCI control acquired by the subject transferred smoothly over to the task of controlling the robot arm.

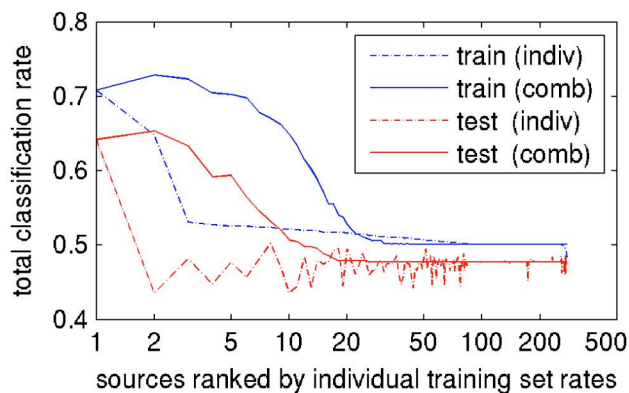


Figure 2: Individual and ensemble classification rates for sources on training and test data.

#### 4 Summary and Conclusion

This work describes an MEG-based BCI system that processes and analyzes high-density, 275-channel MEG data in real-time, and which has been used to control both a computer game and a robot arm. The system uses computationally efficient multi-channel signal processing for feature extraction, combining spatial filtering with DWT-based time-frequency decomposition. An ensemble classification approach offers a simple, objective (and automatic) means of selecting only those underlying sources for BCI processing, whose associated classifiers help to maximize overall performance. While the BCI system described here operates on MEG signals, the feature extraction and ensemble classification approach is as such equally applicable to multi-channel EEG and can be extended to more than 3 classes.

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#### References

[1] Wolpaw, J., Birbaumer, N., McFarland, D., Pfurtscheller, G., and Vaughan, T., Brain-computer interfaces for communication and control, *Electroencephalography and Clinical Neurophysiology*, 113(6), 767-791, 2002.

[2] Pfurtscheller, G., Guger, C., Müller, G., Krausz, G., and Neuper, C., Brain oscillations control hand orthosis in a tetraplegic, *Neuroscience Letters*, 292(3), 211-214, 2000.

[3] Pfurtscheller, G., Müller, G., Pfurtscheller, J., Gerner, H., and Rupp, R., 'Thought' control of functional electrical stimulation to restore hand grasp in a patient with tetraplegia. *Neuroscience Letters*, 351(1), 33-36, 2003.

[4] Lal, T., Schroeder, M., Hill, J., Preissl, H., Hinterberger, T., Mellinger, J., Bogdan, M., Rosenstiel, W., Hofmann, T., Birbaumer, N., Schölkopf, B., A brain computer interface with online feedback based on magnetoencephalography, *Proc. 22nd Int. Conf. on Machine Learning (ICML 2005)*, 465-472, 2005.

[5] Kauhanen, L., Nykopp, T., Lehtonen, J., Jylanki, P., Heikkonen, J., Ratanen, P., Alaranta, H., and Sams, M., EEG and MEG brain-computer interface for tetraplegic patients, *IEEE Trans. Neural Syst. Rehabil. Eng.*, 14(2), 190-193, 2006.

[6] Kauhanen, L., Nykopp, T., and Sams, M., Classification of single MEG trials related to left and right index finger movements, *Clinical Neurophysiology*, 117(2), 430-439, 2006.

[7] Mellinger, J., Schalk, G., Braun, C., Preissl, H., Rosenstiel, W., Birbaumer, N., and Kuebler, A., An MEG-based brain-computer interface (BCI), *NeuroImage*, 36, 581-593, 2007.

[8] Pfurtscheller, G. and Neuper, C., Motor Imagery activates primary sensorimotor area in humans, *Neuroscience Letters*, 239, 65-68, 1997.

[9] McFarland, D., Lefkowitz, T., Wolpaw, J., Design and operation of a brain-computer interface (BCI) with digital signal processing technology, *Behav. Res. Methods Instrum. Comput.*, 29, 337-345, 1997.

[10] Hesse, C.W. and James, C.J., A time-frequency approach to blind source separation using statistically optimal wavelet packets applied to ictal EEG, *Proc. 2nd Int. IEE Medical Signal and Information Processing Conf. (MEDSIP 2004)*, Malta, 5-8 September 2004, pp. 137-144.

[11] Ziehe, A., Laskov, P., Nolte, G., Müller, K.-R., A fast algorithm for joint diagonalization with non-orthogonal transformations and application to blind source separation, *Journal of Machine Learning Research*, 5(7), 777-800, 2004.

[12] Hesse, C.W., Brouwer, C.L., and Jensen, O., Identification of task-related brain activity in the multichannel EEG through joint diagonalization of single-trial cross-covariance matrices, *Proc. 1st Ann. Symp. IEEE EMBS Benelux Chapter*, Brussels, Belgium, 7-8 Dec 2006, pp. 275-278.

[13] Roweis, S. and Ghahramani, Z., A unifying review of linear Gaussian models, *Neural Computation*, 11, 305-345, 1999.

[14] FieldTrip open source Matlab toolbox is available from: <http://www2.ru.nl/fcdonders/fieldtrip>