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Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks

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We studied the reactivity of EEG rhythms (mu rhythms) in association with the imagination of right hand, left hand, foot, and tongue movement with 60 EEG electrodes in nine able-bodied subjects. During hand motor imagery, the hand mu rhythm blocked or desynchronized in all subjects, whereas an enhancement of the hand area mu rhythm was observed during foot or tongue motor imagery in the majority of the subjects. The frequency of the most reactive components was 11.7 Hz ± 0.4 (mean ± SD). While the desynchronized components were broad banded and centered at 10.9 Hz ± 0.9, the synchronized components were narrow banded and displayed higher frequencies at 12.0 Hz ± 1.0. The discrimination between the four motor imagery tasks based on classification of single EEG trials improved when, in addition to event-related desynchronization (ERD), event-related synchronization (ERS) patterns were induced in at least one or two tasks. This implies that such EEG phenomena may be utilized in a multi-class brain–computer interface (BCI) operated simply by motor imagery.

Introduction

A fundamental property of a neural network is the ability of neurons to work in synchrony and to generate oscillatory activity (Lopes da Silva, 1991). One prominent group of such brain oscillations has frequencies between 9–13 Hz in man and 12–15 Hz in cat and originates in sensorimotor areas. These activities are known as “rolandic mu rhythms” or “wicket rhythms” in man (Niedermeyer, 1993; Gastaut, 1952) and sensorimotor rhythms (SMRs) in cat (Chase and Harper, 1971; Howe and Sterman, 1972).

It is well known that planning and execution of hand and/or finger movement block or desynchronize the mu rhythm (Chatrian et al., 1959), and inhibition of motor behavior synchronizes the SMR (Howe and Sterman, 1972). The importance of such an enhancement of 12- to 15-Hz oscillations for biofeedback therapy was documented already in the seventies by Sterman et al. (1974) and confirmed by Egner and Gruzelier (2001) and others. It was already demonstrated that externally paced foot and tongue movement and imagination of foot movement (Pfurtscheller and Neuper, 1994, 1997) can enhance the hand area mu rhythm, similar as observed during reading of words (Pfurtscheller, 1992), pattern vision (Koshino and Niedermeyer, 1975) or flicker stimulation (Brechet and Lecasble, 1965). This ability to suppress or enhance the amplitude of the hand area mu rhythm consciously by directing attention to different body parts or limbs is not only of interest to suppress epileptic seizures by neurofeedback therapy (Sterman et al., 1974) but also for realizing an EEG-based brain–computer interface (BCI) with motor imagery as a mental strategy (Wolpaw et al., 2002; Pfurtscheller and Neuper, 2001).

The goals of this paper are

(i) to study the inter- and intrasubject variability of event-related EEG (de)synchronization patterns (ERD/ERS) in four motor imagery tasks,
(ii) to study whether the same or different frequency components are involved in desynchronization and synchronization patterns recorded from the same cortical areas,
(iii) to report on the distinctiveness between four different motor imagery tasks when single trials are analyzed and classified, and
(iv) to provide recommendations for the realization of a multi-class BCI with improved classification accuracy.

Methods

Subjects and experimental paradigm

Six female and three male healthy right-handed subjects (mean age 26.2 years, range 21–31 years) participated in this

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study. They sat in a comfortable armchair in an electrically shielded cabin watching a 15″ monitor from a distance of about 2 m. Each trial started with a blank screen at second 0. At second 2, a fixation cross was presented at the center of the monitor until the end of the trial at second 7. Simultaneously, a short warning tone occurred at second 2. At second 3, an arrow, pointing either to the left, right, up, or down representing one of four different motor imagery tasks (left hand, right hand, both feet, and tongue, respectively), appeared on the screen for 1.25 s. The period between trials varied randomly between 0.5 and 2.5 s (Fig. 1, right). The subjects were instructed to perform the indicated motor imagery task up to second 7. During the motor imagery task, in particular, the subjects should imagine the indicated movement. They were asked to imagine the (kinesthetic) experience of movement (rather than a visual type of imagery) while remaining relaxed and avoiding any motion during performance. The experiment was divided into 6 runs, consisting of 40 trials each, which led to 60 repetitions of each type of mental task. There were breaks of 3 to 5 min between the runs. Within each run, the tasks were performed in a random order to avoid adaptation.

EEG signals were recorded from a grid of 60 Ag/AgCl scalp electrodes (using a cap by Easycap, Germany) referenced to the left mastoid. The right mastoid electrode served as ground (Fig. 1, left). The closely spaced electrodes with distances of approximately 2.5 cm were placed in a configuration including the electrode positions C3, C4, Cz, Fz, and Pz of the international 10–20 system. The signals were acquired with a SynAmps amplifier (NeuroScan, USA) filtered between 1 and 50 Hz. An additional 50-Hz notch filter was used. The data, including a rectangular trigger signal, were sampled at 250 Hz.

To obtain reference-free EEG data, calculation of source derivation based on the center and the four nearest neighboring electrodes was performed (Hjorth, 1975)—for boundary electrodes, an equivalent calculation was carried out based on the first, second, or third nearest neighbors.

After triggering the data, trials of 10-s length were obtained including 2 s before the warning tone. Single trials were visually inspected for muscle and ocular artifacts, using the software package g.BSanalyze (Guger Technologies, Graz, Austria). Trials containing artifacts were eliminated.

Quantification of ERD/ERS

The quantification of ERD/ERS was carried out in four steps: bandpass filtering of each trial, squaring of samples, and subsequent averaging over trials and over sample points. The ERD/ERS was expressed as percentage power decrease (ERD) or power increase (ERS) in relation to a 1-s reference interval before the warning tone (Pfurtscheller and Lopes da Silva, 1999). The statistical significance of the ERD/ERS values was verified by applying a t percentile bootstrap statistic to calculate confidence intervals with a significance level of $\alpha = 0.05$. This procedure was carried out for overlapping (by 1 Hz) 2-Hz bands in the frequency range between 6 and 42 Hz (for details, see Graimann et al., 2002). The time–frequency maps obtained were used for selection of the alpha (mu) band rhythms with the most significant band power increase or decrease during the motor imagery tasks at the central electrode positions C3, Cz, and C4.

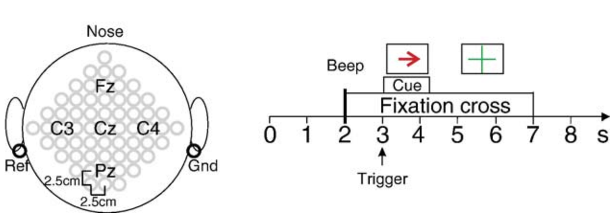

Fig. 1. Electrode positions (left) and experimental paradigm (right).

Analysis and classification of single-trial EEG data

First, the monopolar (raw) EEG data was downsampled from 250 Hz to 125 Hz. Next, adaptive autoregressive (AAR) parameters (of order 3) were estimated for every monopolar channel ($N = 60$) and for every possible combination of bipolar channels ($N = 1770$). Accordingly, 60 + 1770 = 1830 single channel AAR estimates were obtained using the Kalman filtering algorithm (for details, see Schlögl, 2000). Next, the AAR estimates from each trial were divided into segments of 25 samples, i.e., 0.2 s. For each segment, a minimum Mahalanobis distance (MDA) classifier across all trials was calculated and applied to the same segment. This classifier is based on the so-called Mahalanobis distance $d_c(x)$, which is defined as:

$$d_c^2(x) = (x - \mu_c)\Sigma_c^{-1}(x - \mu_c)^T.$$

Here, μ_c is the mean and Σ_c the covariance of the normally distributed class c, estimated from the corresponding training samples. For each testing point x in the n-dimensional feature space, a distance to each class can be calculated, and x is then assigned to the class with the smallest distance. That way, a simple and robust statistical classifier can be obtained which is also applicable to more than two classes.

Accordingly, an average measure for the classification accuracy of the four class problem (four motor imagery tasks) for each segment was obtained. As a measure of distinctiveness, the kappa coefficient κ (Kraemer, 1982) was used. In an M class classification problem, the proper evaluation of the classifier is described by its confusion matrix defining the relationship between the true classes and the output of the classifier. From the confusion matrix H, we can derive the classification accuracy ACC (overall agreement) as follows:

$$ACC = p_0 = \frac{1}{N}\sum_i H_{ii}$$

The chance expected agreement is

$$p_e = \frac{\sum_i n_{oi} n_{io}}{NN},$$

where $N = \sum_i \sum_j H_{ij}$ is the total number of samples, H_{ij} are elements of the confusion matrix H on the main diagonal, and n_{oi} and n_{io} are the sums of each column and each row, respectively. Then the estimate of the kappa coefficient κ is

$$\kappa = \frac{p_0 - p_e}{1 - p_e}$$

with chance probability $p_e = 1/M$. For more details, see also Cohen (1960), Bortz and Lienert (1998) and Kraemer (1982). To compute the kappa coefficient, we used the implementation realized in the BioSig toolbox (Schlögl, 2004).