IMAGINED HAND MOVEMENTS IDENTIFIED FROM THE EEG MU-RHYTHM

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Abstract

It is well established that human hand movements are accompanied by a desynchronisation of the Rolandic mu-rhythm. In this paper we demonstrate that mu-rhythm desynchronisation also occurs when the hand movements are merely imagined. The electroencephalogram (EEG) was recorded with two eleven-electrode arrays placed over the left and right sensorimotor cortex. Subjects performed real and imagined movements in response to an external cue. The EEG was processed to obtain the Laplacian derivation at three sites on each side of the head and the power in the 8-12 Hz mu-band was compared at movement versus baseline times. Imagined movements were identified in 6 out of 7 subjects with an average accuracy of 70%. This suggests that motor imagery could be used to generate signals appropriate for use in an EEG-based communication device.

1 Introduction

Human hand movements are accompanied by event-related changes in the electroencephalogram (EEG). One such change is the Event-Related Desynchronisation (ERD) of the mu-rhythm (Pfurtscheller and Berghold, 1989). This is an 8-12 Hz rhythm in the contralateral motor cortex that disappears during movement execution or planning. In this paper we investigate whether mu-rhythm desynchronisation occurs when the movements are merely *imagined.*

Our motivation for this investigation was as follows. Firstly, we wished to establish whether or not imagined movements could be reliably detected from the EEG in a population of normal subjects. If this were to be successful, further investigations of patients with severe brain injury would be conducted to see if the technique could be used to aid diagnosis in cases, for example, where the patient's ability to understand was not clear. Furthermore, the identification of imagined movements could form the basis of an EEG-based communication device.

EEG-based communication devices utilising the mu-rhythm have been studied by Pfurtscheller et al. (1993) and Wolpaw and McFarland (1994). Although these systems were initially developed using real hand movements, subjects were consequently trained to use the devices through a process of biofeedback. It is therefore unclear as to what cognitive mechanism the users were eventually using. In this paper, we provide direct evidence that motor imagery could be used to generate the appropriate signals.

2 Methods and Materials

2.1 Experimental set-up

EEG data were collected from 7 healthy right-handed volunteers. Informed consent was obtained from all subjects and the study was given ethical approval by the Riverside Research Ethics Committee.

Each subject participated in recording sessions lasting 1 hour. The EEG was recorded from a grid of electrodes shown in Figure 1. The electrodes were positioned over the right and left sensorimotor cortex in a subset of the positions used in Pfurtscheller et. al. (1994). All signals were recorded with respect to a common Cz reference and the impedance between each electrode and the reference was less than 5KΩ. The surface electromyogram (EMG) was recorded from the left and right forearm extensors and the electro-oculogram (EOG) was recorded from the right eye to monitor eye blinks. The signals were digitised to 16 bit accuracy at a sampling rate of 125 Hz. A digital 63 tap FIR (Hamming window) anti-aliasing filter was used with a 3dB cut-off at 50 Hz. Data was stored on computer disk and analysed at a later date.

During each session, 15 blocks of 90-second recordings were made. In each block the subject was exposed to a computerised stimulus sequence shown in Figure 2. This stimulus was identical to that described in Pfurtscheller et al. (1994) and consisted of visual cues appearing on the right or left side of a computer screen accompanied by an auditory stimulus and presented in a known pseudo-random order. The stimuli appeared at a frequency of one every 15 seconds. Subjects were asked to look at a cross in the centre of the screen in order to keep eye movements to a minimum.

In 5 of the blocks, the subject was asked to make a hand movement corresponding to the side of the stimulus; for stimuli on the right the subject was required to make a right hand movement. Each hand movement was an opening and closing of the hand lasting for between one and two seconds. In another set of 5 blocks the stimulus was the same but the subject was asked to imagine making the hand movements. In a third set of 5 blocks the stimulus was the same but the subject was asked to view the stimulus but not to make any movements or imagine doing so. Each of these sets of blocks was performed in a different random order for each subject so as to eliminate any possible effect due to fatigue.

The EEG data was then analysed according to the schematic in Figure 3. Each of the processing steps is described below.

2.2 Laplacian derivation

The EEG signals were transformed by the Laplacian operator (Hjorth, 1975). This transforms recordings at each time point by calculating the difference between each electrode reading and the average reading from its four cardinal neighbours. It has the effect of localising the information received from each channel. In this way, the 22 electrode voltages were reduced to the six Laplacian channels (L1 to L6) shown in Figure 1. The EEG signals were then processed to extract features which discriminate between movement and non-movement.

2.3 Feature extraction

We implemented two different feature extraction schemes. The first was a Fourier transform from which relative changes in band-power were calculated. This provided a measure of the Event-Related Desynchronisation (ERD) of the mu-rhythm. This is the fraction of mu-power at an event-related time with respect to mu-power at a baseline time. The 8-12 Hz band power in each Laplacian channel was evaluated in a sliding 2-second window which moved on 0.2 seconds between calculations. The significance of the ERD was evaluated with the Wilcoxon rank-order correlation statistic (Pfurtscheller and Aranibar, 1979). This measures the proportion of pairs of measurements in a given time window for which the mu-power is lower in the event-related window than it is in the baseline window. This generates a p-value; the probability that the desychronisation occurs by chance. When this p-value fell below 0.05 we had recorded a significant ERD.

The second feature extraction method was a calculation of Auto-Regressive (AR) features (Pardey et al., 1996). This is a linear predictive time series model where the next value in a time series is modelled as a linear combination of the p previous values, where p is referred to as the order of the model. AR models can be used for spectral estimation and have been used by a number of researchers to capture changes in EEG rhythms (Anderson et al., 1995; Peltoranta and Pfurtscheller, 1994).

2.4 Feature selection

For each data record we are interested in comparing signal features at baseline times versus a period 1 to 2 seconds after the stimulus tone. Following Pfurtscheller et al. (1994) the baseline period was chosen to be 4-5 seconds before each stimulus tone. As previously described, the feature values were calculated every 0.2 seconds. The 1 second intervals of interest were deemed to be inclusive. This means that, for mu-power values, we have 6 features per channel per second. For AR features we have $6p$ features per channel per second. Each 1 second period that we are interested in therefore contains 36 mu-power features or $36p$ AR features. As there are such a large number of features and not all of them are necessarily predictive of movement or imagined movement we use a feature selection algorithm to detect those that are.

We used a Sequential Forward Selection (SFS) algorithm based on a linear regression equation (Kleinbaum et al., 1988). This is a forward stepwise procedure which builds up a series of k linear models using 1 up to k input features. The first model uses a single feature, x_1; the one which linearly predicts the class label with the smallest error. The second model uses two input features, x_1, selected at the previous stage, and x_2, which in linear combination with x_1 predicts the class label with the smallest error. This process continues until the error from a model with $k+1$ input features is not significantly smaller than the error from a model with k input features, as measured by an F-test (Kleinbaum et al., 1988).

2.5 Classification

Classifications were made with a linear discriminant classifier and a Bayesian neural network (Neal, 1996). A linear discriminant classifier forms a weighted sum of input features and compares this to a threshold. Input patterns that produce outputs above threshold are deemed to belong to one class (eg. event-related movement) and patterns producing below threshold outputs to another class (eg. baseline). Weights and thresholds are set using matrix inversion (Kleinbaum et al., 1988). A linear discriminant classifier is one of the simplest classification methods but often produces surprisingly competitive results (Penny and Frost, 1996). A Bayesian neural network, on the other hand, is one of the most complex and powerful classification methods. A neural network is a type of nonlinear discriminant classifier (Ripley, 1996). A problem with neural networks, however, is that they are prone to overfitting data, that is, inferring patterns in data sets which are not actually there. A Bayesian neural network, however, does not overfit data. The Bayesian scheme uses a prior distribution over network weights which biases the network to finding simple solutions, though complex solutions can be inferred if they are supported by the data. Network weights are set using a stochastic nonlinear optimisation algorithm (Neal, 1996).

To provide an unbiased measure of the accuracy of a classifier it is necessary to split the data into a training set, on which the classifier is optimised, and a testing set, on which the classifier is evaluated. In this paper, because we have a small amount of data from each subject, we pool the data from all the subjects and use a v-fold cross-validation scheme on the resulting data ensemble. Folded cross-validation is a procedure whereby the data is partitioned into distinct blocks and a classifier is trained and tested for each partition. This procedure results in estimates of classification accuracy which are more reliable than those from a partition of the data into a single training set and a single test set (Ripley, 1996).

We applied the folded cross-validation scheme as follows. The data was first split into v distinct blocks. For each experiment (real, imagined, control) there were a total of 35 blocks of data, 5 from each subject. Each block was a separate 90-second recording (see section 2.1). We therefore chose $v = 35$. The ith block of data was classified using a classifier trained on all the blocks of data except for block i. This training and testing process was repeated 35 times, once for each block. Thus, the movements in a particular recording block from a particular subject were classified using a classifier trained on all data from all other subjects and from data in other recording blocks from that subject.

The feature selection algorithm was applied in each fold of the cross-validation scheme and not to the whole data ensemble. This ensured that each test block was not used in the selection of features that were subsequently used to classify that block, as this would lead to biased results.

3 Results

3.1 Feature extraction

ERD plots, averaged over all subjects, are shown for real left and right movements in Figure 4 and Figure 5. The desynchronisations occur bilaterally and over, or posterior to, the central sulcus. ERD plots, averaged over all subjects, are shown for imagined left and right movements in Figure 6 and Figure 7. The desynchronisations occur contralaterally and over, or posterior to, the central sulcus.

3.2 Feature selection

We analysed the features selected by the SFS algorithm by recording how frequently each Laplacian channel was selected over the 35 runs of the algorithm. The analysis broadly reflected the patterns identified by the ERD plots. For real movements, the most frequently selected channels were bilateral and over, or posterior to, the central sulcus. For imagined movements the most frequently selected channels were contralateral and over, or posterior to, the central sulcus. Channels in front of the central sulcus (L1 and L4) were almost never selected by the feature selection algorithm for real or imagined movements.

3.3 Classification

Table 1 shows classification results based on mu-rhythm power features. Very similar results were obtained with the use of auto-regressive features.

The results show that imagined movements could be identified in 6 out of 7 subjects with an average accuracy of 70 %. Real movements could be identified from the mu-rhythm in all subjects with an average accuracy of 76 %. For the control blocks, in which the subjects were instructed not to respond to the stimuli, the EEG in the period following the stimulus could be discriminated from baseline EEG at the chance rate, 50%.

Marginally more accurate classifications were obtained with the Bayesian neural network classifier; imagined movements, for example, were classified with an accuracy of 71%. This is, however, not a significant improvement.

Classifications were also made using data from each subject in isolation using a leave-1-out validation method (Ripley, 1996). The results were, however, not as good. This validates the approach of combining data from all the subjects before performing the analysis.

4 Discussion

Due to our interest in ultimately performing similar measurements in a population of brain-injured subjects it was necessary to keep the experimental time per subject to a maximum of one hour. This meant that, in comparison with other studies, each subject performed a relatively small number of movements. By pooling the data from all the subjects, however, a data set with 420 patterns was generated. Classification of this data set allowed real movements to be identified with an accuracy of 76%, imagined movements 70% and control trials 50%. The fact that control trials were consistently classified at only the chance rate indicates that the classifiers were not picking up signals evoked by the stimulus. We can therefore be confident that imagined movements, and not some other cognitive component, were causing the ERD.

The accuracy of detecting real movements is on a par with that obtained in other studies (Pfurtscheller et al. 1993). Furthermore, the accuracy could in principle be improved with artifact rejection, that is where trials containing muscle or eye-movement artifact are rejected (see, for example, Gevins et al., 1987) or trials with low baseline mu-power are rejected (Pfurtscheller et al., 1994). We have not employed artifact rejection on this data set, however, as the number of trials was considered too small.

One negative finding of the experiments is that imagined movements were not picked up in one of the subjects. One explanation for this is a possible flaw in the data analysis method concerning the assumption that movements or imagined movements occur at a fixed interval after each stimulus is presented. This assumption, which is central to much research in event-related phenomena, may be invalid; movements may occur at varying time-lags after the presentation of each stimulus. Recent research on monkeys performing delayed localization tasks suggests that event related responses which occur at times that are variable from trial to trial may be detected with Hidden Markov Models (Seidemann et al. 1996). This is an area for future research.

Pfurtscheller and Berghold (1989) found that the execution of real movements was accompanied by ERDs over, or posterior to, the central sulcus that were bilateral. The planning of real movements was accompanied by ERDs over, or posterior to, the central sulcus that were contralateral. Our results on real movements show the same pattern of desynchronisation. Our results on imagined movements show a pattern of desychronisation that is similar to that previously found for the planning of movements. These results are in accordance with a recent review of motor imagery studies (Decety, 1996) in which it was suggested that motor imagery shares neural mechanisms with processes used in actual motor control.

Motor imagery can also be identified from Movement-Related Potentials (MRPs, Cunnington et al., 1997). Unfortunately, due to our non-standard electrode montage we were unable to calculate MRPs. The combination of information from MRPs and ERDs has the potential, however, to allow imagined movements to be identified more robustly than with either signal alone.

A further criticism of our study relates to the ordering of experiments; subjects performed the real, imagined and control experiments in a random order which was different for each subject. It is now suggested, however, that control blocks should always be performed first. This would allow the control blocks to be recorded when the subject had no knowledge of the nature of the experiment. This would therefore reduce the possibility of spurious imagined movements occuring during the control blocks. However, as imagined movements were not identified by the classifiers in the control blocks this was not a significant problem in the present study.

A main finding of this study is that motor imagery could be used to generate signals appropriate for use in an EEG-based communication device. This finding is supported by a recent study by McFarland et al. (1997) who also measured mu-rhythm desynchronisation during real and imagined hand movement.

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Table 1: *Percentage Accuracy of Identification of movements. *The average accuracy for imagined movements is calculated only from those 6 subjects in whom imagined movements could be detected.*

Subject	Real	Imagined	Control
AF	67	72	48
AO	77	73	50
AS	75	70	48
WS	75	65	50
HH	75	70	50
SA	77	67	48
SP	87	50	50
AVG	76	70*	49

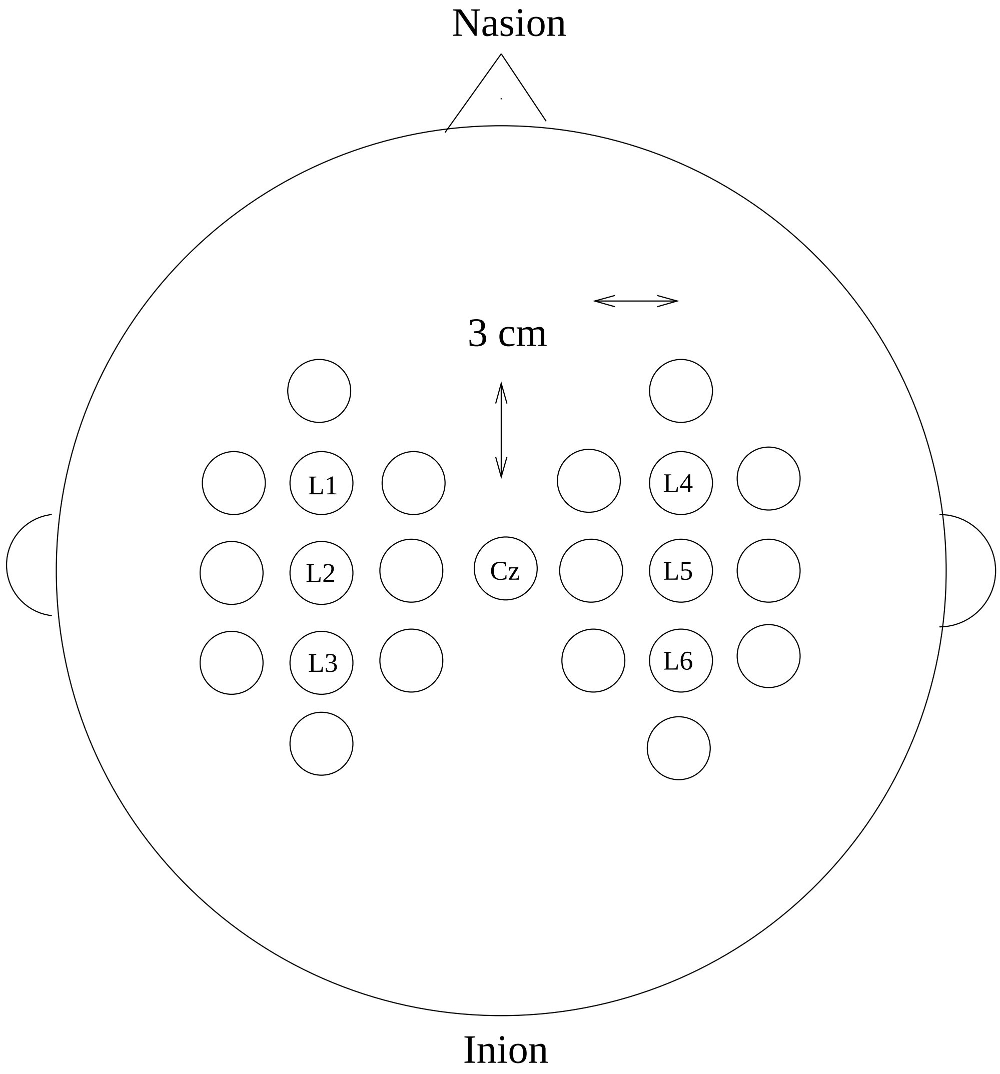

Figure 1: EEG montage: Laplacian channels L2 and L5 correspond to the C3 and C4 positions in the standard 10-20 system. All other electrodes are placed 3cm apart in a grid surrounding C3 and C4. All signals were recorded with respect to a common Cz reference.

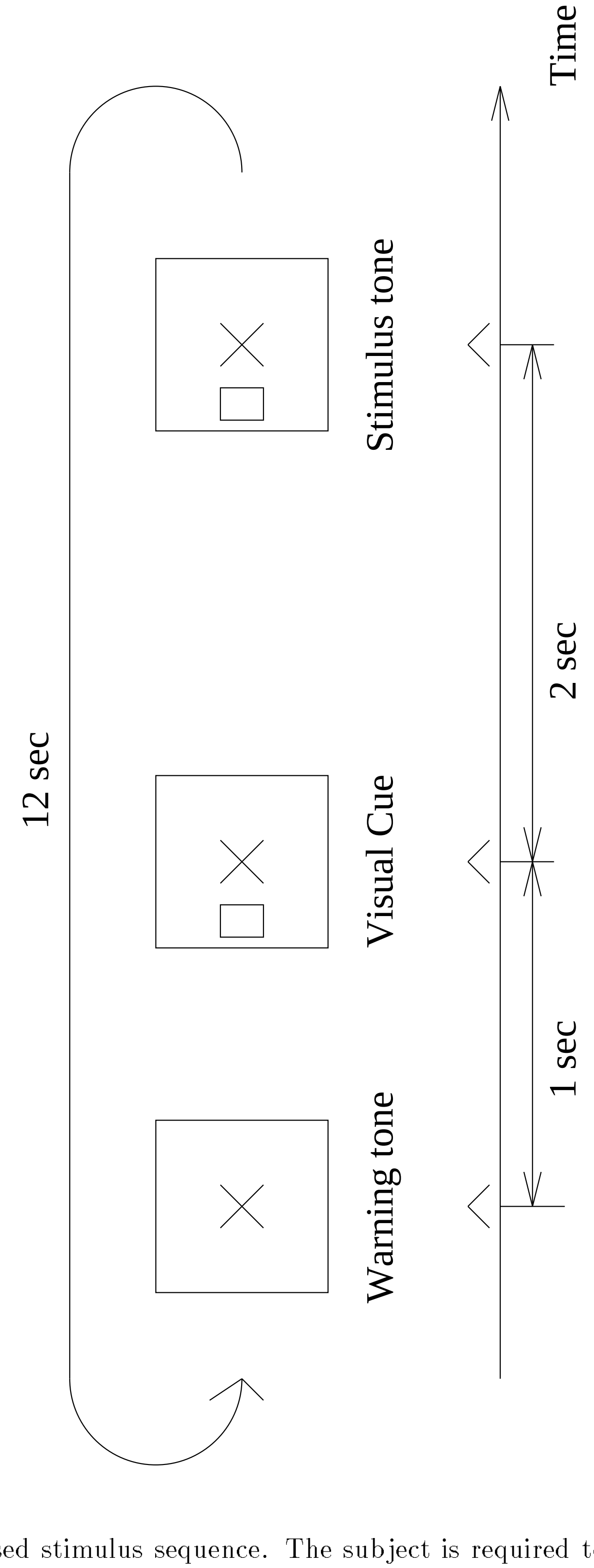

Figure 2: Computerised stimulus sequence. The subject is required to make a (left) hand movement when the stimulus tone is heard. There is always a cross in the centre of the screen at which the subject is required to look.

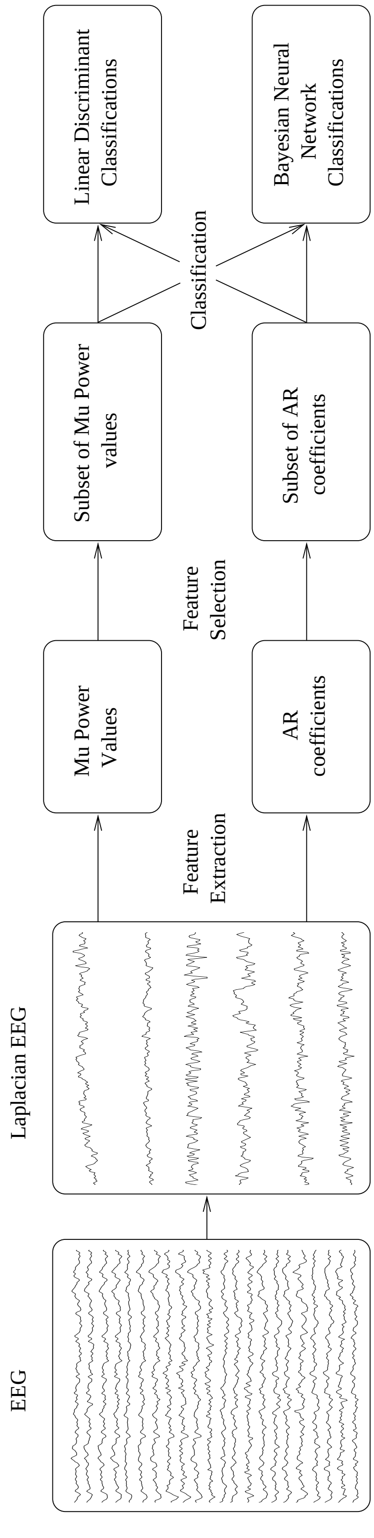

Figure 3: Data analysis flowchart. EEG data is first processed to obtain the Laplacian channels which contain signals localised to the sensorimotor cortex. These signals are then processed to extract two different types of features; mu-power features and AR features. Because there are a large number of such features generated every second and not all of them will be predicitive of movement or imagined movement, a feature selection algorithm is then applied. The resulting subset of features are then classified as movement or baseline by neural network or linear discriminant classifiers.

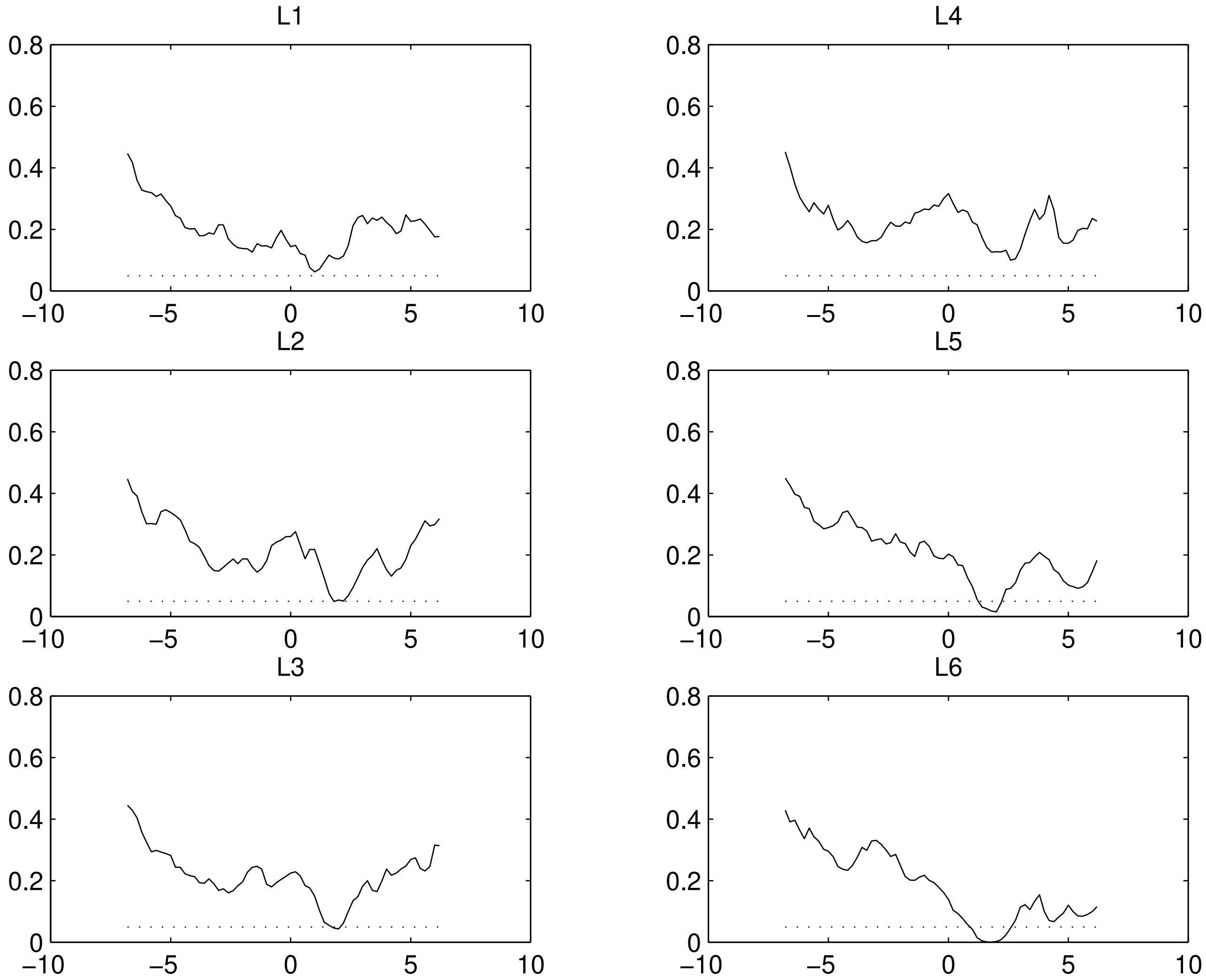

Figure 4: Event-Related Desynchronisation of the mu-rhythm during real left movements at Laplacian channels L1 to L6. The x-axis represents seconds after the stimulus tone and the y-axis is significance of the ERD. Desynchronisations occur bilaterally. The dotted line shows the $p = 0.05$ significance level. These plots have been averaged over all subjects.

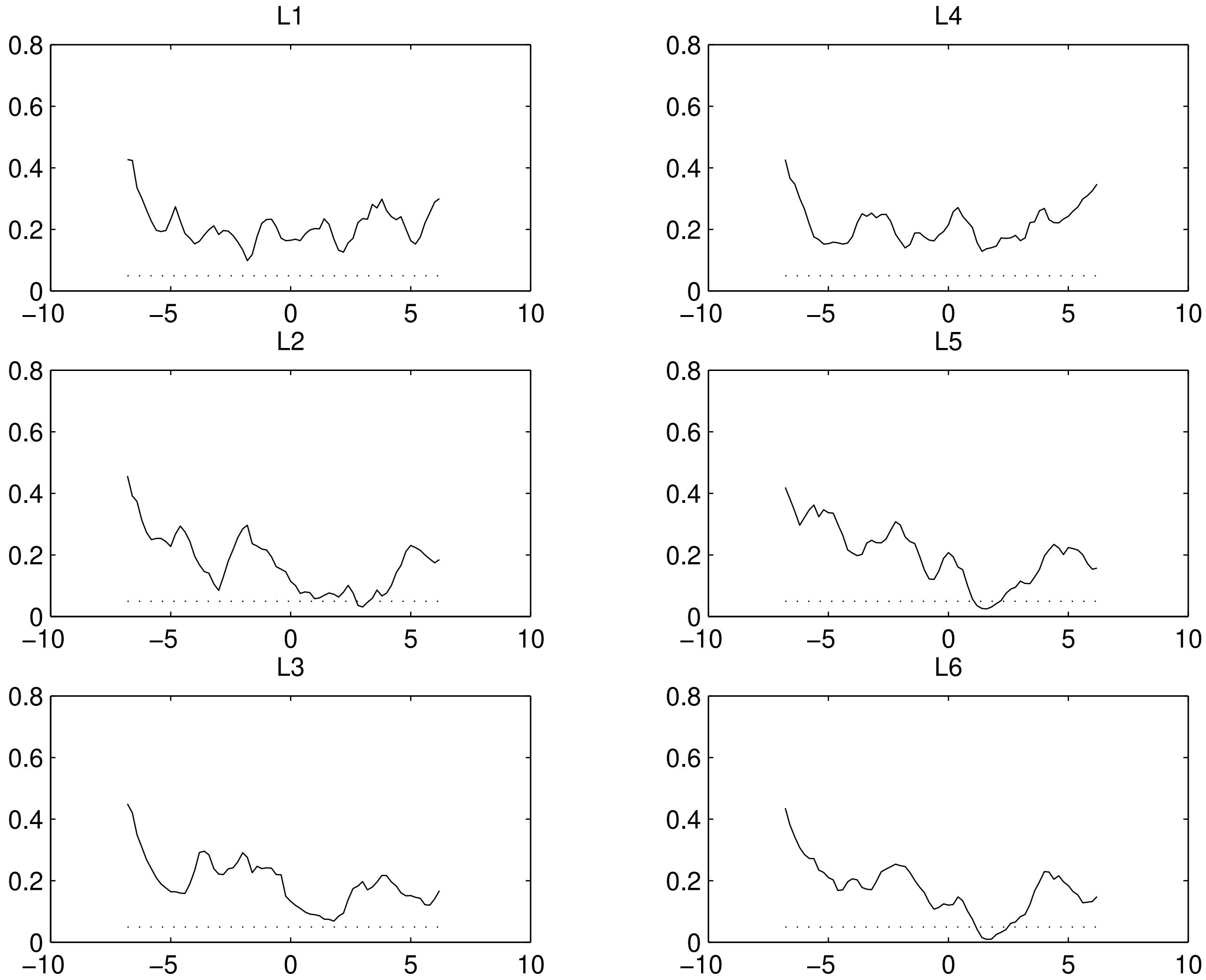

Figure 5: Event-Related Desynchronisation of the mu-rhythm during real right movements at Laplacian channels L1 to L6. The x-axis represents seconds after the stimulus tone and the y-axis is significance of the ERD. Desynchronisations occur bilaterally. The dotted line shows the $p = 0.05$ significance level. These plots have been averaged over all subjects.

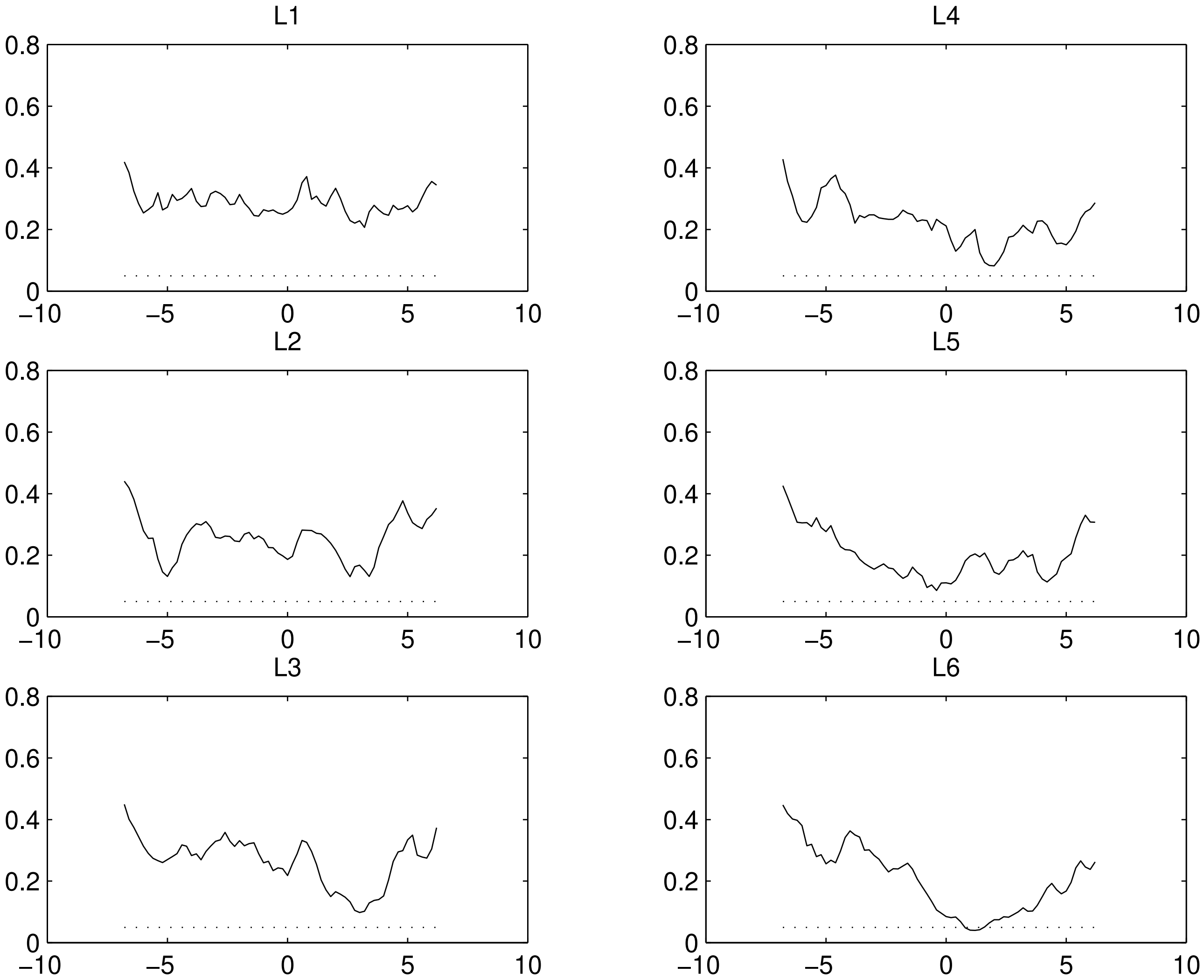

Figure 6: Event-Related Desynchronisation of the mu-rhythm during imagined left movements at Laplacian channels L1 to L6. The x-axis represents seconds after the stimulus tone and the y-axis is significance of the ERD. The dotted line shows the $p = 0.05$ significance level. The primary desynchronisation occurs on the right side of the head at channel L6. These plots have been averaged over all subjects.

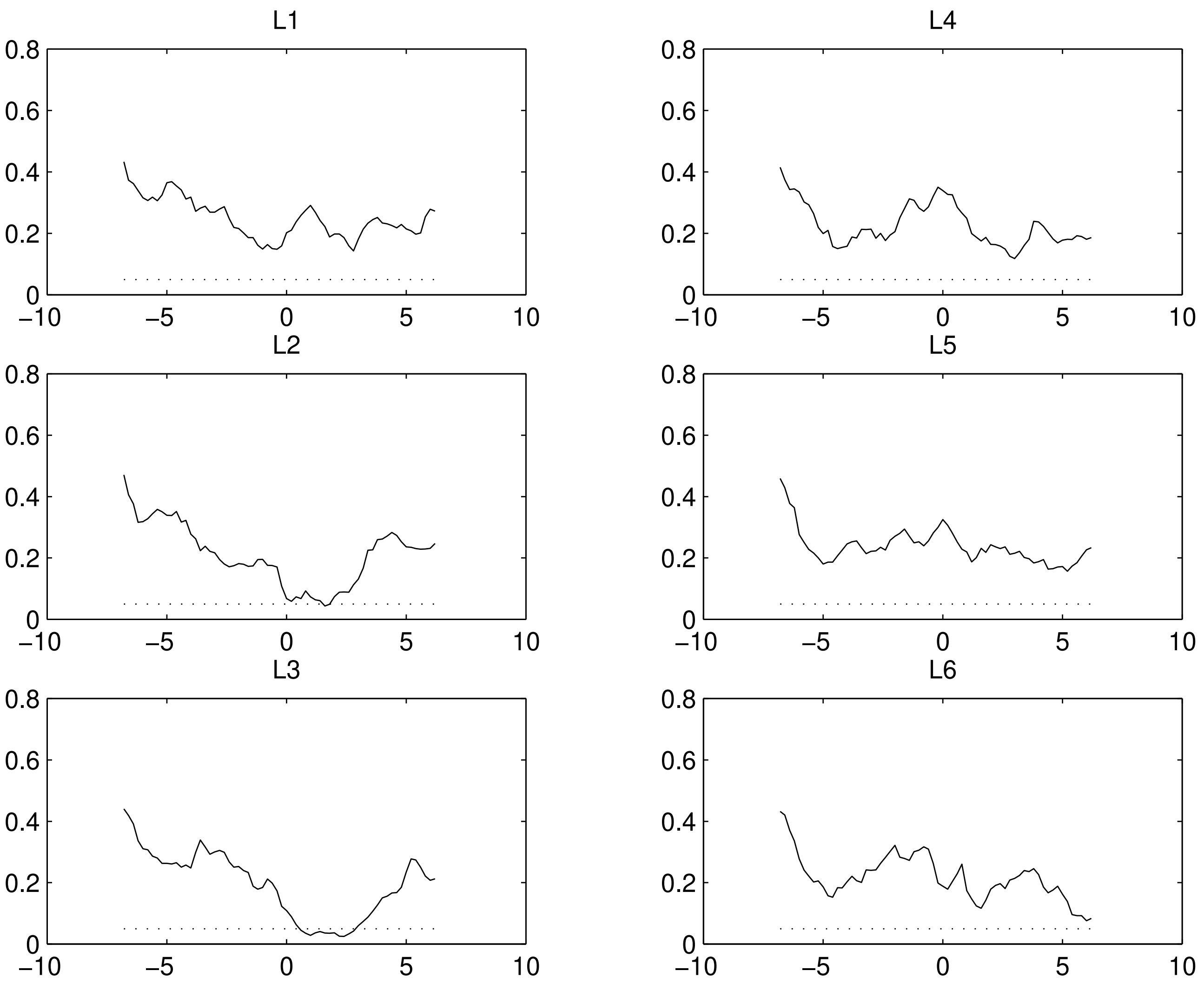

Figure 7: Event-Related Desynchronisation of the mu-rhythm during imagined right movements at Laplacian channels L1 to L6. The x-axis represents seconds after the stimulus tone and the y-axis is significance of the ERD. The dotted line shows the $p = 0.05$ significance level. The primary desynchronisations occur on the left side of the head at electrodes L2 and L3. These plots have been averaged over all subjects.