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Classification of single MEG trials related to left and right index finger movements

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Abstract

Objective: Most non-invasive brain–computer interfaces (BCIs) classify EEG signals. Here, we measured brain activity with magnetoencephalography (MEG) with an aim to characterize and classify single MEG trials during finger movements. We also examined whether averaging consecutive trials, or averaging signals from neighboring sensors, would improve classification accuracy.

Methods: MEG was recorded in five subjects during lifting the left, right or both index fingers. Trials were classified using features, defined by an expert, from averaged spectra and time–frequency representations.

Results: Classification accuracy of left vs. right finger movements was 80–94%. In the three-category classification (left, right, both), accuracy was 57–67%. Averaging three consecutive trials improved classification significantly in three subjects. Instead, spatial averaging across neighboring sensors decreased accuracy.

Conclusions: The use of averaged signals to find appropriate features for single-trial classification proved useful for the two-class classification. The classification accuracy was comparable to that in previous EEG studies.

Significance: MEG provides another useful method to measure brain signals to be used in BCIs. Good performance was obtained when the classified signals were generated by two distinct sources in the left and right hemisphere. The present findings should be extended to multi-task cases involving additional brain areas.

Keywords: Magnetoencephalography; Brain–computer interface; Sensorimotor rhythmic activity; Single trial classification

1. Introduction

A brain–computer interface (BCI) can be used to control applications based on signals measured, invasively or non-invasively, from the human and animal brain. BCIs can thus, e.g. help severely motor-disabled persons to obtain some motor control and ability to communicate. In BCIs, mathematical models, capable of learning, are typically used to recognize and classify brain signals related to some tasks, such as extending a finger. The classes can be associated with computer commands to operate, e.g. a neural prosthesis.

Currently, electroencephalography (EEG) is the best opinion for practical non-invasive BCIs because EEG technology is inexpensive and mobile. During recordings, the users perform tasks specified by themselves or given by an instructor. A set of signal features, such as frequency bands, number of sensors and location of sensors, are specified either automatically using mathematical algorithms or by a human expert. The values of these features are set as values in a feature vector. Finally, a mathematical model is taught to recognize signal categories based on the values in the feature vector. In online use, users receive feedback of the classification performance. Because BCIs should be fast, the classification should be based on a few trials. Averaging tens of signals is not a viable option.

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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 (Hämäläinen et al., 1993). Therefore, magnetoencephalographic (MEG) signals are more local than the corresponding EEG signals which may facilitate selection of those sensors which contain most information. In addition, MEG is sensitive to the tangential components of the cortical currents whereas EEG sees also the radial sources in the cortical gyri so that the interpretation of the signal origin may be more difficult. Because no reference is needed, MEG is 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 (Hämäläinen et al., 1993).

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 human sensorimotor cortex displays a rhythmic activity called the (rolandic) mu rhythm (Gaustaut, 1952; Hari and Salmelin, 1997; Hari and Salenius, 1999). This comb-like rhythmic activity, consisting of 10 and 20 Hz frequencies, can be detected in healthy subjects with both MEG and EEG. Both frequency components are suppressed by movement execution (Pfurtscheller, 1981; Salmelin and Hari, 1994) This contralaterally dominant suppression begins 1–2 s before the movement but becomes bilateral just before the movement begins (Nagamine et al., 1996; Stancak and Pfurtscheller, 1996; Salenius et al., 1997). The movement-related suppression is followed by a contralaterally dominant fast recovery and rebound of the mu rhythm (Salmelin and Hari, 1994; Toro et al., 1994).

An fMRI study on five tetraplegic patients, who had been paralyzed for 1–5 years due to spinal cord injuries, showed that the patients' sensory and motor cortices were activated during attempted hand and foot movements (Shoham et al., 2001). Very similar activations were found in healthy control subjects during real movements. In another fMRI study on nine paraplegic patients, having a complete spinal cord injury between T6 and L1 for 1 month to 33 years, activation patterns during motor attempts resembled those of the control group performing the corresponding movements, but activations were weaker in the patients (Sabbah et al., 2002). The activation patterns, however, differed between motor imagery vs. motor attempts. Both tasks caused activation in the premotor areas, the later also in the central regions (Brodmann area 4) and in the supplementary motor areas.

Portin et al. (1996) classified single MEG trials during left and right thumb movements using self-organizing maps (SOMs). Five subjects performed 40–80 self-paced movements, once every 8 s. For signal analysis, an expert selected frequency ranges and 28–32 sensors. These features were identical for each subject. The classified signals where analyzed using 'temporal spectral evolution' (TSE; Salmelin and Hari, 1994). SOMs were able to detect movement onsets with 85% accuracy, but could not separate the left and right thumb movement. Recently, Parra et al. (2002) classified premovement sensorimotor MEG time-domain signals offline in four subjects. Subjects saw simultaneously two visual stimuli and were asked to press the left- or right-hand button, depending on the side of a target stimulus. Auditory feedback was given of the performance. The 100 ms time-window used for classification was centered at 83 ms prior to movement. The mean classification rate was 79%. In our previous study (Nykopp et al., in press), we investigated the use of different classifiers for categorizing MEG signals during finger extensions. Classification was based on the reactivity of the mu-rhythm to movements. The best mean ($N=5$) classification accuracy was 82%.

Research aiming at non-invasive BCI applications is almost exclusively utilizing EEG signals (for a review see Wolpaw et al., 2002). To our knowledge, only Nykopp et al. (in press) and Parra et al. (2002) have shown that also single MEG trials can be classified for potential use in BCIs. In the present study, our aim was to extend this research by classifying single-trial MEG signals related to finger extensions. Our focus was on the characterization of the features to be classified. We classified signals during real movements because the motor-cortex activity of paralyzed persons during attempted movements resembles that of healthy subjects during real rather than imagined movements. To find the best features for classification, we first characterized the most prominent movement-related signal features from averaged signals of individual subjects. We assumed these features to be valid for single-trial analysis as well. The features were calculated with autoregressive spectral estimation and classified with a radial-basis-function (Nykopp et al., in press). We also examined the effect of the number of MEG channels on the classification accuracy, as well as the effects of averaging single MEG trials.

2. Material and method

2.1. Subjects

Five right-handed subjects (three females, two males; 22–44 years old, mean 27 years) participated in the study after informed consent. When asked, all subjects reported to use right hand for writing and to be strongly right handed.

2.2. Experimental paradigm

Subjects performed a brisk (duration about 0.5 s), index finger extension ($\sim 30°$) with either the right (R) or the left (L) index finger or simultaneously with both (B) immediately after hearing a cue (200 Hz, 200 ms tone), presented once every 3 s to both ears through headphones. The subjects decided themselves which one of the three movements they made but were instructed to perform

Table 1
Number of trials in each task (R = right finger lift, L = left finger lift, B = lifting both fingers) and for each subject (S1–S5) for the training and testing data set

	Training			Testing		
	R	L	B	R	L	B
S1	80	73	77	55	73	94
S2	103	121	96	109	121	97
S3	90	84	97	78	76	103
S4	94	104	118	111	98	130
S5	95	88	136	103	106	134

each movement at equal probability. The subjects where asked to decide upon the following movement soon after they had performed the previous one. Movement onsets were monitored by light port detectors. During task performance, subjects fixated on a cross 120 cm in front of them.

The experiment consisted of two 12 min sessions separated by a 5 min break. There were short breaks (∼20 s) every 3 min to keep the subjects alert. Features used to teach the classifier were selected from the averaged data recorded in the first session. The classifiers were trained with the trials collected in the first session and tested with the trials collected in the second session. The number of samples for each task for each subject is depicted in Table 1. The subjects did not perform the tasks at exactly equal probabilities. We did not want to select data in any way, and therefore no trials containing EOG or other types of artifacts were rejected.

2.3. Recording

Recordings were made in a magnetically shielded room with a 306-channel helmet-shaped neuromagnetometer (Vectorview™, Neuromag, Helsinki, Finland) in the Brain Research Unit of the Low Temperature Laboratory, Helsinki University of Technology. This device consists of 102 identical triple sensor units. Each unit consists of one magnetometer and two orthogonal planar gradiometers. Both horizontal and vertical EOG were measured.

The recording pass-band was 0.1–200 Hz and the sampling frequency 600 Hz. Before further analyses, the signals were down-sampled to 150 Hz.

2.4. Data characterization and feature selection

MEG signals related to the different movements were first visualized and characterized using time–frequency representations (TFRs) and power spectra. Both were averages of all trials related to one movement type. Only signals from the gradiometers, from 1 s before the start of each finger movement to 2 s after it, were examined. TFRs and spectra were calculated for signals in the first session. The square root of the squared sum of the signals from the two orthogonal gradiometers was calculated to get the average power at each sensor location. In addition, the signals were adjusted with respect to a pre-movement baseline from 0.5 s before movement onset to movement onset. All further analysis and classification is based on these signals.

The width of the Morlet basis function used for the calculation of the TFRs (3–45 Hz) was 10 cycle. Each sensor location was represented with a matrix containing time in one and frequency in the other dimension. The values of the matrix represent the power of the signal at a specific time and frequency.

The power spectra were calculated using the transfer function of an autoregressive (AR) model. The estimates for AR coefficients $\hat{a}$ and for the noise variance σ^2 were solved with Yule–Walker method (Therrien, 1992). Model order P was 15, estimated using the normalized maximum likelihood (NML) information criterion (Rissanen, 1999). The amplitude spectra were calculated for a period during which the post-movement rebound of the activation was prominent in all subjects. The frequency with maximum energy and the corresponding sensor location were used as features in the classification. One of the experimenters chose these features from the TFRs and power spectra.

2.5. Classification

Nykopp et al. (in press) compared different methods for classifying the reactivity of the 20 Hz activity to finger extensions. The best results were obtained with features calculated with autoregressive spectral estimation and classified with a radial-basis-function network (RBF). RBF networks, used in the present study, are feed-forward type linear networks, in which the output of the classifier is a linear combination of activation of N_{Φ} basis functions (Orr, 1996). The basis function used in this study is Gaussian.

The width of the basis function was cross-validated from a predefined set of basis function widths. All parameters were cross-validated from the training set.

The number of the basis functions was selected using a forward selection method (Orr, 1996), in which basis functions are added from a predefined set, one at a time, until a defined criterion is fulfilled. The added basis function is the one that minimizes the training set error. The used error functions were sum of squared errors (SSE) and cross entropy (Bishop, 1995). The criterion we used to stop the

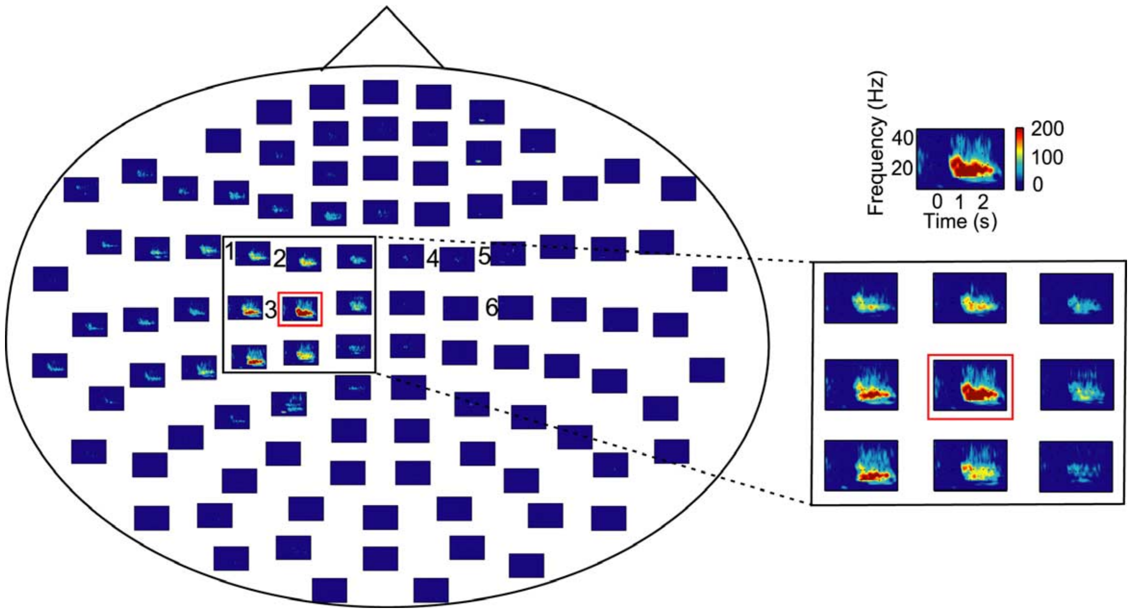

Fig. 1. TFRs of all the 102 sensor locations of subject S1 during the right finger lift. The numbers indicate the sensors showing the maximum response in different subjects over the left and right hemispheres.

basis function increase was minimum description length (MDL) (Rissanen, 1999).

The channel capacity of the classifier, defined as the bit rate per trial for the optimal symbol probabilities, was calculated using an algorithm developed by Blahut (1972). The bit rate per trial allows comparison between two- and three-task classification results, as well as comparison with results obtained in other studies.

Classification accuracies in the different conditions were compared with a within-subject hypothesis test for two proportions, with $P<0.05$ (Milton and Arnold, 1990).

The signals were classified in two ways: (1) the right finger extension vs. the left finger extension, (2) the right finger extension vs. the left finger extension vs. lifting both fingers. Effects of three factors on the two-category classification were examined: (1) The number of sensors per hemisphere (one sensor with a maximal signal vs. that plus eight surrounding channels (Fig. 1). (2) Averaging consecutive trials. Two and three single trials related to the same finger movement were averaged. (3) Averaging signals from near-by sensors. Signals from nine sensor locations (one with the maximum energy and eight surrounding it) were averaged.

3. Results

3.1. Feature selection

Fig. 1 depicts averaged TFRs ($n=80$) of subject S1 from all 102 sensor locations during right finger extensions. The post-movement rebound of the 20 Hz activity is especially prominent over the contralateral left hemisphere. The sensor showing the strongest rebound has a red frame. In addition to this sensor, signals from eight surrounding sensors, shown in the insert, were selected to the feature set. A similar set of sensors, showing rebounds during left finger extensions, was selected over the right hemisphere. The sensor showing the strongest rebound was different in the different subjects. On the right side sensor 3 showed the maximum response for subjects S1, S3 and S5, sensor 2 for S2, and sensor 1 for S4 (Fig. 1). On the left side the corresponding sensors where number 6 for S1 and S3, number 4 for S2 and S5, and number 5 for S4.

Fig. 2 shows averaged ($n\sim100$) TFRs of all five subjects, from the sensor showing the strongest 20 Hz response over the left and right sensorimotor cortex during right finger extension, left finger extension, and extending both fingers. The power spectra, calculated within this window, are depicted only for the right finger extensions. The 20 Hz activity shows a contralateral post-movement rebound in all subjects, starting at about 0.7 s after the movement onset and lasting for about 1 s. Strong contralateral activity in the 20 Hz range can be seen in the power spectra for right finger extensions. When the subjects extended both fingers simultaneously the response was bilateral with no clear hemispheric differences. Due to the relatively small interindividual variation in the timing of the rebound, a time window of 0.7–1.7 s after the movement onset was used in single-trial analysis for all subjects. The peak frequency of the activity showed interindividual variation (Fig. 2).

Classification of single trials was based on features which were chosen on the basis of averaged TFRs and spectra. Fig. 3 illustrates ten single-trial TFRs over the left and right sensorimotor cortex of S3 during right and left finger

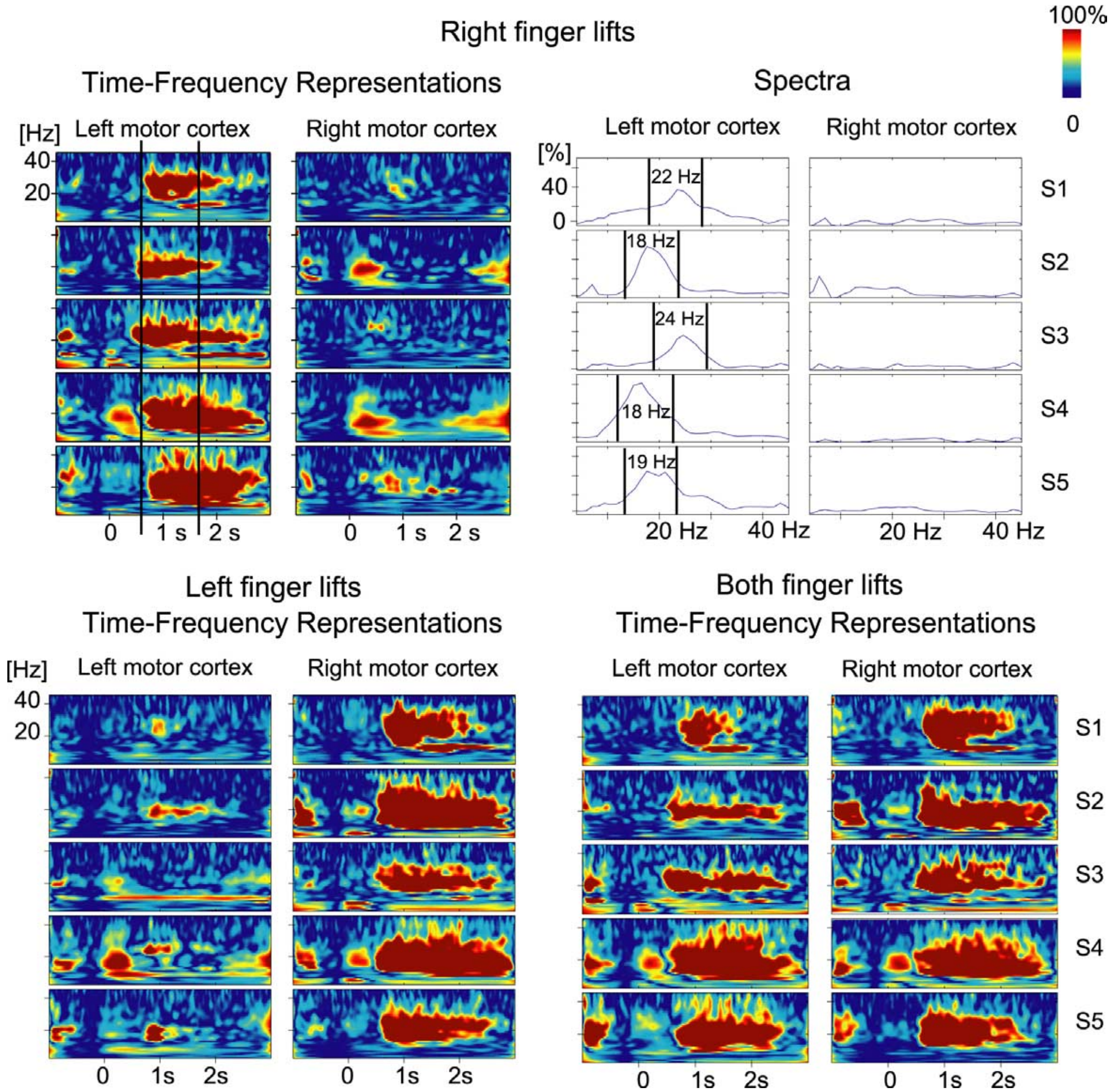

Fig. 2. Upper left side: TFRs of all five subjects over both the left and right sensorimotor cortex during the right finger lift. The 20 Hz contralateral rebound is clearly visible in all subjects. Upper right side: the corresponding power spectra. The peak signal frequencies during the rebound are indicated in the figures. Lower left side: TFRs of all five subjects over both the left and right sensorimotor cortex during the left finger lifts. The 20 Hz contralateral rebound is clearly visible in all subjects. Lower right side: the corresponding TFRs during both finger lifts. The rebound is visible bilaterally.

extensions. In the five upper trials, the contralateral 20 Hz rebound is quite visible. In the lower five trials, either there is very little activity in general or the activity appears bilateral.

Upper part of Fig. 4 shows the mean (90 trials) power spectrum of S3 over the left and right sensorimotor cortices during right finger extensions. The spectrum over the left cortex peaks at 24 Hz. As demonstrated at the bottom of the figure, the peak value varied in different single trials. Similar variation was evident in all subjects. Therefore, a band of 10 frequencies around the peak frequency was used in the feature vector for single-trial analysis. The 10 Hz band for all subjects is depicted in Fig. 2. The feature vector consists of power values of a band of 10 frequencies centered at the peak frequency at one or nine sensor locations on each hemisphere.

3.2. Single-trial classification

The confusion matrixes in Table 2 show the classification accuracies of each subject's trials in the two-category classification task. Single trials from one location showing the largest 20 Hz rebound over the right and left sensorimotor cortices were classified. The mean classification accuracies (averages of classification accuracies related to the left and right finger extensions ± standard deviation) and the optimal channel capacities per trial (bit rates) are also shown. The classification accuracies of individual subjects' data varied from 80.1 to 93.5%. Information transfer rates were 0.28–0.66 bits/trial. The bit rates convey the rate of information transferred per trial. It takes into account both the speed and accuracy of the classification. For N classes the maximum bit rate per trial is

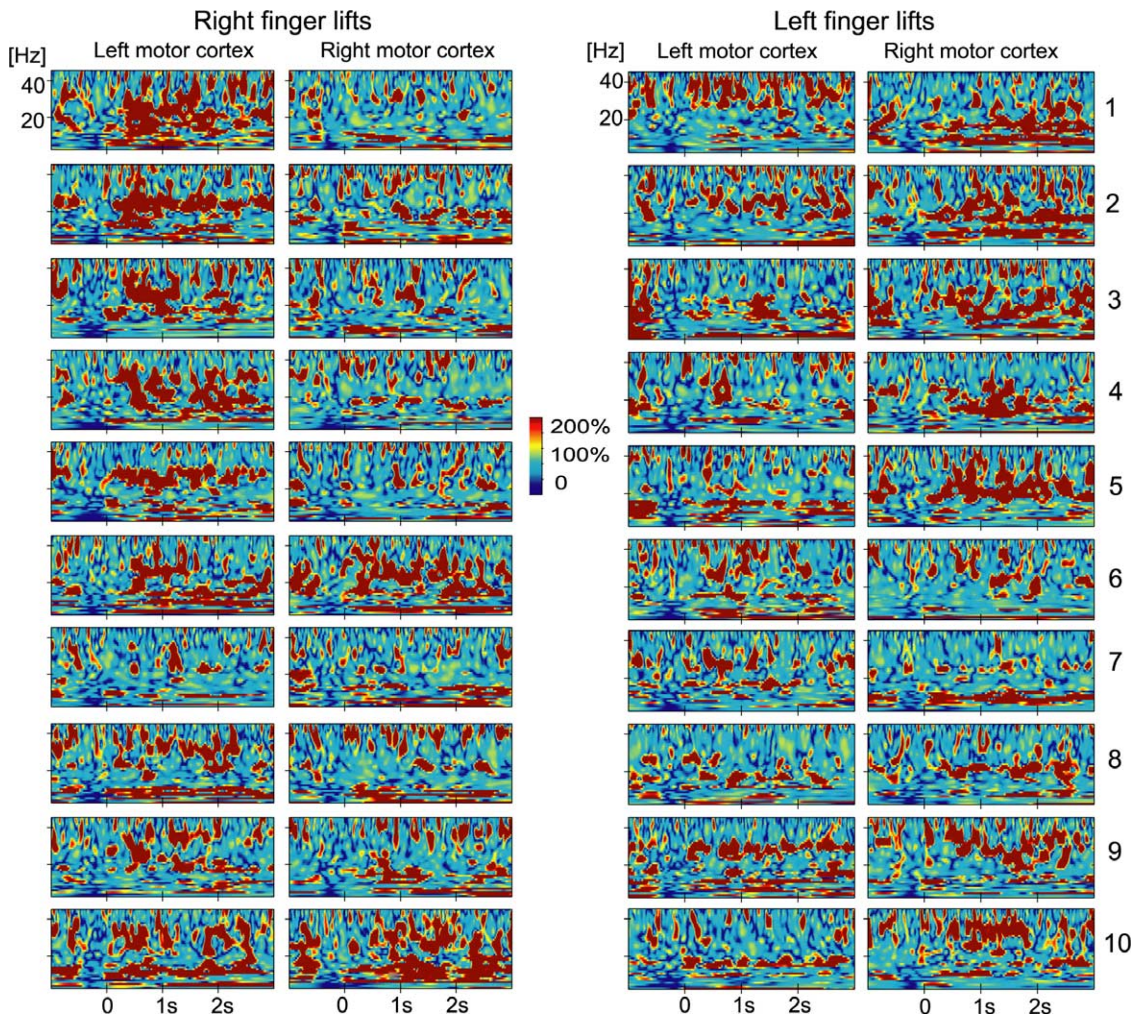

Fig. 3. Left side: ten typical single trial TFRs over both the left and right sensorimotor cortex of S3 when he lifted his left finger and on the right side the corresponding TFRs during right finger lift. The contralateral rebound can be easily seen in the upper ones but not in all the lower ones.

$\log_2(N)$ (Sloane, 1992). For two classes the maximum rate is 1 bits/trial. At chance level classification accuracy of 50%, the bit rate is zero. The relationship between classification accuracy and bit rate is not linear. For example, with accuracy of 93% the bit rate is only 0.66 bits/trial.

The confusion matrixes in Table 3 show the classification accuracies of each subject's data in the three-category classification task. Accuracy was clearly inferior to that obtained in the two-category classification. Three tasks could be separated with a mean accuracy ranging from 56.8 to 66.6%. Confusion matrixes show that that the trials related to the right and left finger extensions were separated better from each other than from extending both fingers in four subjects. Information transfer rates were 0.19–0.46 bits/trial. The maximum bit rate for the three-category classification is 1.73 bits/trial.

From TFRs in Fig. 1 it is relatively easy to detect the sensor showing the maximum energy of the contralateral rebound. We studied whether the classification accuracy improves by adding information from the eight surrounding locations. Table 4 depicts the classification results based on one vs. nine locations per hemisphere for all subjects. When nine rather than one sensor per hemisphere where used in classification, the accuracy improved in four subjects, significantly in two subjects. Compared to the classification based on the signals from the nine non-averaged channels, averaging signals from the nine locations improved

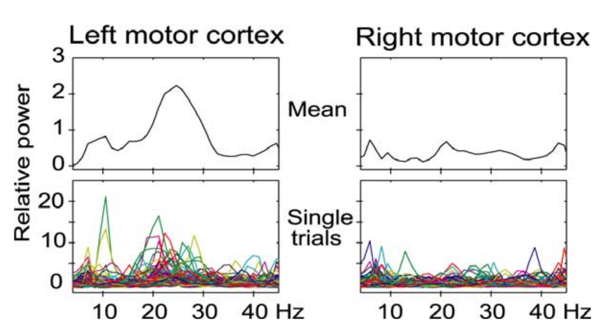

Fig. 4. The upper part shows the mean power spectra of S3 over the left and right sensorimotor cortices, when he lifted his right index finger. The lower part of depicts the corresponding power spectra of all single trials. Notice the variation in the peak frequency of the power spectra in the single trials.

Table 2
Classification of single trials to correct and incorrect categories in each subject in two-category classification (R vs. L)

		R (%)	L (%)	Mean (±SD) %	Bit rate/trial
S1	R	91	9	93.4 (±2.2)	0.66
	L	4	96		
S2	R	92	8	81.6 (±2.6)	0.34
	L	28	72		
S3	R	94	6	93.5 (±2.0)	0.66
	L	7	93		
S4	R	77	23	80.1(±2.8)	0.28
	L	16	84		
S5	R	81	19	81.8 (±2.7)	0.32
	L	17	83		

The mean accuracy and corresponding bit rates are also indicated. Note the fast decrease of the bit rate when the accuracy decreases.

Table 3
Classification of single trials to correct and incorrect categories in each subject in three-category classification (R vs. L vs. B)

		R (%)	L (%)	B (%)	Mean (±SD) %	Bit rate/trial
S1	R	60	13	27	62.8 (±3.2)	0.37
	L	8	75	16		
	B	17	30	53		
S2	R	87	4	9	60.9 (±2.7)	0.34
	L	23	50	27		
	B	29	26	45		
S3	R	78	6	15	66.6 (±2.9)	0.46
	L	8	67	25		
	B	20	25	54		
S4	R	56	7	37	61.1 (±2.6)	0.38
	L	8	71	20		
	B	20	24	56		
S5	R	53	12	35	56.8 (±2.7)	0.19
	L	12	47	42		
	B	13	16	71		

classification in one subject and weakened it in another. Evidently, averaging nearby channels is not advantageous.

The effect of averaging consecutive trials related to the same movement is shown in Table 5. When two trials were averaged, the classification accuracy did not improve significantly in any of the subjects, the mean being 87.1%. With three trials averaged, classification accuracy improved significantly in three subjects, the mean being 90.5%. Bit rate improved in four subjects when three trials were averaged.

4. Discussion

To understand the features to be classified in the single MEG trials during finger extensions, we characterized the signals from averaged TFRs and spectra. The most prominent feature, reacting to the finger extension was the contralateral 20 Hz activity of 1 s duration, starting 0.7 s after movement onset. The peak frequency of the 20 Hz activity varied about ±5 Hz from trial to trial. Therefore, we chose a 10 Hz band for this feature. When MEG trials from nine channels per hemisphere were used in classification, the mean accuracy in the two-category classification was 86%. When three consecutive MEG trials were averaged, the mean classification accuracy improved to 91%. As indicated by the good classification accuracies, our feature selection worked well.

Our classification accuracy was somewhat better than 79% ($N=4$) obtained by Parra et al. (2002). However, details in their experiments, used MEG device, and classified features were quite different from those of ours. Using a similar task as in the present study, but identical

Table 4
Classification rates (% ±SD) of signals based on one and nine sensor locations in each hemisphere

	1 sensor	9 sensors	Mean of 9 sensors
S1	90.0 (±2.6)	93.4 (±2.2)	86.6* (±2.9)
S2	69.1 (±3.0)	81.6* (±2.6)	78.9 (±2.7)
S3	85.1 (±2.9)	93.5* (±2.2)	90.9 (±2.3)
S4	81.0 (±2.7)	80.1 (±2.6)	88.7* (±2.4)
S5	78.9 (±3.0)	81.8 (±2.8)	78.4 (±2.8)

Statistically significant differences in classification due to the sensor number are indicated with stars. The right column indicates classification rates when classification when nine channels over each hemisphere were averaged. The statistically significant differences between when no channels were averaged and when the channels are averaged are indicated with stars.

Table 5
Classification rates (% ±SD) in the two-category classification task when zero, two and three consecutive trials were averaged

	No averages	Bit rate/trial	Two averages	Bit rate/trial	Three averages	Bit rate/trial
S1	93.4 (±2.2)	0.66	93.3 (±2.2)	0.65	95.3 (±1.9)	0.73
S2	81.6 (±2.6)	0.34	81.9 (±2.6)	0.35	86.7* (±2.3)	0.47
S3	93.5 (±2.2)	0.66	93.5 (±2.0)	0.68	92.7 (±2.1)	0.66
S4	80.1 (±2.6)	0.28	83.6 (±2.6)	0.37	86.5* (±2.4)	0.46
S5	81.8 (±2.8)	0.32	83.2 (±2.6)	0.36	91.3* (±2.0)	0.58
Mean	86.1 (±2.5)	0.44	87.1 (±2.4)	0.48	90.5 (±2.1)	0.57

The mean classification rates are also shown. Statistically significant differences in classification of single trials and three trials averaged are indicated with stars.

feature parameters for all subjects, Nykopp et al. (in press) obtained mean ($N=5$) accuracy of 82%, somewhat worse than that obtained in the present study. Because the peak frequency and spatial distribution of mu-rhythm shows inter-individual variability (Salmelin and Hari, 1994), in the present study we defined the peak frequency and the channel picking up the maximal signal from the data of individual subjects.

The classification accuracy of the trials of two subjects improved statistically significantly when nine instead of one sensor were used in each hemisphere, indicating that the added channels provided additional information. In addition, classification accuracy improved in three subjects when three, but not two, consecutive trials were averaged. If signals come from the same distribution, averaging improves the signal-to-noise ratio (SNR) by square root of samples averaged. The better the SNR, the more accurate is the classification. The trade off of averaging is that the time needed for classification increases. In our study, subjects performed movements in random order and two or three movements of the same finger did not usually occur one after another. The effect of averaging might have been stronger if consecutive trials would be averaged.

When signals from near-by sensors are averaged, the time needed for classification does not increase. The neurogradiometer just above the sensorimotor cortices show the strongest activation during the finger extension, but also nearby sensors pick up relatively large activation. We assumed that averaging signals from nine sensors over the sensorimotor cortex would increase the signal to noise ratio and hence improve the classification. However, this did not turn out to be the case, implying that the averaging was not optimal. The signals recorded with different sensors should probably be weighted, the strongest weight given to the signal with the highest signal-to-noise ratio.

Averaged TFRs showed quite distinct contralateral signals for unilateral finger extensions and a bilateral signal when both fingers were extended simultaneously. This led us to hypothesize that the classifier could separate two-finger extensions from one-finger ones, but for single trials this turned out not to be the case. Accuracy in the three-category classification results was 57–67%, too low for practical BCIs. A better classification would presumably have been obtained if the third task would have been a foot movement, during which MEG activity is located quite differently from that during hand movements (Salmelin et al., 1995). Muller-Gerking et al. (1999) classified EEG signals related to the right finger vs. left finger vs. foot movement and received classification accuracies of 94, 90 and 84% for the three subjects. However, about 60% of the trials were rejected due to various types of artifacts whereas we did not reject any data. In their EEG study, Obermaier et al. (2001) compared classification accuracies obtained with two, three, four or five different mental tasks (imaging to move the left hand, right hand, foot, tongue and a mental calculation task) in three subjects. From this is Fig. 5 in ref Obermaier et al., 2001. it appears that in two subjects the best results were obtained with two- and three-task classifications, and in one subject the number of tasks did no influence the accuracy. The overall differences between the classification tasks were very small and the small number of subjects did not allow statistical comparisons. The efficiency of BCIs may be increased by using more than two tasks to be classified, but the increase of the efficiency depends strongly on the selection of the tasks.

In the two-category classification, we obtained bit rates of 0.28–0.66 bits/trial. For the best subject (S3), one bit of information (one binary choice) was obtained in two trials whereas for the worst subject (S4) on average four trials were needed. In the three-category case, the highest bit rate was 0.46 bits/trial (S3). For this subject, little more than two trials were needed for one binary choice. This is better than for three of the subjects in the two-category case. However, there were many classifications errors and in applications additional bits are needed to correct for these errors. Thus, for example, S2 who has the same bit rate in both two- and three-category case would use an application clearly faster based on two-category classification.

Real or attempted finger movements suit well for BCI use, because many tasks require spatial actions (moving a cursor or prosthesis). We chose real movements instead of imagined ones because the fMRI study of (Sabbah et al., 2002) showed that the sensorimotor activations of paralyzed patients during attempted hand movements were very similar to the activation in healthy controls performing real movements. Our preliminary results of the sensorimotor cortical activity during attempted finger movements of three tetraplegic patients suggest that these patients do not display a contralateral rebound of the 20 Hz activity (Kauhanen et al., 2004). This may suggest that some other features have to be used when classifying the data of this kind of patients. However, even though patients do not have clear contralateral reactivity when they start to use a BCI, such activity may gradually appear after training. As an example, Pfurtscheller et al. (2000) 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.

MEG and EEG measure the electric and magnetic fields generated by the same cortical currents. Because MEG signals are more localized, one would expect that with optimal sensor selection, classification of task-related MEG signals would be more accurate than that of EEG signals. However, the classification accuracy obtained in the present study was quite similar to those found in previous EEG studies (for reviews see Blankertz et al., 2004; Wolpaw et al., 2002). One reason might be the simple finger-lifting task, which selectively activates the left and right sensorimotor cortex. Apparently, activities from these two cortical areas can be picked up equally well by MEG and EEG. It remains to be seen weather the good spatial resolution of MEG is advantageous in more than two-category classification, involving activity in spatially separate brain areas.

In this off-line study, we defined the analysis window with respect to finger-movement onsets, which is not possible in real-world BCI application. However, relative accurate information of the onset attempted movements in paralyzed patients can be obtained if they are cued by an auditory or visual stimulus. The used feature extraction and classification methods could be used in an online BCI as well.

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 its BCI use to special cases. Nonetheless, as technology progresses, we may even have portable MEG devices (see e.g. BabySquid®, Tristan Technologies).

In conclusion, the inspection of averaged MEG signals proved to be useful in determining and understanding the features to be used in single-trial classification. Averaging three trials improved classification, but at the cost of increased time. In addition, increasing the number of channels also improved the classification accuracy. However, simple averaging of trials from nearby sensors does not seem to be reasonable. Because of the limited number of subjects, our findings should be regarded as tentative and should be verified in future experiments with more subjects.

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References

Bishop CM. Neural networks for pattern recognition. Oxford: Oxford University Press; 1995.

Blahut RE. Computation of channel capacity and rate-distortion. IEEE Trans Inf Theory 1972;18:460–73.

Blankertz B, Müller KR, Curio G, Vaughan TM, Schalk G, Wolpaw JR, Schlögl A, Neuper C, Pfurtscheller G, Hinterberger T, Schröder M, Birbaumer Nils. The BCI competition 2003: progress and perspectives in detection and discrimination of EEG single trials. IEEE Trans Biomed Eng 2004;51:1044–51.

Gaustaut H. Étude électrocorticographique de la réactivité des rhythmes rolandiques. Rev Neurol 1952;87:176–82.

Hari R, Salmelin R. Human cortical oscillations: a neuromagnetic view through the skull. Trends Neurosci 1997;20:44–9.

Hari R, Salenius S. Rhythmical corticomotor communication. Neuroreport 1999;10:R1–R10.

Hämäläinen M, Hari R, Ilmoniemi RJ, Knuutila J, Lounasmaa OV. Magnetoencephalography—theory, instrumentation, and applications to noninvasive studies of the working human brain. Rev Mod Phys 1993;65:413–97.

Kauhanen L, Rantanen P, Lehtonen J, Tarnanen I, Alaranta H, Sams M. Sensorimotor cortical activity of tetraplegics during attempted finger movements. Biomedizinische Technik 2004;49:59–60.

Milton JS, Arnold JC. Introduction to probability and statistics: principles and applications for engineering and the computing sciences. 2nd ed. New York: McGraw-Hill; 1990.

Muller-Gerking J, Pfurtscheller G, Flyvbjerg H. Designing optimal spatial filters for single-trial EEG classification in a movement task. Clin Neurophysiol 1999;110:787–98.

Nagamine T, Kajola M, Salmelin R, Shibasaki H, Hari R. Movement-related slow cortical magnetic fields and changes of spontaneous MEG- and EEG-brain rhythms. Electroencephalogr Clin Neurophysiol 1996; 99:274–86.

Nykopp T, Kauhanen L, Lehtonen J, Heikkonen J, Sams M. Statistical methods for MEG based finger movement classification. IEEE Trans Rehabil Eng in press.

Obermaier B, Neuper C, Guger C, Pfurtscheller G. Information transfer rate in a five-classes brain-computer interface. IEEE Trans Neural Syst Rehabil Eng 2001;9:283–8.

Orr MJL. Introduction to radial basis function networks: centre for cognitive sciences. Edinburgh: University of Edinburgh; 1996.

Parra L, Alvino C, Tang A, Pearlmutter B, Yeung N, Osman A, Sajda P. Linear spatial integration for single-trial detection in encephalography. Neuroimage 2002;17:223–30.

Pfurtscheller G. Central beta rhythm during sensorimotor activities in man. Electroencephalogr Clin Neurophysiol 1981;51:253–64.

Pfurtscheller G, Guger C, Muller G, Krausz G, Neuper C. Brain oscillations control hand orthosis in a tetraplegic. Neurosci Lett 2000;292:211–4.

Portin K, Kajola M, Salmelin R. Neural net identification of thumb movement using spectral characteristics of magnetic cortical rhythms. Electroencephalogr Clin Neurophysiol 1996;98:273–80.

Rissanen J. Stochastical complexity in statistical inquiry. Helsinki: Helsinki University of Technology; 1999.

Sabbah P, de SS, Leveque C, Gay S, Pfefer F, Nioche C, Sarrazin JL, Barouti H, Tadie M, Cordoliani YS. Sensorimotor cortical activity in patients with complete spinal cord injury: a functional magnetic resonance imaging study. J Neurotrauma 2002;19:53–60.

Salenius S, Schnitzler A, Salmelin R, Jousmaki V, Hari R. Modulation of human cortical rolandic rhythms during natural sensorimotor tasks. Neuroimage 1997;5:221–8.

Salmelin R, Hari R. Spatiotemporal characteristics of sensorimotor neuromagnetic rhythms related to thumb movement. Neuroscience 1994;60:537–50.

Salmelin R, Hamalainen M, Kajola M, Hari R. Functional segregation of movement-related rhythmic activity in the human brain. Neuroimage 1995;2:237–43.

Shoham S, Halgren E, Maynard EM, Normann RA. Motor-cortical activity in tetraplegics. Nature 2001;413:793.

Sloane A. Claude Elwood Shannon, collected papers. Piscataway, NJ: IEEE Press; 1992.

Stancak Jr A, Pfurtscheller G. Event-related desynchronisation of central beta-rhythms during brisk and slow self-paced finger movements of dominant and nondominant hand. Brain Res Cogn Brain Res 1996;4: 171–83.

Therrien CW. Discrete random signals and statistical signal processing. Englewood Cliffs, NJ: Prentice-Hall; 1992.

Toro C, Deuschl G, Thatcher R, Sato S, Kufta C, Hallett M. Event-related desynchronization and movement-related cortical potentials on the ECoG and EEG. Electroencephalogr Clin Neurophysiol 1994;93: 380–9.

Wolpaw JR, Birbaumer N, McFarland DJ, Pfurtscheller G, Vaughan TM. Brain-computer interfaces for communication and control. Clin Neurophysiol 2002;113:767–91.