

Movement-related potentials during the performance of a motor task II: Cerebral areas activated during learning of the task

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Received: 27 December 2000 / Accepted in revised form: 26 April 2001

Abstract. Movement-related potentials (MRPs) recorded from the brain are thought to vary during learning of a motor task. However, since MRPs are recorded at a very low signal-to-noise ratio, it is difficult to measure these variations. In this study we attempt to remove most of the accompanying noise thus enabling the tracking of transient phenomena in MRPs recorded during learning of a motor task. Subjects performed a simple motor task which required learning. A modified version of the matching pursuit algorithm was used in order to remove a significant portion of the electroencephalographic noise overlapping the MRPs recorded in the experiment. Small groups of MRPs were then averaged according to experimental parameters. Our results show that the power of the MRPs does not decay uniformly during learning. Instead, there is a significant peak in their power after 4 or 5 repetitions of the task. This peak is noticeable especially in electrodes placed over the prefrontal region of the cortex at times subsequent to the actual movement. The observed pattern of activity may indicate problem solving related to comprehension of the force against which the user performed the task. It is possible that this problem solving occurs in the prefrontal cortex.

1 Introduction

The cortical electrical activity associated with voluntary movement, known as movement related potentials (MRPs) (Boschert and Deecke 1986), has usually been studied in the context of simple movements, commonly of single limbs. These studies have identified the cortical and subcortical areas involved in this movement (Deecke et al. 1973).

The study of MRPs during complex movements, particularly during a problem-solving task, has not been

considered before. The main reason for this is the extremely low signal-to-noise ratio (SNR) of the MRPs, usually of the order of -15 dB. The noise contaminating MRPs stems from both ongoing electroencephalographic (EEG) activity as well as facial electromyographic (EMG) signals (Akay and Daubenspeck 1999). The conventional method of recovering MRPs is by synchronized averaging of a large number of single trials (see, for example, Deecke et al. 1973; Kristeva et al. 1990). Because of this, it is difficult to study short-term variability associated with learning and problem solving.

Many algorithms have been proposed to detect trial-to-trial variability (Bartnik et al. 1982; Birch et al. 1993; Thakor 1993; Lange and Inbar 1999). Most of these algorithms work well for cognitive evoked potentials with a non-negative SNR, but fail when applied to MRPs which have a highly negative SNR. The few algorithms that do perform well for MRPs usually rely heavily on the average MRP (Lange et al. 1997; Cerutti et al. 1988).

In this paper a variant of the matching pursuit algorithm is used in order to extract MRPs from the surrounding noise. Matching pursuit (Davis et al. 1994) is a greedy algorithm which finds a suboptimal expansion of a signal in a redundant dictionary. We utilize a dictionary of functions to typify noise in order to extract the MRP from noise. We show, by means of a simulation, that this method is viable. Using this procedure improves the SNR of recorded MRPs by approximately 13 dB, making it possible to investigate the MRP during task solving.

This technique was applied to MRPs recorded during a motor task which required simple learning. It was found that the effect of learning and the load against which the subject performed the task could be isolated in both time and space. Results show that learning affects the MRPs recorded over the prefrontal cortex at times associated with proprioceptive feedback and adaptation. Furthermore, the load influences MRPs recorded from prefrontal regions of the cortex during most of the MRPs existence.

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2 Matching pursuit for de-noising

Matching pursuit is a method for the suboptimal expansion of a signal in a redundant dictionary (Davis et al. 1994). This algorithm, combined with a dictionary of Gabor functions, defines a time–frequency transformation. Matching pursuit works by iterative subtraction of the best matching dictionary functions (known as “atoms”) from the signal, with the appropriate amplitude and phase.

Suppose a signal f is to be linearly expanded over a set of vectors \mathbf{D} (the dictionary) which best matches the structure of f . If $g_i \in \mathbf{D}$ is an atom in the dictionary, the signal f can be decomposed into

$$f = \langle f, g_i \rangle g_i + \mathbf{R}_f \quad (1)$$

where \mathbf{R}_f is the residual vector after approximating f in the direction of g_i , and $\langle \cdot, \cdot \rangle$ denotes the inner product. In order to find the best atom for the matching pursuit, it is necessary to choose g_i so that $|\langle f, g_i \rangle|$ is maximal. This procedure can be continued iteratively using \mathbf{R}_f as the signal, until a suitable stopping criteria is reached. Such a criterion can be the energy of the residual signal \mathbf{R}_f , the number of iterations, etc.

As mentioned above, if the atoms are chosen from Gabor functions, the expansion defines a time–frequency transformation. The Gabor function h is computed as

$$h(t) = 2^{\frac{1}{2}} e^{-\pi t^2} \quad (2)$$

In order to transform a nonstationary signal, the basic atoms are computed (Akay and Daubenspeck 1999) using a dilation, translation, and modulation function:

$$h_I(t) = \frac{1}{\sqrt{s}} h\left(\frac{t-u}{s}\right) e^{j\eta t} \quad (3)$$

where η represents the frequency of the atom, u is the translation of the atom, s is the scaling parameter, and I is the chosen set of parameters.

Theoretically it is necessary to include atoms corresponding to all possible sets of parameters I . In practice it is possible to include only a representative subset of these. Then, after computing (1), it is necessary to perform an optimization of parameters. This can be done, for example, using a steepest descent optimization algorithm.

In building the dictionary in this article we used, for a signal of N samples, $t = 1, 2, \dots, N$; $s = 2^0, 2^1, \dots, 2^{\log_2 N} = N$; $u = 2^{s-1}, 2^s, \dots, N$; and $\eta = \pi \cdot (2^{-s}, 2^{-s+1}, \dots, 2^{s+1})$. After the signal was generated, it was divided by the root of its norm so that each atom has a norm of 1.

Using such a representative subset of parameters, we empirically found that twenty iterations of a Nelder–Mead multidimensional unconstrained nonlinear minimization (Coleman et al. 1990) were sufficient for matching the best parameters for an atom, using the best-matching atom in the dictionary as the initial guess.

Since the noise contaminating MRPs overlaps it in both time and frequency, it is impossible to distinguish between atoms representing noise from atoms representing parts of the MRP (Akay and Daubenspeck 1999). It is therefore not feasible to remove the noise from recorded MRPs using conventional matching pursuit.

Hence, a modification of the matching pursuit algorithm is needed in order to de-noise MRPs. Observation of the averaged MRPs from several subjects (an example can be seen in Fig. 3) leads to the conclusion that most of the MRP energy is located between 300 ms before the movement until 500 ms after it. Consequently, we propose to prune the matching pursuit dictionary and remove from it those atoms that have most of their energy or amplitude concentrated in that region, which we define as the region of interest (ROI). This leaves the dictionary with atoms that either have their energy concentrated outside the ROI, or that have their energy spread both inside and outside that region. This will make it possible for the dictionary to describe spike noises outside the ROI, and EEG signals, which can be described by a process with lags (such as an autoregressive process; Lange and Inbar 1999) if they are spread over the MRP.

3 Simulation

A simulation was employed to test how well the modified matching pursuit algorithm de-noises a deterministic signal resembling an MRP. This was done in order to ascertain the gain in SNR as well as the remaining deviation from the deterministic signal. The extra deviation is due to the noise that the algorithm could not remove as well as to changes in the signal introduced by the algorithm.

An averaged MRP from one of the subjects was embedded in noise at an SNR of -15 dB. The noise was Gaussian white noise filtered using an autoregressive process of order 9. The parameters of the process were estimated from a 4-s recording of EEG. One hundred “single trials”, each with a different noise sequence, were generated.

Each “single trial” was de-noised using the modified matching pursuit algorithm with the parameters described above. Then, the average SNR before and after the de-noising was calculated. It was found that, on average, the SNR increased from -15 dB to -2 dB.

The stages of the simulation can be seen in Fig. 1. It is evident that after the de-noising process it is necessary to average only a few trials in order to achieve good approximations of the original signal. However, one should note that in some subjects the MRPs were slightly deformed by the de-noising process (see Fig. 3).

We thus conclude that the modified matching pursuit algorithm can indeed remove a significant part of the noise. It is not surprising that some of the noise was not removed. This is due to the fact that noise which can be represented by atoms that have most of their energy inside the defined ROI will not be removed.

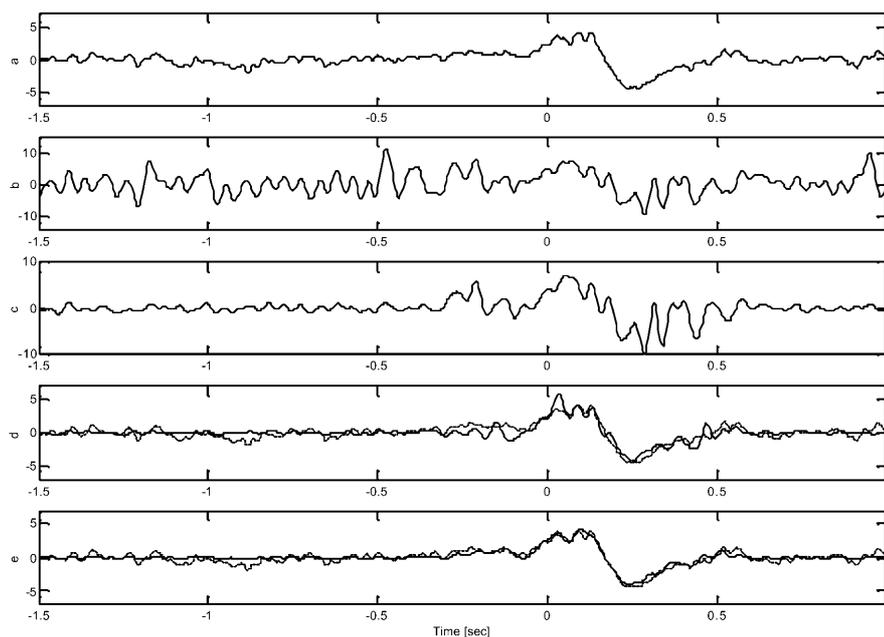


Fig. 1a–e. Stages of cleaning a sample MRP contaminated by noise. **a** The averaged MRP which served as the deterministic signal for the simulation. **b** A single MRP contaminated by noise at an SNR of -15 dB. **c** The signal from **b** after the de-noising process. **d** An average of 10 de-noised signals (*solid lines*) compared to the MRP of **a** (*dotted*). **e** An average of 100 de-noised signals (*solid lines*) compared to the MRP of **a** (*dotted*). It is evident that an average of only 10 de-noised trials closely matches the original MRP. Note the different scales for graphs **b** and **c**

4 Materials and methods

4.1 Experimental protocol

Four subjects (three males and one female aged 25–29 years old) participated in the study. The subjects did not suffer from neurological or muscular disorders. Informed consent was obtained from the subjects.

The subject was seated on an armchair, approximately perpendicular to a lever attached to a vertical rod. Subjects held the vertical rod using their right hand and used their right index finger to pull the lever. A microswitch was used to sense the beginning of the lever's movement.

The force needed in order to pull the lever was changed by connecting 1–4 rubber bands in the direction opposite to that of the movement. Each rubber band generated a force with a force constant of $k = 22.6$ N/m (SD 5.9 N/m). This implies that the minimum force constant was 22.6 N/m and the maximum one was 90.4 N/m. Subject 2 repeated the experiment after several months, this time with only two loads that had force constants of 22.6 N/m and 90.4 N/m.

Twenty recording runs, five for each of the four possible loads, were recorded. Each recording lasted for 45 s. During that time the subject was instructed to pull the lever – self paced – as quickly as possible, pausing for approximately 3 s between each pull. Before the beginning of each run the number of rubber bands pulling the lever was changed randomly, but the subject could not see the number of rubber bands nor feel their force until the first pull of the lever.

Cortical potentials were recorded using electrodes placed over FP_1 , FP_2 , F_3 , F_4 , C_3 , and C_4 , all referenced to an electrode over Cz (according to the international 10–20 system, using an Electro-Cap). The surface EMG signal was recorded by placing a pair of electrodes over the flexor carpi radialis muscle of the right hand and

amplifying the electrical potential between them. The electrodes were circular Ag–AgCl surface electrodes with a diameter of 6 mm. The resistance between the electrodes was less than $5\text{ k}\Omega$. The state of the lever (stationary or nonstationary) was recorded in order to synchronize the MRPs.

The EEG and EMG channels were amplified using a custom-made optically isolated amplifier with a gain of 10 000 and a 0.01–40 Hz pass band. The amplified signals were digitized and sampled, together with the lever state, at 250 Hz using a PCI-DASK 9118HG 12-bit analog-to-digital converter card in a PC. Custom-made data acquisition software was used to drive the sampling card and store the data on the PC's hard disk.

4.2 Data processing

The data were cut into single trials from 1.5 s before the beginning of the lever's movement, until 1 s after it (a total of 625 samples). Movements with a peak-to-peak amplitude larger than $35\ \mu\text{V}$ in frontal channels were rejected so as to exclude trials containing electrooculographic noise.

The movement time was calculated by measuring the delay between the beginning of the lever's movement until it was completely closed. The EMG power associated with a given movement was computed by calculating the integral of the rectified EMG signal from 300 ms before the beginning of the movement until 200 ms after it, after high-passing it at 20 Hz. This filtering was necessary so as to reduce movement artifacts.

A pruned dictionary with 128 samples per atom was used in order to keep the number of computations reasonable. Therefore, prior to de-noising each trial was resampled at a rate of 51.2 Hz after using an appropriate anti-aliasing filter.

The de-noised MRPs were then averaged in groups according to two factors which we have previously shown (Yom-Tov et al. 2001) to influence the MRP. These factors are:

1. The serial number of the lever pull in a recording run, which corresponds to the learning of the load during the specific run. See below for a detailed explanation.
2. The force pulling the lever, which is the load against which the subject had to work.

As stated above, the load is changed before each recording run. The subject does not know what the new load is before the first pull of the lever, and needs to learn it anew during every recording run. Thus, the serial number of the lever pull is consistent with changes in the MRP due to the learning of the load during a recording run. As shown in Sect. 5, speeds of movement remained roughly constant during the experiment; thus the changes in the MRPs are probably not due to fatigue.

It is important to stress that we use the term “learning” in this article to describe the adjustment of the subject’s motor actions to the environment in the face of changes. This type of learning is sometimes described in the literature as adaptation (Karniel and Inbar 2000), while learning is then used to describe the process of creating and establishing a new skill.

Finally, the power in different segments of these averaged MRPs was calculated and plotted. The segments of the MRP (Fig. 2) and their times were:

1. The premotor potential (also known as Bretschäftspotential): from 1.5 s before the lever pull until 0.2 s before it. These times are related to the preparatory process before the movement, preceding the premotor positivity as defined by Deecke et al. (1973).
2. Motor cortex potential: from 0.2 s before the lever pull until 0.15 s after it. These times include the premotor positivity, the motor potential (Deecke et al.

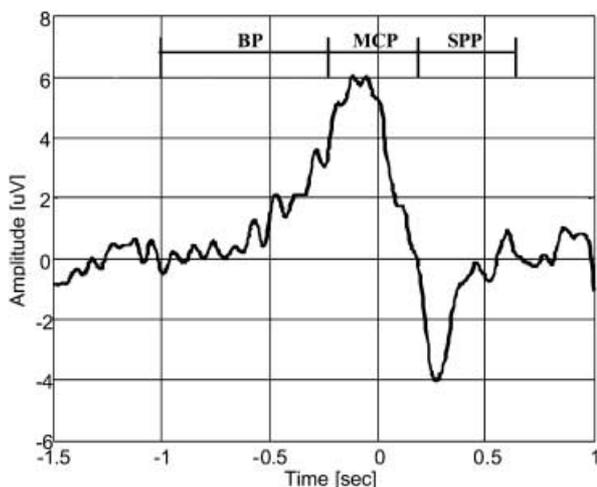


Fig. 2. An example of the average MRP showing its different segments. This example is an average of 100 single trials from F_{P1} of subject 1. Zero time marks the beginning of the lever movement

1973), and the somatosensory feedback from the movement (Yom-Tov and Inbar 2000).

3. Skilled performance positivity: from 0.15 s after the lever pull until 0.6 s after it. These times include signals which are related to the subject’s assessment of the task and to the evaluation of his or her performance (Cerutti et al. 1988).

5 Results

A de-noising process should make minimal alterations to the signal of interest. Figure 3 shows a comparison between the average MRPs for all six channels computed both before and after the de-noising process. This figure demonstrates that the signal undergoes only slight distortion at times following the beginning of the movement. However, the deformation at times preceding the movement is larger, especially in the frontal channels. This deformation can be reduced by enlarging the ROI of the de-noising algorithm, but this causes a degradation in the performance of the algorithm because less atoms are included inside the dictionary. Thus, for the ROI used, variations in the premovement potentials may be lost during the de-noising process, especially in the frontal channels.

When MRPs were grouped according to their serial number in the recording run, a significant peak was found in the power of the MRPs between 200 ms before the movement and 150 ms after it (Fig. 4). This peak in power occurs only in MRPs recorded over the prefrontal cortex (channels F_{P1} and F_{P2}). It was visible in three of the four subjects after four pulls of the lever, and after five pulls of the lever in one of the subjects. The MRPs recorded from two of the subjects displayed a smaller peak after six pulls of the levers as well. A smaller peak in the power of the MRPs is evident when this power is calculated from 150 ms after the movement until 600 ms after it. This peak appears after four lever pulls of the lever in two of the subjects and after five lever pulls in the other two subjects. As in the peaks described above, this peak is visible only in the MRPs recorded over the prefrontal cortex, and never in the other recording channels. It is interesting to note that if the de-noising process was not performed, the peak of activity was far less prominent, although it was usually discernable.

Measurement of the time needed to complete the movement showed that it was approximately constant, and not correlated to the serial number of the lever pull. This demonstrates that the trend seen in the power of MRPs recorded over the prefrontal cortex is not related to fatigue.

The power of the EMG signals showed a gradual decline, which reached a baseline level after 3–4 lever pulls. This is consistent with the findings of Inbar and Yafe (1976), who have shown that when subjects are presented with a new motor task, they begin it by making movements with a high stiffness of both antagonistic muscles. This stiffness (reflected by an increase in EMG activation) gradually decreases until it reaches a

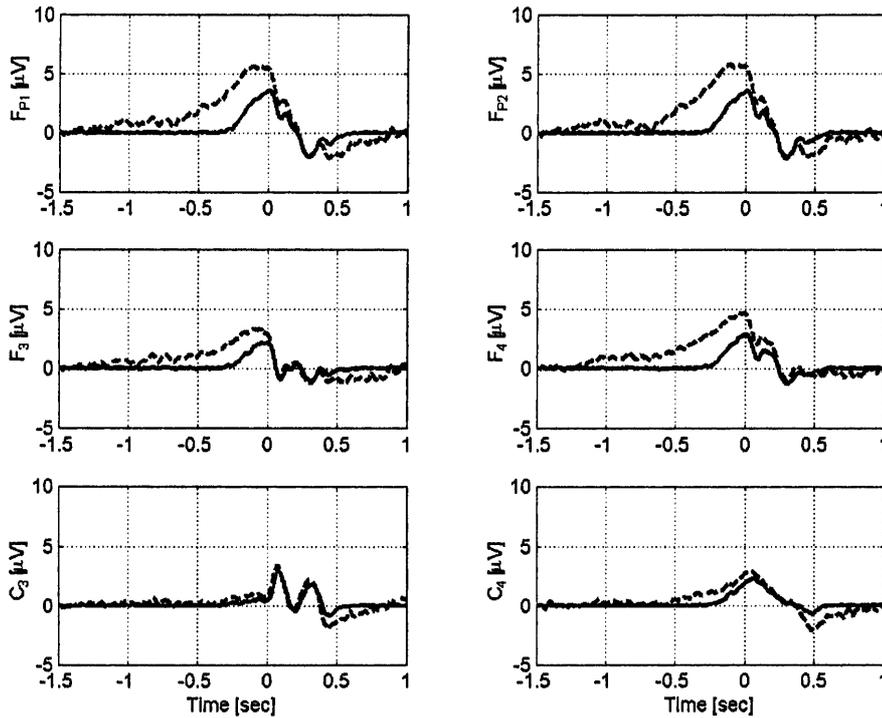


Fig. 3. Comparison of the grand average of the raw MRPs (*dotted line*) to the grand average of the de-noised MRPs (*solid line*). The main difference between the averages is in the power of the premotor potential, but there is a good match between the averages after the lever pull and in the prominent features of the signal, as well as in the morphology of the premotor potential. Zero time marks the beginning of the lever movement

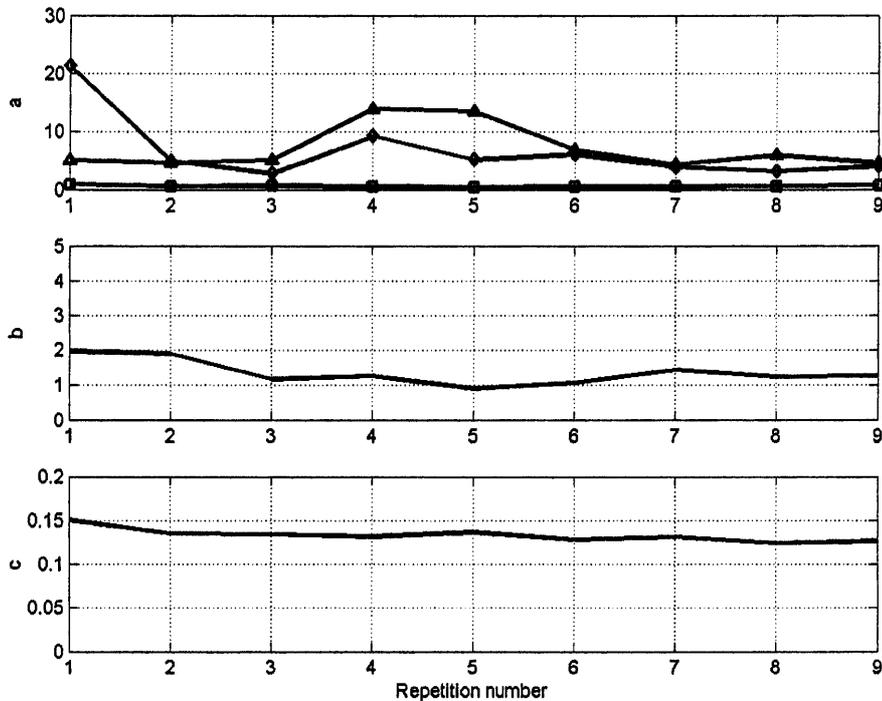


Fig. 4a-c. The power of the average de-noised MRPs by time interval, the power of EMG activity and movement time, separated by serial number of the lever pull in a recording run. **a** The power of the average MRPs of all four loads recorded from F_{P1}: the line marked by *boxes* is the power from 0.6 s before the lever pull until 0.2 s before it, the line marked by *triangles* is from 0.2 s before the lever pull until 0.15 s after it, and the line marked by *diamonds* is from 0.15 s after the lever pull until 0.6 s after it. **b** The average power of the flexor carpi radialis EMG activity. **c** Average movement times. This figure is the grand average of the data collected from the four subjects. Two peaks in the

power of the MRPs are evident: one after four lever pulls in times associated with feedback and the other after four or five lever pulls in times associated with learning. Both peaks appear exclusively in areas over the prefrontal cortex. Also visible is the gradual decline in EMG activity, which reaches a baseline value after three pulls of the lever, and movement times, which remain approximately constant during the sequence of lever pulls. The *horizontal axis* of the graphs shows the serial number of the lever pull in a set. The *vertical axis* in **a** is the power of the averaged MRP in μV^2 , in **b** it is the power of the EMG activity in $10^{-12} \mu V^2$, and in **c** it is time in seconds

baseline value after 3–4 iterations of the task. It is interesting that the baseline level in our experiment was reached before the peak of activity registered in the power of the MRPs recorded over the prefrontal cortex, as seen in Fig. 4.

Using averaging techniques, Kristeva et al. (1990) found a difference between MRPs when the subject moved their finger against a load as opposed to when they moved their finger with no load present, but no difference was seen between the MRPs recorded when subjects operated against two nonzero loads. They isolated the difference to 100 ms before the movement to the start of the movement in electrodes over the motor cortex, and from the instant of movement to 100 ms after it in electrodes over the motor cortex and over the parietal cortex. In our experiments the subjects were not asked to execute the task with no load present. Nevertheless, we have found that the force against which they moved their finger contributes to the power of MRPs, especially those recorded over the prefrontal cortex, beginning 200 ms before the movement and continuing to (at least) 600 ms after it. This result is evident in Fig. 5, as is the finding that there is no linear trend between force and the power of MRPs.

Figure 6 shows that the load against which the user performed the movement generated small changes in the power of the EMG, and insignificant variations in the time taken to complete the movement. This demonstrates that the force needed to carry out the movement was sufficiently small so as to make similar speeds of movement possible without causing fatigue. Conversely, subjects could feel the difference in load and most could, after several lever pulls, report the number of rubber bands connected to the lever.

6 Discussion

Movement-related potentials recorded from the scalp are known to vary due to a variety of factors, including sensory adaptation, learning of the task, and variability of the task itself. This variability in MRPs is lost when they are processed by simple synchronized averaging, making it impossible to study short-term changes in the MRP, such as those associated with learning.

There have been several previous attempts at removing the additive noise from MRPs. As described above, the main problem with MRP processing is the highly negative SNR of these signals. This necessitates a priori knowledge about the MRP. This knowledge is either the averaged MRP itself (as in Cerutti et al. 1988; Birch et al. 1993) or components derived from it (Lange et al. 1997). Such an approach permits only relatively minor deviations of the de-noised MRP from the averaged MRP. Indeed, this may explain why Cerutti and his colleagues found no correlation between experimental paradigms and changes in the MRP.

In this article a new approach is proposed whereby initially the SNR of MRPs is significantly improved using a modification of the matching pursuit algorithm. The only a priori assumption about the MRPs is that most of their energy lies in a known region of time. Although the proposed algorithm does not remove all the additive noise, it makes it possible to study averages of a small number of MRPs grouped according to the criteria presented in the first part of this article.

Results of testing the algorithm on data obtained in a simple learning-task experiment show (Fig. 5) that the load against which the user performed the task influences the power of MRPs over both the anterior regions of the cortex as well as its frontal regions. This is not

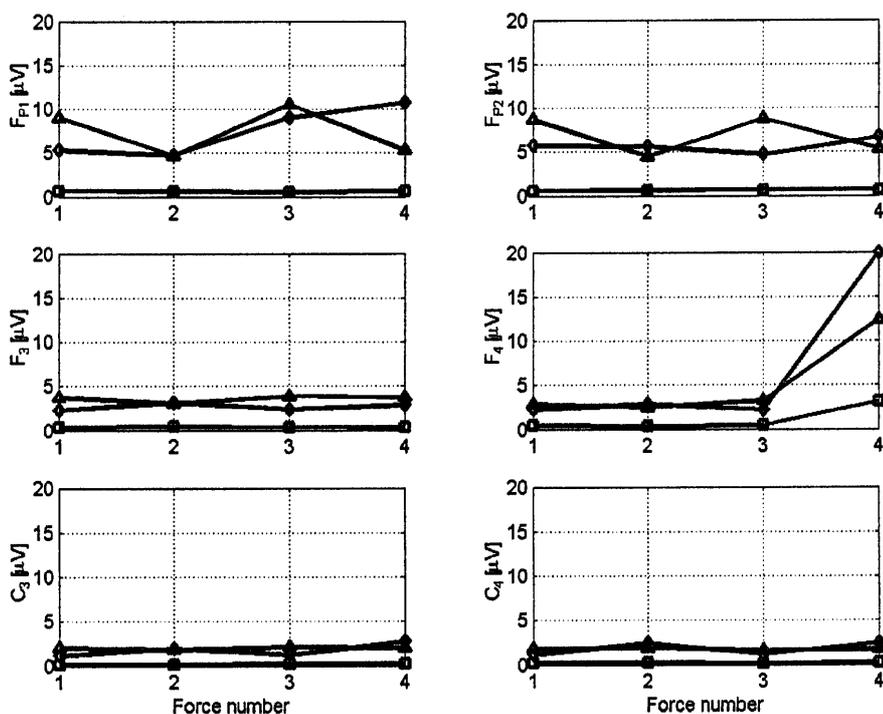


Fig. 5. The power of the average de-noised MRPs by time interval and location, separated by force. The line marked by boxes is the power from 1.5 s before the lever pull until 0.2 s before it, the line marked by triangles is from 0.2 s before the lever pull until 0.15 s after it, and the line marked by diamonds is from 0.15 s after the lever pull until 0.6 s after it. This figure is the grand average of the data collected from the four subjects. The figure shows that there is a change in the power of MRPs associated with an increase in the force especially in those MRPs recorded in channels over the prefrontal cortex. This change is evident in times associated with feedback, and to a lesser extent in times associated with learning. The horizontal axis of the graphs shows the number of rubber bands connected to the lever, while the vertical axis is the power of the averaged MRP in μV^2

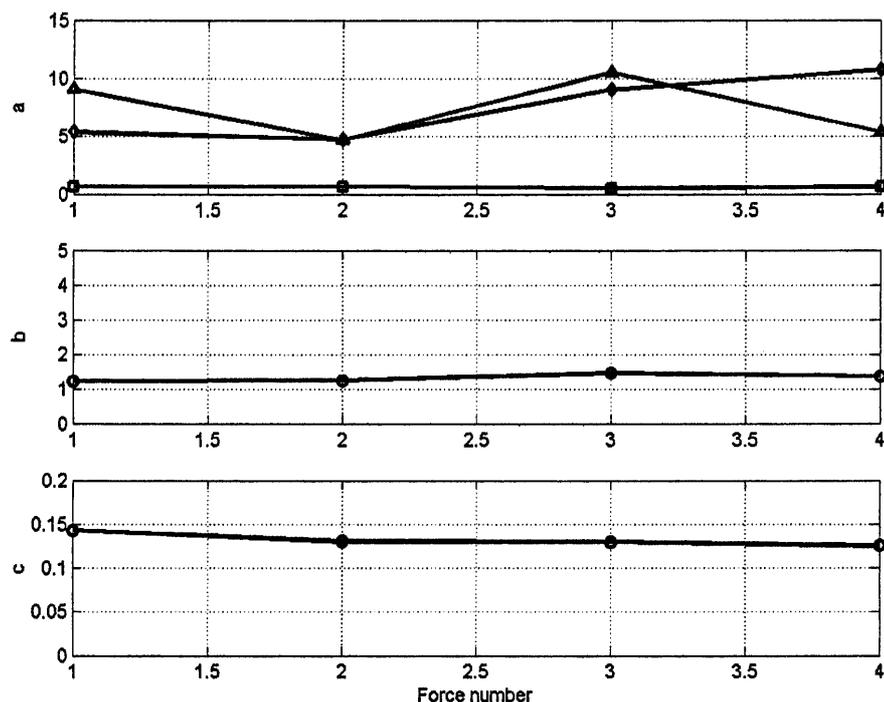


Fig. 6a-c. The power of the average de-noised MRPs by time interval, the power of EMG activity and movement time, separated by force. **a** The power of the average MRPs recorded from F_{P1} : the line marked by *boxes* is the power from 1.5 s before the lever pull until 0.2 s before it, the line marked by *triangles* is from 0.2 s before the lever pull until 0.15 s after it, and the line marked by *diamonds* is from 0.15 s after the lever pull until 0.6 s after it. **b** The average power of the flexor carpi radialis EMG activity. **c** Average movement times. This figure is the grand average of the data collected from the four subjects. It is apparent that the force needed to perform the movement caused only relatively minor increases in EMG activation (and none in movement velocity), suggesting that the forces were small compared to the maximal possible contraction force. The *horizontal axis* of the graphs shows the number of rubber bands connected to the lever. The *vertical axis* in **a** is the power of the averaged MRP in μV^2 , in **b** it is the power of the EMG activity in $10^{-12} \mu V^2$, and in **c** it is time in seconds

surprising considering that many regions of the brain should change their activation in accordance with the force of the movement.

Kristeva et al. (1990) did not find a difference in the power of MRPs obtained when the subject worked against different inertial loads (as opposed to the difference they found when the subject operated against no load at all). Our results do not contradict this finding because, as is seen in Fig. 5, the difference in power is not uniform. The power can be similar for different forces, as may have been the case in Kristeva et al. (1990).

The most intriguing outcome of our study concerns the activity of the cortex during learning. Contrary to what may be expected, activation of the cortex does not gradually decay to some constant level during learning. Instead, there is a marked peak of activity after 4–5 attempts at the task. This activity appears solely in MRPs recorded from electrodes placed over the prefrontal cortex, and seems to be related to both feedback and learning (although the de-noising algorithms may have obscured such peaks of activity in pre-movement times, for reasons discussed above). Furthermore, the peak of the activity during feedback appeared in some subjects at the same iteration as that of the peak in learning, while in others it appeared in the iteration following it. This means that the feedback is not directly caused by activation during times associated with learning. Instead, we propose two possible explanations for these findings. One is that a third process controls both the feedback and the learning. It is likely that this process is not time-locked to the movement, which is why it was not detected after our time-locked processing. The second feasible explanation is that these two processes, namely feedback and learning, are

independent, although both take place in the same areas of the brain.

In addition to the relation between the peaks of activity in the MRP at different times, one should note the relation between this activity and the EMG activation levels. As seen in Fig. 4, the baseline activity level of the EMG is always reached before the appearance of the peaks in MRP activity. This implies that the process governing the gradual decrease in EMG activation completes before the processes in the frontal areas of the cortex begin.

It is probable that the peak in the power of the MRPs is generated in the prefrontal cortex because, as was stated above, it appears only in those electrodes placed over the prefrontal cortex. Had the activity been generated elsewhere it is expected that some of it would have been evident in other recording electrodes. Despite this, additional studies are needed to confirm this assumption.

It would thus appear that the peak of activity, at least that associated with learning, is the manifestation of problem solving which occurs after the brain has collected enough information for the problem to be solved. The information is collected during the first pulls of the lever. It is interesting to note in this respect that the peak of activity for subject 2 was after five iterations when working against one of four possible loads, and after four iterations when only two loads were present.

We are currently investigating if the type and number of the possible loads significantly affect the number of iterations before the peak in power of the MRPs during learning. This will help to ascertain if the peak is indeed related to problem solving, as we suggest here.

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