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Plasticity following skilled learning and the implications for BCI performance

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Abstract

Brain Computer Interfaces (BCIs) rely on robust detection and classification algorithms for stable and accurate device control. Here we investigate the effects of skilled motor learning on the stability of movement related cortical potentials (MRCP). Eight subjects were trained for 32 min on a task known to induce plasticity. Significant increases in performance were accompanied by significant increases in the variability of the EEG signal from two to one second prior to movement onset. The implications of these results for the use of the MRCP for online device control are discussed.

1 Introduction

Current research on brain computer interfaces (BCIs) has been almost exclusively limited to a single session trial where the performance is of acceptable accuracy (Wolpaw, 2013). Essentially, the user is trained to fit into the performance of the BCI governed by a classifier or a detector. But, the brain is undergoing continuous adaptation through learning and shifts in attention to task (Sanes & Donoghue, 2000). While the human nervous system is adaptable, current BCIs lack this capability. There is a need for adapting the BCI to the user, thus paving the way for bidirectional adaptation of either the BCI or the user, depending on the reasons for alterations in brain activity. Any design of a BCI must use the changing brain and thus the principles related to how the brain acquires, improves and maintains its natural function as a guide.

For the past 10 years, our research group has successfully implemented the slow cortical potential arising during movement or its intention as a control signal, also called the MRCP. We have shown that a MRCP-based BCI can detect movement or movement intention at high (above 75%) accuracy in the online mode (Xu *et al.*, 2014) and due to the possibility of such detection prior to movement onset, it provides a fast device control. In this study we aim to quantify the alterations in the MRCP morphology after healthy subjects participate in a novel skill learning motor task. We predict that since skill-learning is associated with significant plasticity at the level of the motor cortex, MRCP will be affected significantly.

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2 Methods

Eight healthy, volunteers (3 females, 5 males; 25-43 years) with no prior history of neurological conditions participated in this study. All procedures were approved by the Scientific Ethics Committee of Northern Jutland (Reference number: N-20130039) and subjects gave their written consent.

2.1 EEG and EMG recordings

Ten channels of monopolar EEG were collected using the EEG electrode system and g.USBamp amplifier from gTec, GmbH at a sampling frequency of 256 Hz. Electrodes were placed on FP1, Fz, FC1, FC2, C3, Cz, C4, CP1, CP2 and Pz, according to the standard international 10-20 system. The ground electrode and reference electrode were placed on Fpz and the right earlobe, respectively.

Surface electrodes (20 mm Blue Sensor Ag/AgCl, AMBU A/S, Denmark) were used to record the electromyographic (EMG) activity of the tibialis anterior (TA) muscle of the dominant leg for all aspects of the experiments. EMG data were collected at a sampling frequency of 2000 Hz using a custom made Labview program (Follow-me, Knud Larsen, Aalborg University).

2.2 The learning protocol

Subjects were seated comfortably in an armchair with the dominant leg flexed in the hip (120°), the knee (160°) and the ankle (110° of plantarflexion). The foot was resting on a foot-plate and a computer screen was positioned approximately 1.5 m in front of the subjects at eye level. The learning task was comprised of a series of six randomized figures each sketching a different series of combinations of dorsi- and plantarflexion movements (Figure 1A). Upon appearance of the trace on the screen, a countdown of 3 s was visually shown and on the word 'go', the activity of the subjects EMG was displayed in real-time overlaying the respective trace. Subjects were instructed to follow these traces by controlling the activation level of their TA muscle. Each trace lasted 3-4s and a single training run lasted for 4 min followed by a 2 min rest period. A total of eight training runs were completed leading to a total training time of 32 min.

2.3 Data analysis

Analysis of the EEG data was performed for training run one and eight and only from the Cz channel since Cz is located over that area of the motor cortex that has direct connections to the target muscle TA. It is here where most alterations due to the learning paradigm are expected based on past studies using a similar paradigm. EEG were band pass-filtered (0.05-10 Hz, 2nd order Butterworth filter) and continuous EEG data divided into epochs of 4 s (from 2 s before to 2 s after the onset of EMG in the TA). The onset of the TA EMG activity was used as time zero since it is at this time-point when the subjects commenced to track the traces and where an MRCP is expected to occur. Following appropriate segmentation, the following parameters were extracted from single trials during the first and last training run respectively: (i) average EEG signal from -2 to -1 s prior to task onset, (ii) standard deviation of the signal from -2 to -1 s prior to task onset, (iii) the peak negative value timing within a 500 ms window on either side of the task onset and (iv) the amplitude of the peak negative value (Figure 2A). To quantify any alterations in performance of the task, the correlation between the trace and the actual subject performance was calculated for the first and the last 4 min of training. Paired t - test was used to compare the r2 values, the PN latency, amplitude and the mean EEG signal and its SD for the first and last training run respectively. Significance level was set to $p < 0.05$.

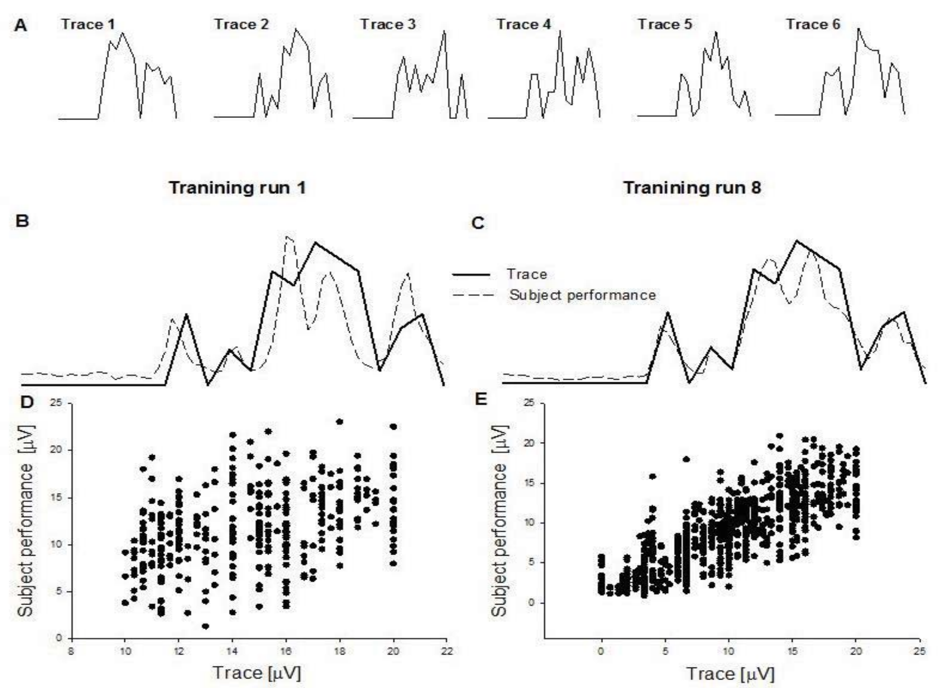

Figure 1: The 6 traces (A) Trace and subject performance during the first (B) and last (C) training run. Relationship between trace and subject data for all data point during the first (D) and last (E) training run (n=1)

3 Results

3.1 Motor performance

The effect of the training for one subject is illustrated in Figure 1B-E. Figure 1B and 1C show the data for one of the traces selected for analysis during training 1 and training 8, while Figure 1D and 1E shows the scatter plot between the exerted TA activation and the target level for each interval of time during training runs 1 and 8. For this subject the correlation between shown traces and actual subject performance increased from 0.84 to 0.91. Across all subjects there was a significant increase in correlation between the first and last session (p=0.0005) indicating an improved performance.

3.2 Movement related cortical potential (MRCP) during the tracking task

Four parameters were extracted from the MRCPs generated during training session 1 and 8 (Figure 2A). Figure 2B shows the average MRCP for training session 1 and 8 for one subject. The average EEG amplitude within 1-2 s prior to movement onset remained relatively stable (session 1: -4.23 μV vs session 8: -3.39 μV; p=0.42). However, the variability of the EEG activity during this time (the SD within the time window), increased significantly (session 1: 1.96 μV vs session 8: 2.54 μV; p=0.01). Both the time of peak negativity in relation to task onset (session 1: -40 ms vs session 8: -50 ms, p=0.35) and its amplitude (session 1: -17.07 vs session 8: -17.92, p=0.36) did not change significantly.

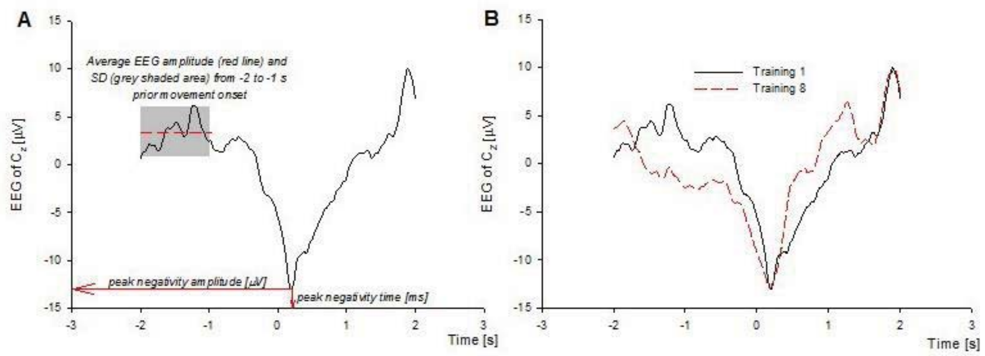

Figure 2: A. Illustration of four variables extracted from individual MRCP traces for each movement trace performed in the first and last training session. B. MRCP data from one representative subject during the first (black trace) and last (red trace) training session.

4 Discussion

Results demonstrate that significant improvements in task performance are accompanied by a significantly greater variability of the MRCP 2-1 s prior to movement onset. This has important implications in the design of any MRCP-based BCI for online detection of movement. Here the algorithm has a role in identifying when the EEG activity attains a specific threshold level. Once detected, the algorithm proceeds to implement device control. For a BCI designed for neuromodulation this may take the form of turning on an orthotic device that performs a desired movement or an electrical stimulator that triggers nerve stimulation to induce contraction of specific muscles. Typically such a use of BCI intends to induce plasticity at the level of the motor cortex. Data presented here suggested that the performance of the algorithm could be affected as plasticity is induced. Previous studies have shown significant plasticity within the motor cortex and likely also connected sites during the acquisition of a new motor skill. Such plasticity results in an expansion of the motor maps – i.e. those areas of the motor cortex that when stimulated will result in a contraction of the target muscle. As the motor skill manifests itself, the motor maps tend towards their normal size. However evidence also exists that motor maps differ between skilled versus novice athletes. Any BCI designed to induce neuromodulation must ensure that shifts in EEG patterns are taken into account with the acquisition of new or indeed the relearning of old motor skills. The MRCP seems to be robust to effects of motor learning at least in healthy subjects. However, since online detecting relies on threshold values for the period prior to movement onset, the findings here suggest that BCI performance will decline with skill acquisition unless the algorithm is adapted to the new level of activity. This is one of our current areas of investigation.

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