THE BERLIN BRAIN-COMPUTER INTERFACE FOR RAPID RESPONSE

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ABSTRACT

The Berlin Brain-Computer Interface (BBCI) project is guided by the idea to train a computer using advanced machine learning and signal processing techniques in order to improve classification performance and to reduce the need of subject training. Instead of having the human adapt to a predefined feedback that is computed from a fixed set of features, the BBCI adapts to the user's brain waves by learning ('let the machines learn'). One aspect of the BBCI is the capability of giving fast-response feedback. This was investigated in keyboard typing paradigms with self-paced as well as reactive finger movements in a time critical task. In both settings a prediction of the laterality of upcoming movements was possible before EMG onset.

1. INTRODUCTION

A brain-computer interface (BCI) is a communication channel from a human's brain to a computer which does not resort to the usual human output pathways as muscles, [1]. A BCI could, e.g., allow a paralyzed patient to convey her/his intentions to a computer program. But also applications in which healthy users can benefit from the direct brain-computer communication are conceivable, e.g., to speed up reaction times.

In the setting of man-machine interfaces, there are two different adapting systems involved: the operator and the computer. One approach to BCI technology is therefore to rely on the ability of the human brain to adapt quickly to new tasks. The strategy confronting the user with a biofeedback can take months until it reliably works [2].

The BBCI pursues another objective in this respect, i.e., to impose the main part of the learning task on the machine. Modern machine learning techniques allow for extracting relevant information from high-dimensional noisy data like multi-channel EEG, even in a small sample statistics scenario, and offer ample possibilities for incorporating neurophysiological characteristics of the data [3].

Below, we report on experiments where the lateralized readiness potential (LRP) can be used to classify a motor task before the actual movement even in time critical situations. Combination strategies for using lateralized movement potentials and the ERD approach [4] that lead to promising results are discussed elsewhere, see [5].

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2. EXPERIMENTAL PARADIGM

Before accomplishing motor tasks, a negative readiness potential can be observed at the scalp, reflecting the preparation. Multi-channel EEG-recordings of unilateral finger movements show that this negative shift originates on the frontal lobe in the area of the corresponding motor cortex, i.e., contralateral to the performing hand, cf. [6]. Based on the laterality of the pre-movement potentials it is possible to discriminate multi-channel EEG recordings of upcoming left from right hand movements.

We investigated the LRP in two different experimental settings. In an earlier study we recorded spontaneous motor activity during self-paced finger movements where the subjects performed the typing on a computer keyboard with their index and little fingers in a deliberate order and on their own pace. We were able to classify the pre-movement potentials of left vs. right hand finger movements before EMG onset, cf. [3]. These findings suggested that it might be possible to use a BCI system to enhance reaction times in time critical applications.

To pursue this idea further we designed another experiment where subjects had to react with finger movements in a "d2"-test. 8 healthy subjects had to respond as quickly as possible to *targets* with a keypress with the right index finger and to *non-targets* with the left index finger. A target is a visual stimulus consisting of the letter "d" with exactly two horizontal bars that may occur in four possible positions each, while non-targets either have the letter "b" or show a wrong number of bars. The experiments, which were per-

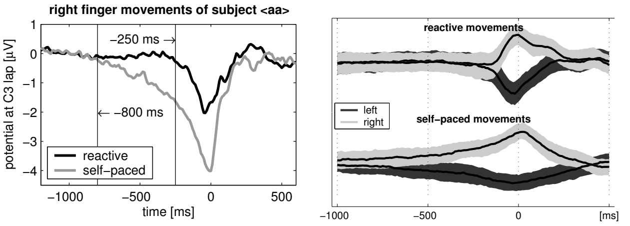

Fig. 1: The figure on the left shows the averaged readiness potential in the case of spontaneous selfpaced (grey) and reactive (dark) finger movement. The figure on the right indicates the distribution of the continuous classifier output in both experimental settings, see text for details.

formed on one day, comprised 400–500 keypresses per finger with a distance of 2 seconds. It turned out that with our LRP-based approach ([7, 3]) it was possible to distinguish the pre-movement potentials between the classes "left" and "right" before EMG onset even in this reaction time task. Besides multi-channel EEG, surface EMG at both forearms was recorded to determine EMG onset.

3. RESULTS

On the left side of Fig.1, the EEG signals at channel C3, averaged over all "right" trials of subject *aa*, show LRPs for both experimental settings. For self-paced typing the negative shift in this subject starts 800 ms before the keypress. The reactive potential, as produced in the time-critical d2 experiment, starts just 250 ms before the keypress.

The right side of Fig.1 shows the distribution of the continuous output of our classifier (traces), which was trained to output negative values for left and positive values for right hand trials. To determine the classifier trace to one trial for this analysis, we train the classifier on all other trials (leave-one-out methodology) and then apply it to a window that is sliding over the test trial. The end point was varied between -1000 and 500 ms. After doing this for all trials we determine the distribution of classifier outputs for each time point separately for classes "left"and "right". The figure shows the range between 15 and 85 percentile (shaded) and the median (line). In the classifier output for the spontaneous movements, we note that the traces of both means for "left" and "right" trials are diverging already from the beginning, such that 350 ms before the keypress, even the 85-percentile tubes are separated, whereas in the reactive movement the tubes are still indistinguishable at this point in time. However, 100 ms before the keypress, a separation of the tubes becomes apparent. This indicates a robust classification of the laterality of the movement already at this point in time.

While the BCI system will use only EEG signals, we analyzed the EMG classification to determine the average point in time of EMG onset for every subject. At that point, we calculated the EEG classification results (table 1), so that only EEG data prior to EMG onset were used for classification.

	aa	*ab*	*ac*	*ad*	*ae*	*af*	*ag*	*ah*	∅
cl	12.8	16.8	9.4	14.8	25.7	26.3	12.5	27.7	18.3
os	-80	-70	-110	-100	-100	-120	-120	-110	

Table 1: The first row shows for 8 different subjects the classification error (left vs. right hand, cl) and their mean in percent on a 10×10-fold cross validation on LRP features using linear discriminant analysis with regularization (RLDA) in the "d2"-experiments; the second row shows the point in time for EMG onset (os), which is the rightmost point for the EEG classification window of each subject.

4. DISCUSSION

The use of readiness potentials for early classification of motor tasks even before the actual EMG onset was exemplified with classification on data from different experimental setups. These properties of the readiness potential confirm its value for the use in time-critical BCI applications.

5. REFERENCES

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