Subject-Independent Detection of Movement-Related Cortical Potentials and Classifier Adaptation from Single-Channel EEG

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***Abstract*—Brain-computer interfaces have been proposed for stroke rehabilitation, but there are some impeding factors for them to be translated into clinical practice. One of them is the need for calibration. In this study it was investigated if subject-independent calibration is possible for detecting movement-related potentials associated with hand movements, and what the optimal number of movement epochs is to maximize the detection performance. Twelve healthy subjects performed 100 palmar grasps while continuous EEG was recorded. Template matching was performed between movement and idle epochs. 72±10% of all epochs were correctly classified using the subject-independent approach while 78±9% of the epochs were correctly classified using the individualized approach. The highest classification accuracies were obtained when using 54±23 movement epochs for calibration. In conclusion, it is possible to use a subject-independent approach for detecting movement-related cortical potentials, but the performance is slightly lower compared to individualized calibration.**

I. Introduction

Brain-computer interfaces have been proposed for stroke rehabilitation over the past years. It has been shown in several studies that neural plasticity, the underlying factor of motor recovery, can be induced [1] and gains in functional scores have been reported in stroke patients [2]. A Brain-Computer Interface (BCI) can induce neural plasticity by pairing movement-related brain activity with temporally correlated somatosensory feedback from e.g. electrical stimulation of nerves and muscles or passive movement from rehabilitation robots and exoskeletons [3]. It is not known how strict the temporal association between movement-related activity and inflow of somatosensory feedback has to be. It has been suggested that there should be a very strict timing where the intended movement is predicted [4], while other findings have suggested that such a strict temporal association may not be needed [5]. However, if a strict temporal association is needed, the movement-related activity has to be predicted from single-trial EEG. This is possible through detection of movement-related brain activity that precedes a movement, which can be done from either movement-related cortical potentials (MRCPs) or event-related desynchronization (ERD) [6]. It has been shown in several studies that these two phenomena can be detected from single-trial EEG with accuracies in the range of 70-80% in stroke patients [7]. To be able to utilize this in a BCI, a number of movements (roughly 30-50 movements) needs to be performed such that a classifier can be trained to discriminate between movement and idle activity. This takes time, especially in a potential rehabilitation scenario where the therapist needs to mount the EEG cap and perform the system calibration. It is likely that this will take too much time for the therapist, and this wasted time may be deducted from the actual training with the patient. To increase the acceptance of a BCI-approach for stroke rehabilitation, it would be ideal if the patient could mount the cap him/herself [8], and that the BCI would not require any calibration, or at least a very low number of movement trials for calibration. It has been shown previously in a couple of studies that ERD [9], [10] and MRCPs [11], [12] can be detected using a global approach where previously recorded data from multiple subjects can be used for calibration hence removing the calibration time. For the MRCP, it has been reported for foot movements. In this study, it will be investigated if similar findings are obtained for hand movements. The aims of this study are to: 1) compare the detection of MRCPs associated with hand movements from single-trial EEG using a global and individualized detector approach, and 2) determine the relationship between detection performance and number of movements used for calibration.

II. Methods

A. Subjects

Twelve healthy subjects participated (28±3, two females). The subjects gave their written informed consent prior to participation. The local ethical committee (N-20130081) approved all procedures.

B. Recordings

Nine channels of EEG were recorded from F3, Fz, F4, C3, Cz, C4, P3, Pz and P4 (EEG amplifiers, Nuamps Express, Neuroscan). The channels were referenced to the right mastoid bone and a ground electrode was placed on the forehead. The signals were sampled with 500 Hz. The impedance of the electrodes was below 5 kΩ.

C. Experimental Setup

The subjects were seated in a comfortable chair. They performed 100 visually cued ballistic palmar grasps of the right hand. A digital trigger was used to synchronize the visual movement cues with the EEG. The subjects were

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instructed to sit as still as possible and minimize blinking and activity of the facial muscles during the recordings. Each movement was separated by a 10-second rest period.

D. Data Analysis

Only Cz was used for the data analysis. The raw EEG was bandpass filtered from 0.05 to 5 Hz using a 4th order Butterworth filter with zero phase shift and downsampled to 25 Hz to reduce the processing time. The processed continuous signal was divided into two types of trials/epochs 1) movement epochs (from -1.5 to 0.5 s with respect to the task onset), and 2) idle epochs (from -5 to -3 s with respect to the task onset). 100 movement and idle epochs were extracted in total. The mean value of each epoch was subtracted from the respective epoch. To investigate the global approach, a linear discriminant analysis (LDA) classifier was trained on all movement and idle epochs from the subjects that were available except for the test subject (all the epochs from the test subject was used for testing). A template was obtained from all movement epochs (average across epochs), and the autocorrelation was calculated between the template and each epoch, movement and idle. To investigate the effect of the number of movement epochs for the individualized calibration, the first five movement epochs were used to extract a template and to calibrate the LDA, and the remaining epochs were used for testing. The number of epochs was increased by one hence increasing the number of movement epochs for calibration until 20 epochs remained for testing. A paired t-test was performed between the classification accuracies obtained for the global approach and for the highest classification accuracy in the individualized approach.

III. RESULTS

The results are summarized in Table 1 and Fig. 1. 72±10% (across subjects) of the epochs were correctly classified for the global approach while 78±9% of the epochs were correctly classified in the individualized approach. The accuracies were significantly higher for the individualized approach ($t_{(11)}=-3.5$; $P=0.005$). The highest accuracies in the individualized approach were obtained when 54±23 movements were performed; however, there is a large standard deviation.

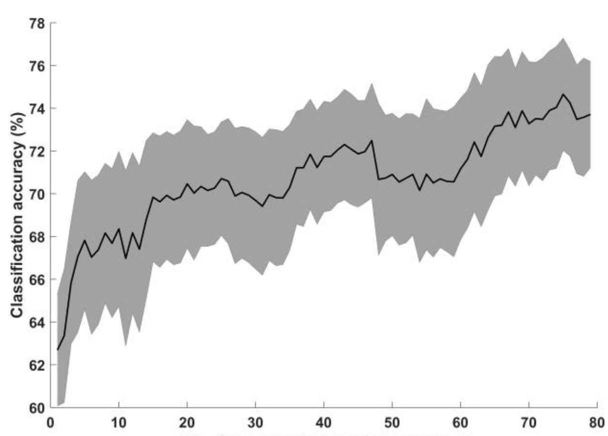

TABLE I
GLOBAL VS INDIVIDUALIZED CLASSIFICATION

Subject	Global [%]	Individual [%]	No. Epochs for best performance
1	82	86	67
2	79	76	43
3	65	81	65
4	60	71	79
5	69	73	75
6	84	88	64
7	78	76	38
8	69	78	74
9	76	80	59
10	86	91	6
11	61	74	62
12	56	59	18
Mean±std	72±10%	78±9%	54±23

Fig. 1. Average and standard error of the classification across subjects for the individualized calibration.

IV. CONCLUSION

It was possible to use a subject-independent approach for detecting MRCPs associated with hand movements, although the performance was slightly lower compared to the individualized approach. This may have implications for the calibration strategies of MRCP-based BCIs.

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