Time Coded Motor Imagery BCI to Control an Artificial Limb with Additional Discrete Feedback to Detect Error Potentials

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Introduction

The time coded Brain-Computer Interface (BCI) introduced in this poster uses motor imagery (MI) [1] of the right hand to control an artificial arm for various amounts of time. The moving arm, thus, represents a continuous visual feedback. Additionally, to allow the recording of error potentials (ErrPs) [2], a discretization of the feedback was achieved by mounting flashing LEDs on the arm. This step was necessary to trigger clearly assignable ErrPs which are time- and phase-locked.

Methods

Ten unexperienced subjects participated in the experiment. At the beginning, one short training run was conducted to check for feasible patterns that could be used for online control of an artificial arm. After observing ERD/ERS maps [3] which were generated from the EEG, recorded over the contralateral hemisphere of the brain, the most promising frequency bands were selected to set up a threshold, depending on the band power. This threshold was used to detect MI during the following online experiment. Figure 1 shows an example of subject aq1's significant ERD patterns between 8–12 Hz and 20–26 Hz.

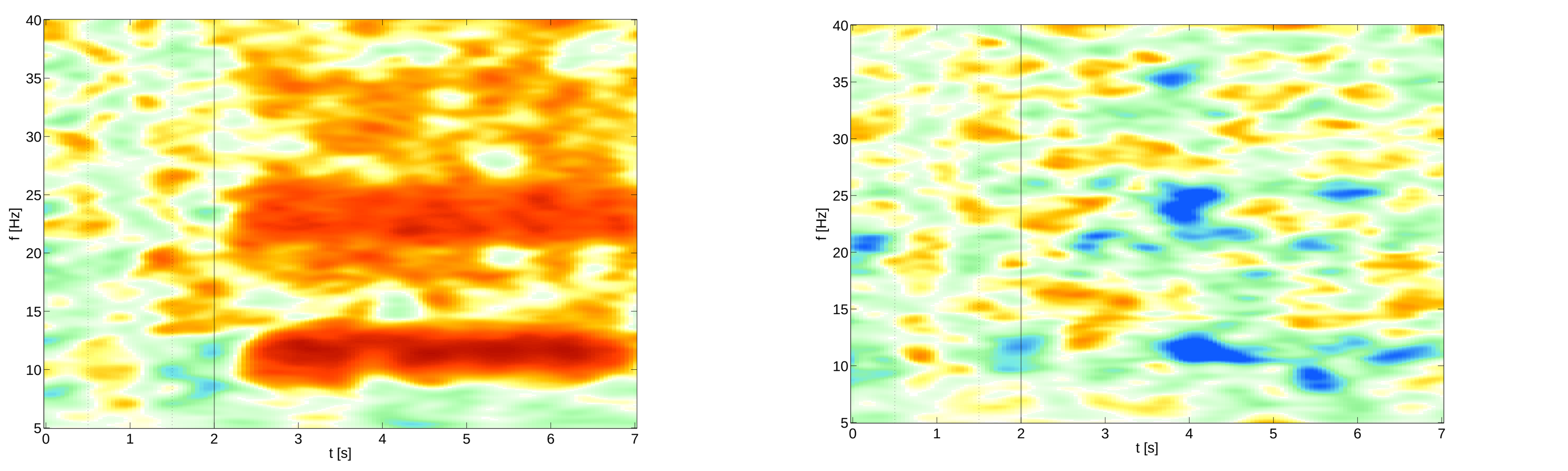

Figure 1: ERD/ERS map of subject aq1, MI of right hand and rest. The red area in the left figure demonstrates a band power decrease relative to the band power during the reference period (0.5–1.5 s). The line at 3 s visualizes the appearance of a cue within a 7 s trial.

In the online experiment, the subjects were presented a random number (1, 2, 3, or 4), referring to how long they should concentrate on performing MI. Shortly afterwards, a bargraph started to fill (always for 5 s), indicating the lapse of time. The participants were told to reach at least the presented number of seconds, but should not exceed it for more than 1 s. Thus, a target of 2 s should have resulted in a MI period lasting between 2–3 s. Figure 2 demonstrates this first part, still without feedback.

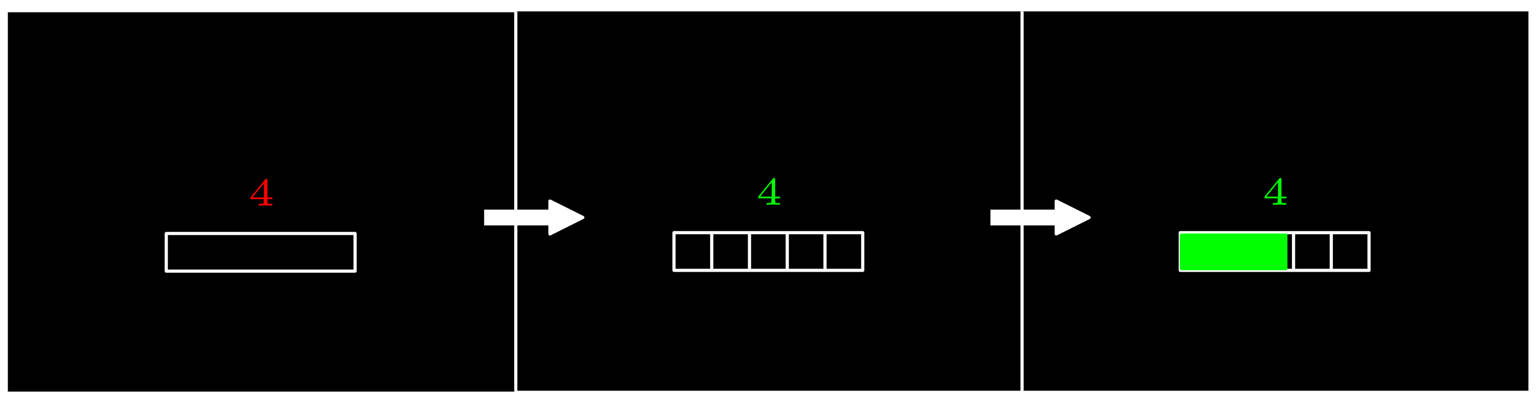

Figure 2: MI sequence, consisting of target presentation (red number) at 0–1 s, followed by the active MI time period (1–6 s), represented by a growing green bargraph.

During the filling of the bargraph, the system counted the time when the threshold was exceeded. Corresponding to this time, the artificial arm started to move just as long.

On top of this continuous feedback, blinking LEDs indicated the remaining movement time before every second. Here, a white LED preceded at least a whole second of movement, whereas a red light indicated a stoppage within the second. Due to this discretization it was possible to record ErrPs after unexpected flashes. Another important requirement was that the subjects were aware of the correct chronology of events, e.g. for a target of 3 s it was 3 white lights and 1 red. Figure 3 visualizes a scheme of the artificial arm with the additional LEDs.

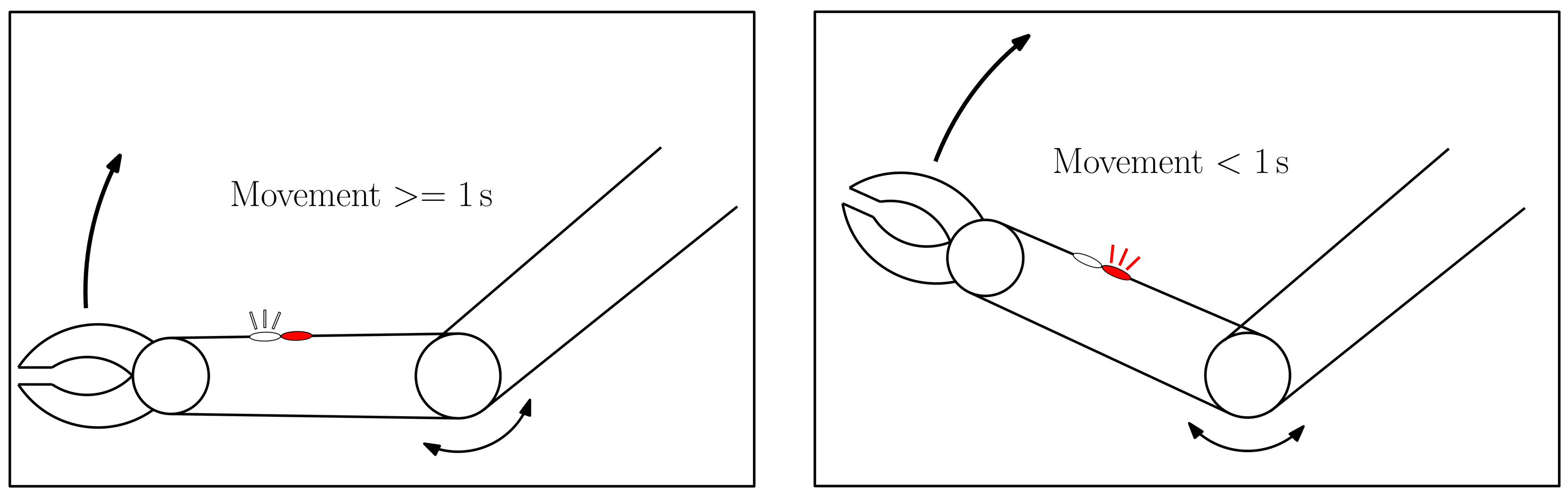

Figure 3: The artificial arm moves up or down continuously. The white LED blinks before each whole second of movement. The red LED indicates a stoppage in the space of a second. The blinking frequency is 1 Hz.

Results

Most of the subjects were able to generate significant patterns after only one setup run. During the online experiment, the subjects performed MI exactly as requested (e.g. a target of 1 s calling for MI between 1 and 2 s) in 26% of the trials, 45% of the trials were in a range between ± 0.5 s of the target time period, and 68% between ± 1 s. The discretization resulted in an error rate of 26% on average over all subjects (unexpected LEDs blinking), which is a good basis to record ErrPs. Concerning the detection of these ErrPs, it could be shown that all of the participants produced waveforms similar to interaction ErrPs [2] over the anterior cingulate cortex (ACC) [4], however, with a delay of about 200 ms. The average MI time over all subjects and the average recorded ErrP waveform can be seen in Figure 4.

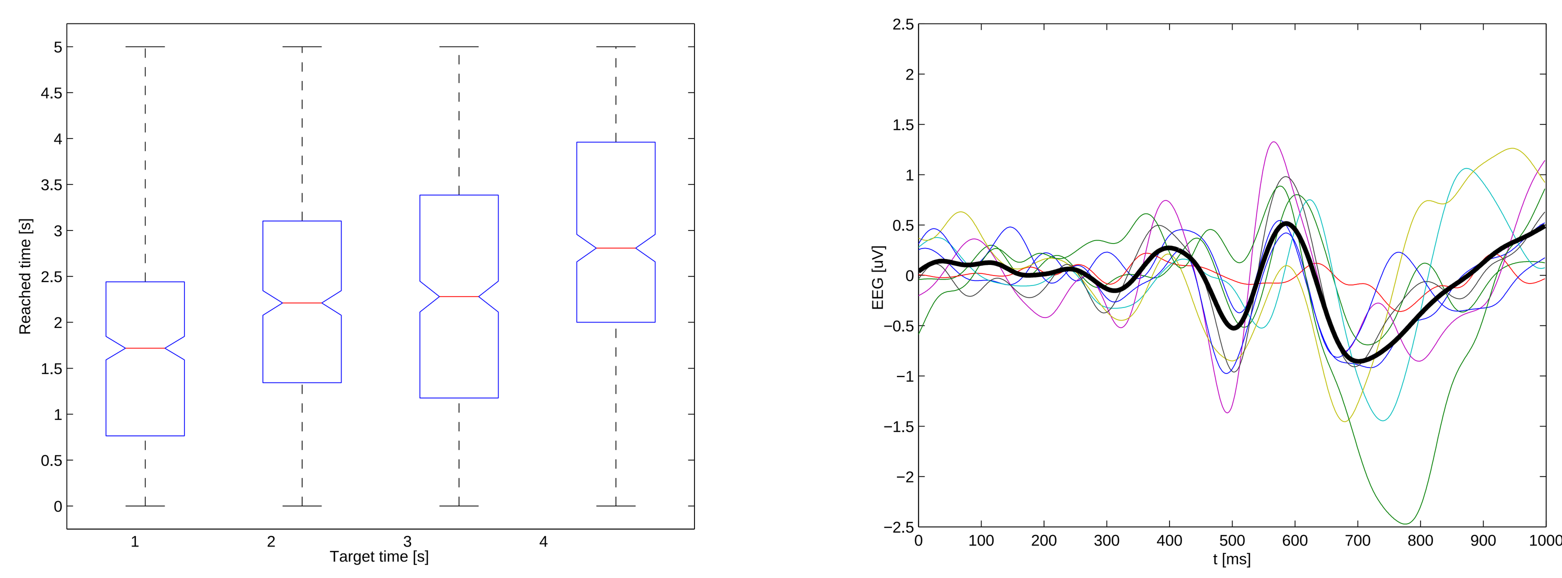

Figure 4: Boxplot of the achieved MI times (left) and averaged ErrP over all subjects.

Discussion

Very simple mental tasks like hand MI with little training efforts are sufficient to control neuroprostheses when time coded, although it is difficult to reach target times precisely. ErrPs, usually impossible to detect in asynchronous BCIs with continuous feedback, could be measured by simply adding discrete feedback to the continuous one.

References

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Acknowledgments

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