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# Time domain classification of grasp and hold tasks

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*Introduction:* Brain-Computer Interfaces (BCIs) enable its users to interact with their environment only by thought. Earlier studies indicated [1, 2] that BCI might be a suitable method for controlling a neuroprostheses, which could assist people with spinal cord injuries (SCI) in their daily life. One drawback for the end user is that only simple motor imaginations (MI) are available for control e.g. MI of both feet to control ones arm is abstract and in contradiction to an associated natural movement. Therefore we are looking for means to design a more natural control modality. One promising scenario would be to use MI of different grasps to actually control different grasps of the neuroprosthesis. In this study we attempt to classify the execution of different grasp types in low-frequency time-domain EEG signals.

*Methods*: Fifteen healthy participants from age 23 to 37 participated in the experiment. In a cue guided paradigm (see figure 1), subjects were instructed to perform 3 different reach-grasp-hold tasks on 3 different objects: palmar grasp (cylinder), pincer grasp (needle) and key grasp (key). To introduce a control condition, one spot was deliberately left empty and users were asked to not perform any movement. We recorded 72 trials per condition (288 in total) over 8 runs and varied the position of the objects so that every object was positioned equally often on each position. We recorded 61 active electrodes (g.tec, g.GAMMAsys) as well as data from a data glove (5DT) and a switch button to obtain the movement onset. We rejected artifact contaminated trials and channels using a statistical outlier rejection. We down-sampled the EEG to 16 Hz and applied a bandpass-filter between 0.3 and 3 Hz ($4^{th}$ order, Butterworth, zero-phase) to extract the low-frequency signal. Using 5 fold crossvalidation to avoid overfitting and a random forests classifier [3], we investigated all grasp versus grasp combinations. To score significantly higher than chance level ($p = 0.05$, Bonferroni corrected for multiple comparisons over trial time), the accuracy level had to be higher than 64.7 %. Table 1 displays the results.

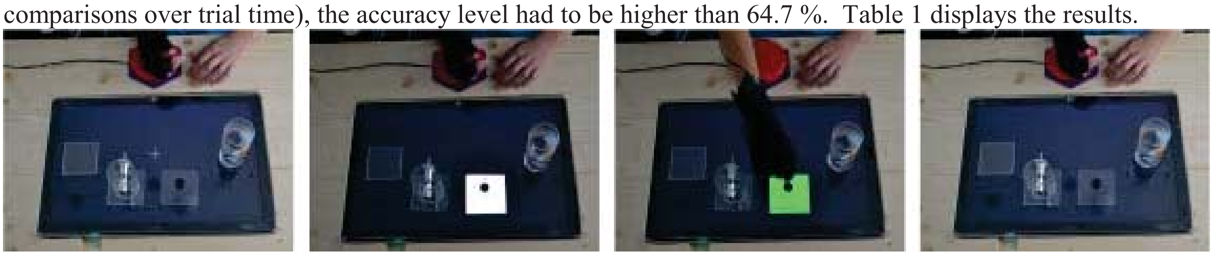

**Figure 1: Paradigm:** Participants were instructed to rest the hand comfortably on a pressure button. At second 0, a cross appeared on the screen to focus users' attention. At second 2, one of the objects was highlighted in white for a random time period. As soon as the highlighting turned green, participants performed the reach and grasp tasks and held the object as long as the green highlighting remained. Thereafter participants returned their hand to the pressure button.

| Grasp vs Grasp | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | S10 | S11 | S12 | S13 | S14 | S15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Pal vs Pin | 61.5 | **78.8** | 61.7 | **73.0** | **76.8** | **69.7** | **65.9** | **69.9** | **69.6** | 60.6 | **71.2** | **68.0** | **74.3** | 63.7 | **69.2** |
| Pal vs Key | **70.0** | **74.4** | 64.1 | **76.9** | 63.6 | **68.5** | 64.6 | 63.6 | **66.2** | **65.7** | **70.7** | **71.1** | **66.2** | **66.7** | **67.5** |
| Pin vs Key | 64.4 | **68.9** | 63.0 | **67.1** | **66.7** | 61.3 | **66.1** | 63.0 | **66.9** | 65.7 | **69.7** | **66.4** | 62.2 | **70.7** | **69.3** |

**Table 1:** Peak accuracies after movement onset over all trials in percent. (Pal = Palmar, Pin = Pincer, Key = Key Grasp). Bold values indicate performance levels significantly higher than chance.

*Discussion:* We could confirm that grasp versus grasp classification in the low-frequency time-domain is possible. Fourteen out of 15 participants scored significantly better than chance in at least one combination, whereas 8 participants' performance topped 70%. Peak performances occurred within the first one and a half seconds after movement onset, but different for each subject. We believe this is due to the varying movement speed towards the object. No significant predictions could be made before actual movement onset. So far these results only reflect motor execution of a grasping task – there is still need to investigate whether these results can be achieved with motor imagery. Furthermore it is still unknown whether user can be trained to boost classification to a robust level.

*Significance:* We could show that executed grasp versus grasp classification is possible. We believe that these findings will contribute to a more intuitive and natural form of control for neuroprostheses.

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