

The grasp detected: Time domain classification of grasp and hold tasks

Andreas Schwarz¹, Patrick Ofner¹, Joana Pereira¹, and Gernot R. Müller-Putz¹
andreas.schwarz@tugraz.at, gernot.mueller@tugraz.at

¹Institute for Neural Engineering, Graz University of Technology, Austria

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.

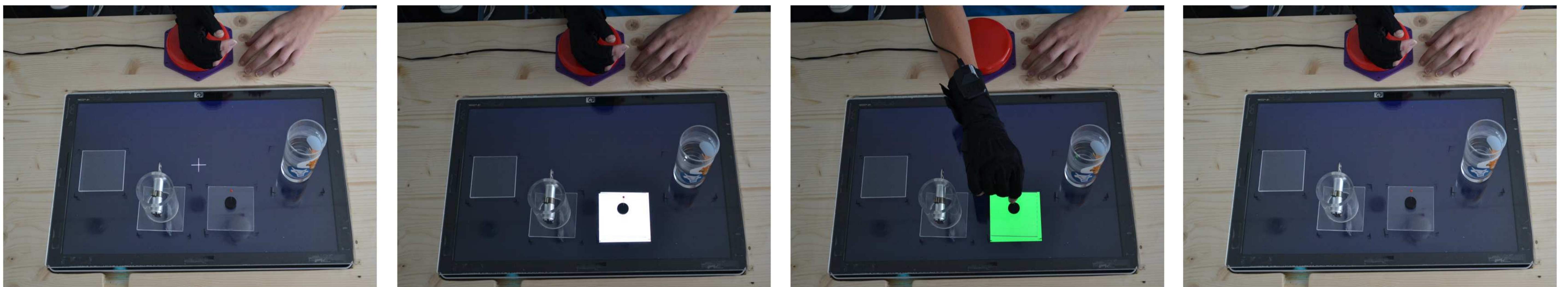


Figure 1: Paradigm: Participants were instructed to rest the hand comfortably on a pressure button. At second 0, a cross appeared on the screen to focus users' attention. At second 2, one of the objects was highlighted in white for a random time period (1-1.75s). As soon as the highlighting turned green, 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.

Methods

Methods: We down-sampled the EEG to 16 Hz and applied a bandpass-filter between 0.3 and 3 Hz (4th order, Butterworth, zero-phase) to extract the low-frequency signal. Using 10 times 5 fold cross-validation to avoid overfitting and a shrinkage LDA classifier, 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% (53.4 % for grand average over all subjects).

Participants: 15 healthy volunteers from age 23 to 37

Recording: EEG acquired from 61 active electrodes (g.Tec GammaSys), 3 active electrodes (g.Tec GammaSys for EOG), 18 channels from a data glove (5DT), pressure button to detect movement onset.

Experiment Setup: recorded 72 trials per condition (288 in total) over 8 runs. Positions of the objects varied after each run, so that every object was positioned equally often on each position.

Paradigm: 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.

Results

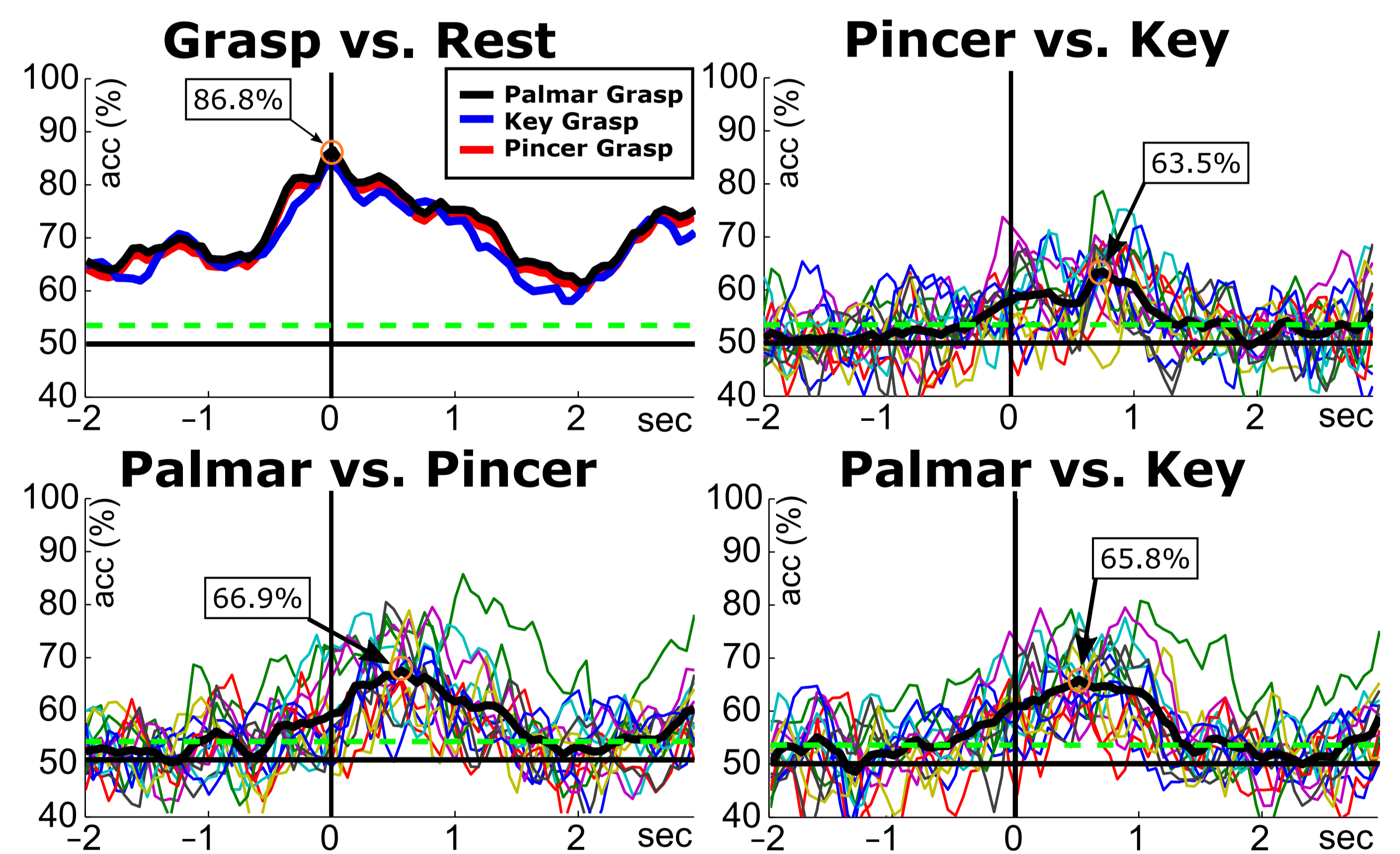


Figure 2: Classification results of grasp and hold tasks of all subjects: The top left plot shows the grand average of all investigated grasp types against the rest condition. The green dotted line displays the significance threshold. The black perpendicular line shows the point of movement onset. Plot top right and the underlying plots show the grasp versus grasp performances. The black bold curves show the the grand average over all subjects. Notice that the peak accuracies of every subject differ. This may be due to different execution speeds of the grasp for each subject.

Discussion

We could confirm that **grasp versus grasp classification** in the low-frequency time-domain **is possible**. All participants scored significantly better than chance in at least one combination. 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. 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.

References

1. Pfurtscheller G, Müller GR, Pfurtscheller J, Gerner HJ, Rupp R. "Thought"-control of functional electrical stimulation to restore handgrasp in a patient with tetraplegia. *Neuroscience Letters*, Vol.351 33-36, 2003.
2. Rupp R, Rohm M, Schneiders M, Kreiling A, Müller-Putz G.R. Functional Rehabilitation of the Paralyzed Upper Extremity after Spinal Cord Injury by Noninvasive Hybrid Neuroprostheses. *Proceedings of the IEEE* Vol.103(6) 954-968, Jun 2015. DOI: 10.1109/JPROC.2015.2395253

Acknowledgments

This work was supported by the Horizon 2020 Project MoreGrasp(No.643955) and the ERC Consolidator Grant "Feel your Reach". This paper only reflects the authors' views and funding agencies are not liable for any use that may be made of the information contained herein.