Decoding Movements of the Upper Limb from EEG

Patrick Ofner[1], Andreas Schwarz[1], Joana Pereira[1], Gernot R. Müller-Putz[1]
patrick.ofner@tugraz.at, gernot.mueller@tugraz.at
[1]*Institute of Neural Engineering, Graz University of Technology, Graz, Austria*

Introduction

A neuroprosthesis can restore movement functions of persons with spinal cord injury. It benefits from a brain-computer interface (BCI) with a high number of control classes. However, classical sensorimotor rhythm-based BCIs can often only provide less than 3 classes, and new types of BCIs need to be developed. We investigated whether **low-frequency time-domain signals** (i.e. movement-related cortical potentials [1]) can be used to **classify hand/arm movements of the same limb**. A BCI based on attempted movements may be used to control a neuroprosthesis more naturally and provide a higher number of control classes.

Paradigm

- 15 healthy subjects
- 6 classes: hand open/close, supination/pronation, and elbow extension/flexion (60 trials per class)
- 61 EEG channels + joint angles (for movement onset detection)

Figure 1: Left: Subjects executed movements using an Armeo Spring rehabilitation device (Hocoma, Switzerland). **Right:** These movements were classified.

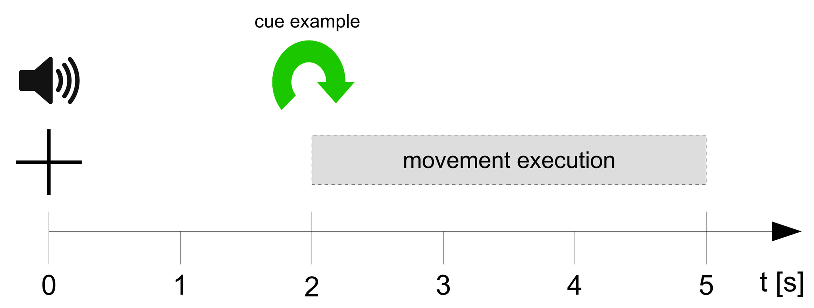

Figure 2: Sequence of a trial.

Methods

- Artefact removal
- **0.3 - 3 Hz** 4-th order zero-phase Butterworth filter
- Different EEG **time windows** were used as classifier input (0 to 1s)
- Shrinkage regularized linear discriminant analysis (**sLDA**) classifier
- 1-vs-1 classification strategy
- 10x10-fold cross-validation
- Calculation of **sLDA patterns** [2] and transformation to **source space** with sLORETA, see Figure 3

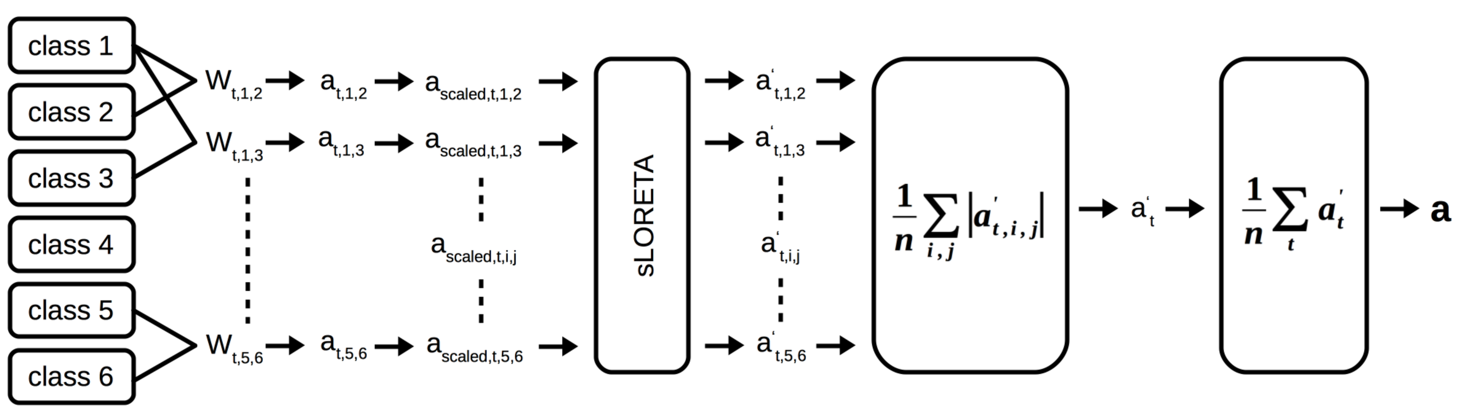

Figure 3: Patterns were calculated from each 1-vs-1 classifier; subsequently scaled and transformed into the source space; then we calculated the absolute value, and averaged over patterns and from -0.4 s to 0.4 s relative to movement onset.

Results

- Average classification accuracy: **maximum of 55 %** (9 % standard deviation) at **0.25 s** for the 1s time window, see Figure 4
- Significance level of the average classification accuracy: 18 %
- $\alpha = 0.05$, Bonferroni corrected wrt. the length of the presented time window
- **All subjects reached significant classification accuracies**
- The confusion matrix in Figure 4 indicates that movements involving the **same joints** (e.g. hand open vs hand close) are **less discriminable** than movements involving different joints (e.g. hand open vs arm extension)

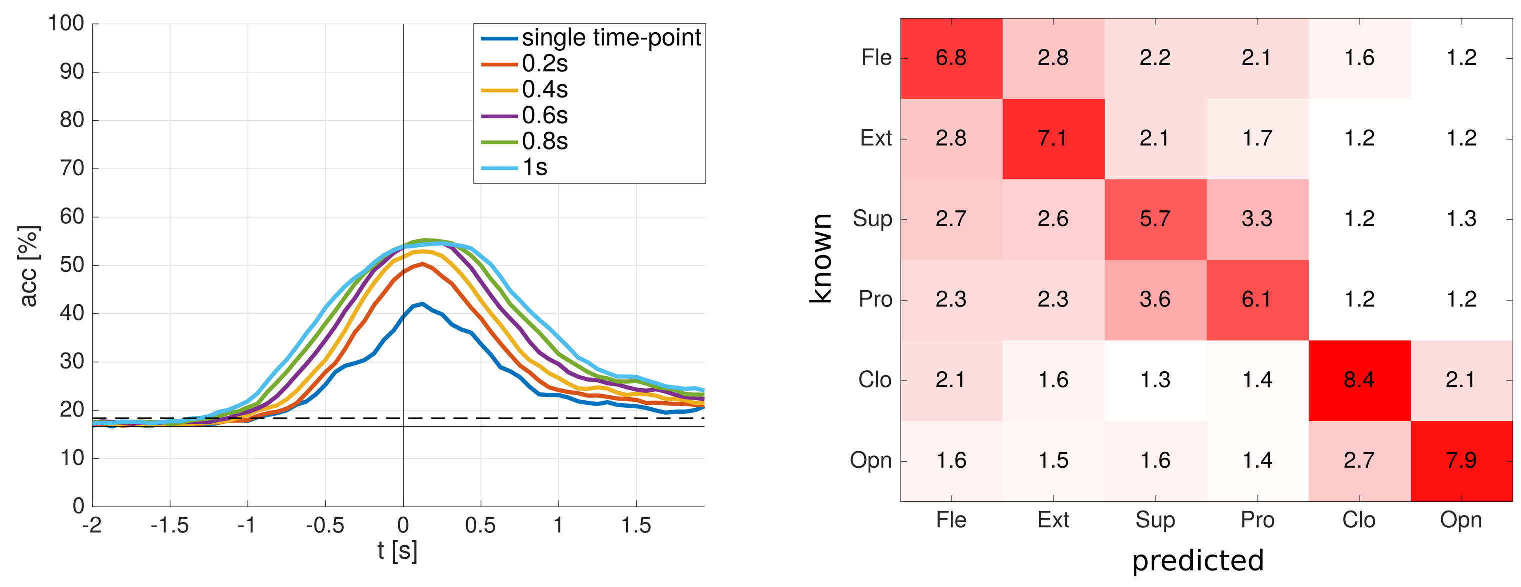

Figure 4: Left: Grand average classification accuracies (time locked to movement onset) for each time window. The solid line is the chance level; the dashed line is the significance level. **Right:** Confusion matrix with relative values.

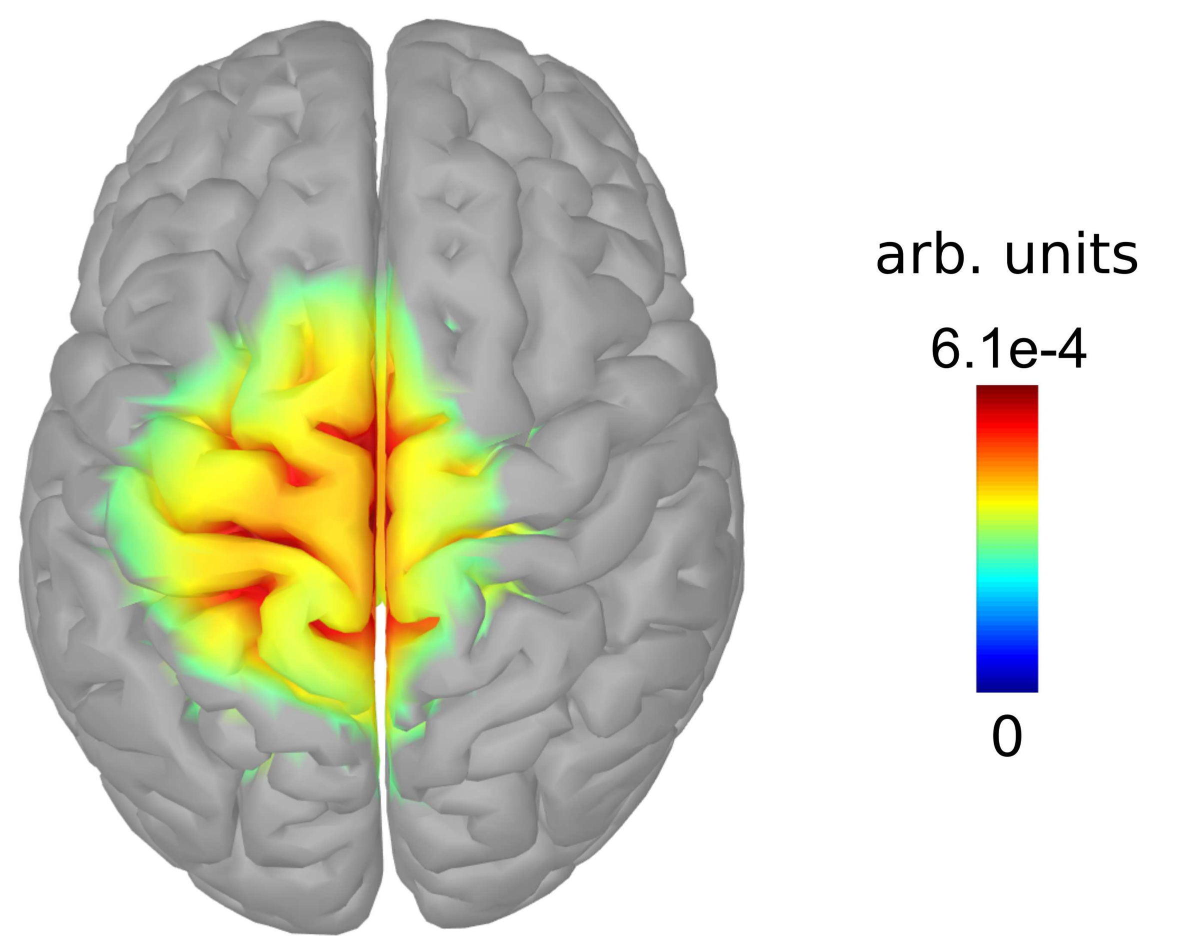

Figure 5: Classifier pattern averaged over all subjects. Only significant voxels are colored ($\alpha = 0.05$, nonparametric permutation testing).

Discussion

We have shown that low-frequency time domain signals can be used to **discriminate between different movements of the same upper limb**. Movement accuracies peak after the movement onset but reach significantly high classification accuracies before the movement onset. This shows that upcoming movements can be **classified from the movement planning phase**. This is crucial for a BCI applicable for end users with SCI who cannot execute all movements anymore. Furthermore, movements involving different joints are better disciminable than movements involving the same joints.

References

1. H Shibasaki, S Hiroshi, and H Mark, What is the Bereitschaftspotential? *Clin Neurophysiol*, 117(11), 2341-2356, 2006
2. X Liao, D Yao, D Wu, and C Li, Combining Spatial Filters for the Classification of Single-Trial EEG in a Finger Movement Task *IEEE Trans Biomed Eng*, 54(5), 821-831, 2007

Acknowledgments

This work is supported by the European ICT Programme Project H2020-643955 "MoreGrasp" and the ERC Consolidator Grant ERC-681231 "Feel Your Reach".