Classifying Speed and Force From Movement Intentions Using Entropy and a Support Vector Machine

M. Jochumsen[1], I. K. Niazi[1], D. Farina[2], K. Dremstrup[1]
[1]HST, Aalborg University, Denmark; [2]BCNN, University Medical Center Göttingen, Georg-August University, Göttingen, Germany

Correspondence: K. Dremstrup, Department of Health Science and Technology, Fredrik Bajers vej 7D, 9220 Aalborg Ø, Denamrk.
E-mail: kdn@hst.aau.dk

Abstract. In this work, we classified movement-related cortical potentials (MRCPs) associated with two levels of task force and speed with a linear and an optimized support vector machine (SVM). Features were extracted using Approximate Entropy (ApEn), Sample Entropy (SaEn) and Permutation Entropy (PeEn) calculated from the initial negative phase of the MRCP. Classification accuracies for the optimized SVM reached 68 ± 7% and 71 ± 10% (force and speed, respectively); with the linear SVM they reached 59 ± 8% and 64 ± 13%.

Keywords: Movement-related cortical potentials, movement intention, neuromodulation, task variability, entropy, support vector machine

1. Introduction

Brain-computer interfaces (BCIs) have been used as means for paralyzed patients to communicate or control an external device using brain signals. The combination of BCIs with sensory stimulation, such as electrical stimulation, could be used for neuromodulation in a rehabilitation setting for stroke patients. For this purpose, a protocol was proposed by Mrachacz-Kersting et al. [2012], where plasticity was induced when pairing the peak of maximum negativity of the MRCP from motor imagination with peripheral electrical stimulation. The protocol was implemented as an asynchronous BCI system by Niazi et al. [2012], where the movement intention (initial negative phase of the MRCP) was detected online with limited latency and triggered an electrical stimulator. To improve this intervention, afferent feedback from the electrical stimulation should match the movement intention and in this way close the motor control loop. In this scenario, it would also be possible to introduce task variability, which is important when relearning a motor skill [Krakauer, 2006]. To replicate various types of movements, it is necessary to decode the information about speed and force from the brain signals. Speed and force is encoded in the MRCPs [Nascimento et al., 2006] and different levels have been classified from single-trial EEG using optimized wavelets as features [Farina et al., 2007]. To improve the classification accuracies, the non-linear dynamic methods ApEn [Pincus, 1991], SaEn [Richman and Moorman, 2000] and PeEn [Bandt and Pompe, 2002] could potentially be applied as features. Entropy has previously been used as features in other BCI applications (e.g. [Wang et al., 2012]). In this work the possibility of using ApEn, SaEn and PeEn to discriminate between two levels of force and speed from the movement intention was explored.

2. Material and Methods

Six healthy subjects (two women and four men: 30 ± 6 years old) performed three types of cued isometric dorsi-flexions of the right ankle, which was fixed to a pedal with a force transducer. The maximum voluntary contraction (MVC) was determined at the start of each session followed by 50 repetitions of each cued movement type. The tasks were I) 0.5 s to reach 20% MVC, II) 0.5 s to reach 60% MVC and III) 3 s to reach 60% MVC. These were performed in three blocks. To assist the subjects in performing the movements with the correct speed and force, they were cued by a custom made program. Force was used as input to the system so the subjects were continuously provided with visual feedback on how well they matched their movements to the desired force profile. Ten channels of continuous monopolar EEG (sampled at 500 Hz) were recorded from FP1, F3, F4, Fz, C3, C4, Cz, P3, P4 and Pz, with the reference electrode on the right earlobe and ground electrode at nasion. The recordings were divided into epochs so data from the movement onset (determined from the force), and 3 s prior, was kept for further analysis. Epochs containing eye activity (125 µV in FP1) were rejected from further analysis (≈ 6 per task). The data was bandpass (0.05-10 Hz) and spatially (Large Laplacian) filtered. For discriminating between force (task I vs. task II) and speed (task II vs. task III) the ApEn, SaEn and PeEn were calculated for each epoch and used as features. The false-nearest neighbors' algorithm was used for determining the optimal embedding dimension (m = 2). The tolerance was 0.2x standard deviation and the time lag was 1. Each combination of features was classified using an SVM with a linear or with a non-linear decision boundary. A Gaussian kernel with an optimized kernel width and regularization parameter was used. The two optimization processes allowed maximization of the classification accuracy when applied to the training set. The optimized parameters were applied to the test set for evaluation of the classification accuracy. Classification accuracies [%] were obtained using 3-fold cross-validation.

3. Results

The results are presented in Table 1. The best performance for the linear SVM was obtained using SaEn as a feature when discriminating between the two levels of force (59 ± 8%) and ApEn for discriminating between the two levels of speed (64 ± 13%). For the optimized SVM the best performance was obtained when combining ApEn with PeEn for discriminating between the two levels of force (68 ± 7%) and ApEn with SaEn when discriminating between the two levels of speed (71 ± 10%). The highest classification accuracies were obtained with the optimized SVM.

Table 1. *Classification accuracies (mean ± standard deviation across all subjects) for each task pair using a linear and an optimized SVM for each set of features (left column). Fast 20 (% MVC) = Task I, Fast 60 = Task II and Slow 60 = Task III.*

Features	*Fast 20 vs. Fast 60 Linear SVM [%]*	*Fast 20 vs. Fast 60 Non-linear SVM [%]*	*Fast 60 vs. Slow 60 Linear SVM [%]*	*Fast 60 vs. Slow 60 Non-linear SVM [%]*
ApEn	59 ± 12	66 ± 8	64 ± 13	69 ± 11
PeEn	54 ± 9	64 ± 7	54 ± 11	65 ± 6
SaEn	59 ± 8	66 ± 9	59 ± 15	69 ± 11
ApEn+PeEn	57 ± 11	68 ± 7	62 ± 13	71 ± 11
ApEn+SaEn	55 ± 10	67 ± 9	61 ± 15	71 ± 10
PeEn+SaEn	56 ± 12	68 ± 8	59 ± 16	70 ± 11
ApEn+PeEn+SaEn	58 ±11	68 ± 8	62 ± 13	71 ± 11

4. Discussion

The classification accuracies that were found when using the different types of entropy indicate that entropy can be used for discriminating between the two levels of force and speed. However, the classification accuracies that were obtained are in general lower compared to preliminary results using four temporal features (76 ± 9% and 82 ± 10% for force and speed, respectively) and what has been found previously using optimized wavelets [Farina et al., 2007]. Therefore, it should be investigated further if the features, extracted from the non-linear dynamics methods could complement the four temporal features and optimized wavelets to improve the classification accuracies further.

References

Bandt C, Pompe B. Permutation Entropy: A Natural Complexity Measure for Time Series. *Phys Rev Lett*, 88(17), 2002.

Farina D, Nascimento OF, Lucas MF, Doncarli C. Optimization of Wavelets for Classification of Movement-Related Cortical Potentials Generated by Variation of Force-Related Parameters. *J Neurosci Meth*, 162(1–2):357-363, 2007.

Krakauer JW. Motor Learning: its relevance to stroke recovery and neurorehabilitation. *Curr Opin Neurol*, 19(1):84-90, 2006.

Wang L, Xu G, Yang S, Guo M, Yan W, Wang J. Motor Imagery BCI Research Based on Sample Entropy and SVM. In Proceedings of the Sixth International Conference on Electromagnetic Field Problems and Applications (ICEF), 2012.

Mrachacz-Kersting N, Kristensen SR, Niazi IK, Farina D. Precise Temporal Association between Cortical Potentials Evoked by Motor Imagination and Afference Induces Cortical Plasticity. *J Physiol*, 590(7):1669-1682, 2012.

Nascimento OF, Nielsen KD, Voigt M. Movement-Related Parameters Modulate Cortical Activity during Imaginary Isometric Plantar-Flexions. *Exp Brain Res*, 171(1):78-90, 2006.

Niazi IK, Mrachacz-Kersting N, Jiang N, Dremstrup K, Farina D. Peripheral Electrical Stimulation Triggered by Self-Pace Detection of Motor Intention Enhances Corticospinal Excitability. *IEEE Trans Neural Syst Rehabil Eng*, 20(4):595-604, 2012.

Pincus SM. Approximate Entropy as a Measure of System Complexity. *Proc Natl Acad Sci USA*, 88(6):2297-2301, 1991.

Richman JS, Moorman JR. Physiological Time-Series Analysis using Approximate Entropy and Sample Entropy. *Am J Physiol Heart Circul Physiol*, 278(6):H2039-H2049, 2000.