Runtime Calibration of Online EEG based Movement Prediction using EMG Signals

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Abstract: Prediction of voluntary movements from electroencephalographic (EEG) signals is widely used and investigated for applications like brain-computer interfaces (BCIs) or in the field of rehabilitation. Different combinations of signal processing and machine learning methods can be found in literature for solving this task. Machine learning algorithms suffer from small signal-to-noise ratios and non-stationarity of EEG signals. Due to the non-stationarity, prediction performance of a fixed classifier may degrade over time. This is because the shape of motor-related cortical potentials associated with movement prediction change over time and thus may no longer be well represented by the classifier. A solution is online calibration of the classifier. Therefore, we propose a novel approach in which movement onsets, detected by the analysis of electromyographic (EMG) signals are used to recalibrate the classifier during runtime. We conducted experiments with 8 subjects performing self-initiated, self-paced movements of the right arm. We investigated the differences of online calibration versus applying a fixed classifier. Further the effect of varying initial training instances ($\frac{1}{3}$ or $\frac{2}{3}$ of available data) was examined. In both cases we found a significant improvement in prediction performance ($p < 0.05$) when the online calibration was used.

1 INTRODUCTION

Online movement prediction based on single-trial EEG is becoming a popular tool in various fields of application. Examples are brain-computer interfaces (BCIs) or rehabilitation robotics (Ahmadian et al., 2013) (Ibáñez et al., 2011) (Niazi et al., 2011) (Kirchner et al., 2013).

However, the online prediction of voluntary movements from EEG signals is a challenging task. Usually different sophisticated signal processing and machine learning methods are used in the prediction process. These methods have to be calibrated with subject specific data that is acquired in a separate training session.

Unfortunately, motor-related cortical potentials (MRCPs) may change over time, due to exhaustion of the subject or by resistance changes or movements of EEG electrodes. A fixed classifier may struggle to detect movement intentions from ongoing EEG in case the activity in the movement preparation phase changes in comparison to data that was acquired in the initial training phase. Since movement prediction has to be performed on single-trial EEG data due to the strict time constraints, such changes are even more critical and may have a strong impact on the performance in movement prediction.

Furthermore, for optimizing the preprocessing and to train a classifier on the EEG signals, the start of movements needs to be labeled as accurately as possible. For this reason one may use devices containing microswitches, inertial sensors or motion tracking or video systems (Tabie and Kirchner, 2013)(Ibáñez et al., 2011). These devices can only be used in specific experimental setups or laboratory environments and require additional effort for their operation and maintenance.

Since these devices are only used to generate labels, one would like to eliminate any dependencies on them. Usually, for future applications, one would like to acquire these labels solely on physiological signals to be able to construct *simple* and *integrated* systems that can be operated without additional equipment.

An obvious approach is the usage of electromyographic (EMG) signals from muscles that are contributing to the movement, which is supposed to be predicted itself. Therefore, in this paper we propose an approach where only onsets found in EMG sig-

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nals, that are recorded from the right arm, are used to train and, during the application, recalibrate a classifier (Passive Aggressive 1) for predicting movements from the EEG.

We compare two different procedures: 1) the usage of a classifier that is only calibrated based on an initial training phase, which is kept fixed during the actual application, and 2) another one that is additionally adapted during the application, whenever an onset in the EMG is detected.

2 MATERIALS AND METHODS

2.1 Experimental Setup

Eight healthy right-handed male subjects (age 29.9 ± 3.3 years) participated in the study. The subjects were seated in a comfortable chair in front of a table. A monitor and two switches, a flat board and a buzzer, were located on the table. During the experiments both input devices were used to determine the begin or the end of a movement.

The subjects were asked to perform 40 voluntary self-paced movements of their right arm starting from the flat board to the buzzer and back. The events from the input devices (pressing/releasing) were marked in the recorded EMG and EEG data. For each subject three runs were recorded.

The experiments were designed and executed using Presentation (Neurobehavioral Systems, Inc.). During the experiments a green circle with a black fixation cross was shown on the monitor. A resting time of 5 s between two movements had to be maintained. A wrong movement was indicated to the subject by changing the color of the circle from green to red for 100 ms. Wrong movements were defined as moving before the resting time (5 s) was expired. Wrong movements were not taken into account for data analysis, compare Figure 1. In order to get the same amount of movements from each test person, a run was finished after 40 valid movements. To determine the physical begin of a movement a motion tracking system was used to track the position of the right hand. These labels were later used for performance evaluation.

2.2 Data Acquisition

The EEG data was acquired with a 128 electrode (extended 10-20-System) actiCAP system sampled at 5 kHz using four 32 channel BrainAmp DC amplifier (BrainProducts GmbH, Munich, Germany), filtered between 0.1 and 1000 Hz and stored. Four elec-

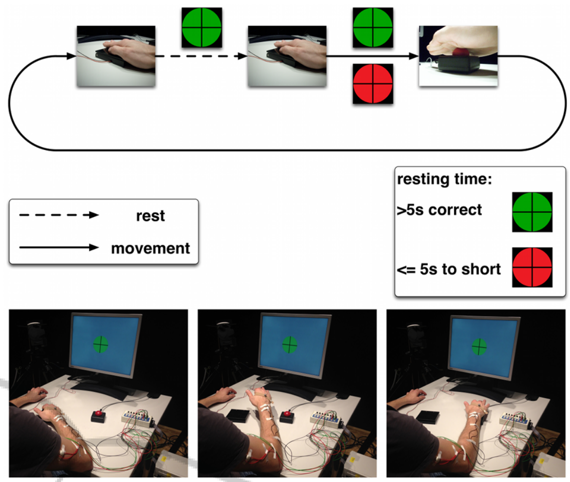

Figure 1: Illustration of the conducted experiments. At the top of the figure the paradigm is visualized. In the resting phase (dashed line) a fixation cross is displayed in a green circle. When the subject starts to move (solid line) it is evaluated, whether the minimal resting time of 5 s seconds was observed. Was this not the case, the circle around the fixation cross changes its color to red for 100 ms. At the bottom of the figure three pictures of the setup are given, showing from left to right, the resting phase, the movement phase and the end of the movement. After pressing the buzzer in the very right figure the subject moves back to the starting position and is again in the resting phase.

trodes (I1, OI1h, OI2h and I2) were used to measure the vertical and horizontal electrooculogram (EOG), these channels were discarded for further processing. EMG was recorded from four muscles of the right arm (M. brachioradialis, M. biceps brachii, M. triceps brachii and M. deltoideus) simultaneously with the EEG using a BrainAmp ExG MR bipolar amplifier. The EMGs and EEGs were stored together in one file.

In order to have ground truth data for physical movement onsets from subjects a motion tracking system was used to record movements of the testpersons' right hand. Three cameras of the type ProReflex 1000 (Qualisys AB, Gothenburg, Sweeden) were used. A passive infrared marker placed on the back of subjects' hand was tracked with a frequency of 500 Hz. For later synchronization a trigger was used to start and end a measurement, these events were also marked in the EEG/EMG files.

2.3 Data Processing

All described analyses were done offline, however the processing, especially the size and step in between processing windows, were chosen in a way that an online implementation is also possible with a standard PC.

2.3.1 EMG Processing

The processing of EMG-signals was originally designed to detect movement intentions. For preprocessing and simultaneous feature generation the variance of the signal was used. An adaptive threshold was used to detect movement onsets based on EMG analysis, this was done separately for each of the four channels and additionally on a virtual channel derived as the mean of all channels. The variance filter is defined as,

$$v(t) = \frac{1}{N-1}\sum_{i=0}^{N} x^2(t-i) - \left(\frac{1}{N-1}\sum_{i=0}^{N} x(t-i)\right)^2, \quad (1)$$

with, N the length of the window used for filtering and x the raw EMG signal. The adaptive threshold is given as,

$$T(t) = \mu(t)_N + p\sigma(t)_N, \quad (2)$$

with μ the mean value, σ the standard deviation, N the length of the window for the mean and standard deviation and p the sensitivity factor of the threshold. The parameter for the variance and the adaptive threshold as well as the best EMG channel were optimized for each subject using a grid search. For further details please refer to (Tabie and Kirchner, 2013).

Each found onset in the EMG signals was later used for training and online calibration of the classifier that was applied for EEG based movement prediction. Since classification of movement intentions from EMG signals does not work perfectly, a few of the found onsets are false positive detections (not related to movements) and some movements were not predicted by EMG analysis.

2.3.2 EEG Processing

124 EEG channels were used for data analysis, as mentioned before 4 channels were used for EOG measurements and therefore discarded from the processing. In the processing MRCPs are separated from ongoing EEG signals, i.e. the classifier training and online calibration is designed to detect the lateralized readiness potential (LRP). The LRP is a MRCP related to movement planing which can be detected directly before the movement onset and is hard to abort (Blankertz et al., 2006).

For data analysis we used the pySPACE software framework (Signal Processing And Classification Environment) (Krell et al., 2013).

The processing flow was performed as follows:

Windowing. All data processing was performed on windows of data of the same length, i.e., 1 s of duration. Predictions were performed every 0.05 s, so adjacent windows overlapped by 0.95 s.

For training and online calibration, windows were cut in a range from -4 s to -1 s (examples for no movement class) and from -1.05 s to 0 s (examples for movement class) in front of each found EMG onset, i.e. $[-5,-4],[-4.95,-3.95],\ldots,[-2,-1]$ s (no movement class) and $[-1.05,0.05],[-1,0]$ s (movement class).

We only used two windows for the movement class and skipped the range from $[-1.95,-0.95]$ to $[-1.1,-0.1]$ s, since we assume that these windows contribute most to the LRP which the classifier shall detect (Straube et al., 2013)(Seeland et al., 2013).

For testing windows were cut in a range from -4 s to 0 s in front of the markers generated from the motion tracking system, where windows from -4 s to -1 s account for the no movement class and the remaining for the movement class.

All windows were processed independently from each other.

Preprocessing and Feature Generation. The data was preprocessed in several steps. First, all windows were standardized channel-wise with the z-score transformation (zero mean and standard deviation one), i.e., the mean value of the window was subtracted and the result was divided by the standard deviation. Next, the data was decimated to reduce the sampling rate from 5000 Hz to 20 Hz together with an anti-alias finite impulse response filter. The resulting window was further filtered from 0.1 to 4.0 Hz. Afterwards, the windows were reduced to the last 200 ms since the latest relevant information for an evolving MRCP is expected in this time range. For further data reduction the xDAWN spatial filter (Rivet et al., 2009) was applied to reduce the number of remaining channels to four. Data from the remaining channels were merged to one feature vector and, again the z-score transformation was applied.

Classification and Movement Probability Estimation. We used the Passive Aggressive Perceptron variant 1 (PA-1) (Crammer et al., 2006) for classification. Training and testing was done individually for each subject with a cross-validation over runs. For training either each run was used and the classification was done on the two remaining sets (1vs2) or the data from two runs were concatenated for training and testing was performed on the remaining run (2vs1).

2.4 Online Calibration of the Classifier

We used supervised online calibration of the classifier to adapt the classifier. The classifier was first pre-trained on a training data set. During the application phase, the data $\{\mathbf{x}_1, \mathbf{x}_2, \dots\}, \mathbf{x}_t \in \mathbb{R}^n$ arrives one at a time. At time t, the classifier makes a prediction p_t. Afterwards, the true label $y_t \in \{-1, 1\}$, i.e. whether a movement was performed or not is inferred based on the EMG. Based on this label, the classifier suffers a loss ℓ that can be used to update the classifier to improve its performance in future predictions. Over the whole run, the classifier tries to minimize a specific loss function, in the case of the PA-1 this is the hinge loss $\ell_h(p_t, y_t) = \max\{0, 1 - y_t p_t\}$.

3 RESULTS

The classification results are summarized in Table 1. Statistical analysis with separated t-tests for training on 1 or on 2 datasets showed that in both cases adaptivity leads to significantly higher classification performances ($p < 0.001$ and $p < 0.05$ for 1vs2 and 2vs1, respectively). This effect is bigger for less training data (1vs2), there the increase is 0.1 in comparison to 0.07 in case of more training data (2vs1).

Further, another effect can be seen when the subjects are grouped according to the achieved performance in the non-adaptive classification case. Let the two groups be *i*) worse and *ii*) better, the discrimination can be made based on subjects mean performance compared to the mean performance of all subjects. Subjects with a lower performance belong to group *i*) and subjects with higher performance accordingly to the group *ii*). Considering this, subjects 2,3,4 and 7 belong to group *i*) and the remaining subjects to group *ii*), this is true for both training cases. When comparing the mean improvements of these two groups it can be seen, that for both training cases the group *i*) has the higher benefit: 1vs2: *i*) 0.12 and *ii*) 0.08; 2vs1: *i*) 0.11 and *ii*) 0.04. Therefore, it seems that adaptivity is even more advantageous when the non-adaptive classifier tends to be worse.

Table 1: Movement prediction performance in balanced accuracy (BA) for 1vs2 training left and 2vs1 right, both for non-adaptive (N_A) and adaptive (A) testing. For each Subject (Sub) the mean BA for N_A and A as well as the difference ($A - N\_A$) is given.

	Training 1vs2			Training 2vs1		
Sub	N_A	A	D	N_A	A	D
1	0.84	0.94	0.09	0.88	0.95	0.07
2	0.72	0.89	0.17	0.77	0.89	0.12
3	0.79	0.92	0.13	0.82	0.91	0.09
4	0.81	0.91	0.1	0.81	0.91	0.10
5	0.89	0.95	0.06	0.94	0.96	0.02
6	0.82	0.93	0.11	0.86	0.92	0.06
7	0.75	0.82	0.07	0.73	0.86	0.13
8	0.91	0.96	0.05	0.92	0.92	0.00
Mean	0.82	0.91	0.1	0.84	0.91	0.07

4 DISCUSSION AND CONCLUSIONS

In this paper we investigated the impact of online calibration on the prediction accuracy for online movement prediction based on single trial EEG data. We showed that training and online calibration of the classifier is possible solely on physiological signals, i.e., by labeling the data for training and calibration based on onsets found in EMG signals. We used a motion tracking system as a ground truth in the evaluation procedures.

Our results show that 1) if the initial training is based on the EMG onsets a sufficiently high prediction accuracy can be achieved, and 2) if an additional online calibration of the classifier is performed in the application phase, the prediction accuracy can be significantly improved.

The high prediction results were achieved even though a certain amount of label noise was introduced due to false movement detections in EMG signals.

In future, we want to improve the EMG onset detection to minimize the label noise and therefore, hopefully, improve the prediction accuracy further.

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