Online Movement Prediction in a Robotic Application Scenario*

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***Abstract*— Current movement prediction systems based on electroencephalography were mainly developed and evaluated in highly controlled scenarios, in which subjects concentrate only on the desired task with as few as possible disturbing sources present. However, it has not been addressed sufficiently how the suggested methods perform in more complex and uncontrolled environments. In this work we predict arm movements online in a robotic teleoperation scenario and present a completely online running methodology. The system is evaluated on ten sessions from three subjects. Evaluation criteria are the overall classification performance and the success in predicting an upcoming movement in the application. Our results confirm that it is possible to predict movements in less restricted applications motivating the transfer of these methods to real world applications.**

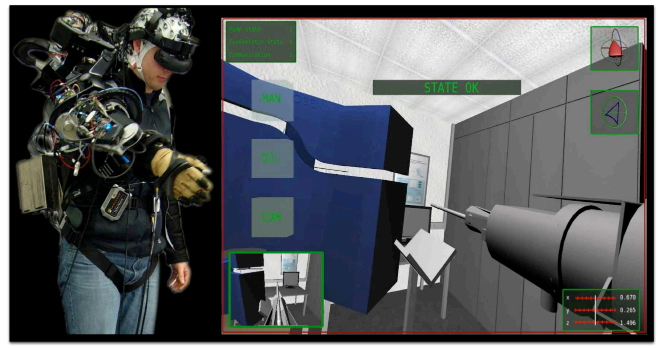

Fig. 1. Experimental setup. Left – operator equipped with exoskeleton, HMD and EEG cap. Right – operator's view.

I. INTRODUCTION

The possibility to know in advance if and when the body will move has inspired the development and design of novel devices, e.g., supporting humans during rehabilitation [1]–[4], or enabling fluent interaction with machines [5]. Since a prediction here is the inference of a future event from present data, it is in itself a challenging task and the prediction system has to come up with an online capable signal processing scheme that is fast enough to perform continuous classification. The movement prediction can be realized from measurements of brain activity such as the electroencephalogram (EEG) where signals are evaluated that mostly reflect preparatory processes before a movement. In the EEG mainly two different signal types which are both strictly time-locked to the movement have been applied for such a prediction: a) event-related potentials contain several pre-movement components denoted as movement-related cortical potentials (MRCPs) including the early and late readiness potential and the motor potential [6], [7]; b) frequency components termed event-related desynchronization (ERD) [8].Both signal types have been used successfully, e.g., to set up brain computer interfaces (BCIs) (see [1] for an overview).

While the feasibility of movement prediction using these signals in the EEG has been demonstrated in rather controlled scenarios [3], [9] that have only been partly conducted online [2], [10], it remains to be shown how the suggested methods perform embedded in a real application where the human can act freely within the limits set by the application itself. In the rather controlled scenarios, users are often instructed to avoid eye blinks, swallowing and other movements not belonging to the task (see, e.g., [9], [10]), since these increase noise and thus hinder successful detection of the relevant signal. In addition, experiments are usually conducted with the user in *one* comfortable position and reduced only to the desired task, e.g. in [2], [3]. For a final application this is usually unrealistic. Subjects would want to blink, swallow or change their position, or in other ways act unrestricted with respect to the application.

Here, we follow a different approach by predicting movements in a more unrestricted scenario to make a step towards a real world application. Instead of reducing as many external influences as possible, the subjects in the reported scenario perform a demanding teleoperation task, are free-standing, can move their head and body relatively freely, and are not restricted in blinking, swallowing or moving their eyes. Still, we demonstrate successful online prediction of upcoming movements, presenting two evaluation schemes characterizing the classifier performance and its effective output for the application.

II. APPLICATION: TELEOPERATION WITH AN EXOSKELETON

Teleoperation of a robotic system can be quite complex and requires even for simple tasks a notable amount of training and concentration. In the application scenario, which has been extensively described elsewhere [5], [11], [12], an exoskeleton is used as an intuitive command interface.

During exoskeleton control the operator might want to stay in position (see Fig. 1 left) but not to actively hold

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the arm in position all the time. In this case it would be comfortable if the exoskeleton compensates the arm weight of the operator. While the transition from teleoperation mode to such a weight-compensation mode can be triggered without any effort on the operators part, e.g., by a certain time the operator is not moving the exoskeleton, the transition back to teleoperation mode requires action of the operator. For example, a certain pressure against the force sensors integrated in the exoskeleton over a certain time can be a trigger to switch back to teleoperation mode. However, this is perceived by the operator as resistance to his intention to move. To make the transition more intuitive and smoother, we use information from the movement prediction to reduce the time the operator has to press against the exoskeleton's sensors. For the prediction, the EEG data of the operator is continuously analyzed with the here presented movement prediction system. Further details on the scenario and the integration of movement prediction can be found in [5], [12].

To summarize, the experimental setup was as follows: Participants were wearing an exoskeleton in order to teleoperate a robotic manipulator arm (Fig. 1). They had two main tasks: a) to steer the end-effector of the robotic arm through a labyrinth and b) to perform movements out of a rest position in which the exoskeleton carried the participant's arm weight. During both tasks participants had to respond to warnings from the operator monitoring system.

In addition to the exoskeleton, participants were equipped with a head mounted display (HMD) on which the teleoperation site (including surroundings, labyrinth and robot) could be seen. Information from the control system, a camera picture of the real scene and tools like a gyroscope depicting the orientation of the end-effector were at any time in the operators field of view. Head and hand movements of the operator were tracked (InterSense, Billerica, USA) and used to update the HMD as well as to generate event markers for supervised machine learning.

III. DATA AND METHODS

A. Description of Empirical Data

Three male subjects (age 27.33 ± 2.52) participated in the experiments. A total of ten sessions were recorded. The movement prediction system was active in four out of the ten sessions (online sessions) and inactive in the other sessions (pseudo-online sessions). Pseudo-online sessions were afterwards evaluated in an online fashion, i.e., the data of all sessions were treated the same way.

A 64-channel actiCap system and two amplifiers (both from Brainproducts, Munich, Germany) were used to acquire the EEG data with 5 kHz sampling rate. Since both, EEG cap and HMD were mounted on the head (see Fig. 1 left) four electrodes (FC5, FC6, FT7, FT8) of the extended 10-20 system were omitted. Together with the EEG stream the occurrence of events was stored, of which two were relevant for the analysis: a) transition change from teleoperation mode to weight-compensation mode (lock-in event), b) arm movement of 5 cm out of a rest position in one direction based on the hand tracking data (movement event). Since event b) was on average 0.25 s after the actual movement onset (determined by average ERP analysis), we corrected every movement marker by subtracting 0.25 s.

Pseudo-online sessions consisted of three, and online sessions of four runs, each containing 24 ± 8 movements (mean and standard deviation). Between two runs there was a short break of 2-3 min, except before the last run in the online sessions where the movement prediction system had to be trained and thus the break lasted around 10 min. The last run of each session was used for evaluation, in particular *every* time period from lock-in to movement onset. The training data consisted only of valid movements from the remaining runs. At least 5 s of rest preceded each valid movement.

B. Processing methods

We used our software pySPACE (Signal Processing And Classification Environment)[1] for online and pseudo-online data analysis. The overall processing time of a window (preprocessing and classification) took ≈ 25 ms. The used processing system is structured as follows:

1) Windowing: All subsequent processing was performed on equally-shaped windows of data with 1 s of duration, which were overlapping by 0.95 s to generate time slices of 0.05 s distance in time. All windows were processed independently from each other.

2) Preprocessing and feature generation: The data was preprocessed in several steps. First, the data were standardized channel-wise, i.e., the mean signal value of the channel was subtracted and the result divided by the standard deviation of the channel in the corresponding signal window. Next, a decimation with an anti-alias finite impulse response filter was performed to reduce the sampling rate of the data from 5000 Hz to 20 Hz. These operations were parallelized channel-wise using OpenMP [13] to achieve the required performance for online usage of the system. This was followed by another band pass filter with pass band from 0.1 to 4.0 Hz. Subsequently, the window was reduced to the most recent 200 ms since the latest relevant information for an evolving MRCP is expected in this time range. The number of channels of the remaining data is reduced to four retained channels by applying the xDAWN spatial filter [14]. The remaining four samples per channel of this preprocessed data are combined to a feature vector, which is standardized by subtraction of the mean and division by the standard deviation for each feature separately.

3) Classification and movement probability estimation: We used a support vector machine (SVM) with a linear kernel for classification. For integration into the exoskeleton control, we used the predicted score instead of the binary label prediction as a measure of *confidence* of the prediction. This is mapped to a probability estimation by fitting a sigmoid curve on the training data scores [15] using Newton's method with backtracking [16].

[1] publication planned in July at http://pyspace.github.com/pyspace

4) Training and parameter optimization: Since the extracted data instances are highly unbalanced with respect to the class, and labeling of instances in the transition area between *no movement preparation* and *movement preparation* is ambiguous, not all time slices were used for training. Instead, two time windows around the movement onset (ending at $-0.15\,\mathrm{s}$ and $0.05\,\mathrm{s}$ relative to movement onset) and non-overlapping windows during lock-in at least $2\,\mathrm{s}$ prior to movement onset were used for the *movement preparation* and *no movement preparation* class, respectively.

To optimize the complexity parameter of the SVM, a grid search (tested values: $10^{-6}, 10^{-5}, \ldots, 10^{0}$) and an internal 5-fold cross validation were used, where the validation data contained all time slices from -3.75 to $0\,\mathrm{s}$ with the training data as described above.

C. Evaluation procedures

We evaluated the data in two different aspects: classifier performance and success in the later application.

1) Classifier evaluation: Performance evaluation of the classifier simply shows the ability to distinguish between the two classes. For such an evaluation we essentially need the true class labels. Since we are in a situation of prediction, we cannot externally mark the onset of the MRCP.

To compensate for this and generate true labels, we propose the following approach: The true class label function f for movement prediction is defined as a step function

$$f(x(t)) = \begin{cases} S^{noMP} & \text{if } t < c \\ S^{MP} & \text{if } t \geq c \end{cases}, \quad t \leq 0. \tag{1}$$

Input of f is any data window $x(t)$ that has been extracted at time t relative to the upcoming movement onset at $t = 0$. The binary output of f corresponds to the true brain states[2] *no movement preparation* (S^{noMP}) and *movement preparation* (S^{MP}) and depends on the label change point c. Specifying c means defining when exactly movement preparation starts. Since stability of classifier predictions, i.e., being most similar to f irrespective of c, was more important in our application than a constant time lag to the actual movement onset, we did not fix c a priori to a specific value but limited c to be in a feasible range ($-1\,\mathrm{s} \leq c \leq -0.05\,\mathrm{s}$). Within this range c was determined for every movement by going back in time from the actual movement onset until the first stable prediction was found. Here, we defined *stable prediction* as the first *movement* prediction after the last three consecutive classifications of *no movement*.

Since the class ratio in the data is highly imbalanced, the usage of the accuracy as classification metric is inappropriate. Instead, the Balanced Accuracy (BA) is used for the evaluation, which is based on the True Positive Rate (TPR) and True Negative Rate (TNR) and therefore rather insensitive to imbalanced class ratios. The BA is given by:

$$\mathrm{BA} = 0.5 \cdot \mathrm{TPR} + 0.5 \cdot \mathrm{TNR}. \tag{2}$$

[2]For more information on formalism of biosignal integration the interested reader is referred to [12].

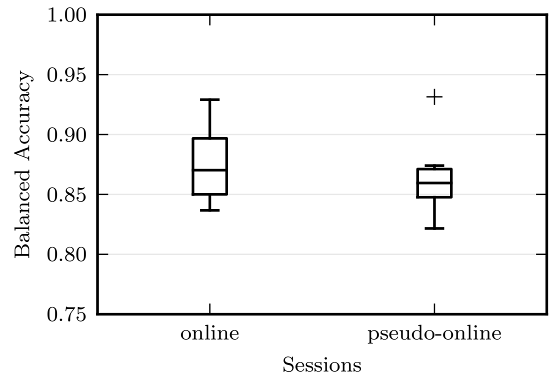

Fig. 2. Classification performance in terms of balanced accuracy across pseudo-online and online sessions.

2) Application oriented evaluation: In the application not every classifier prediction may be of relevance. Instead it is more important that the event, i.e., the movement, is correctly predicted. Therefore, the TPR and the number and duration of false positives (FPs) characterize the system's performance. However, the application itself may tolerate misclassifications [5], so that a particular benefit or drawback can only be evaluated with respect to the integration.

IV. RESULTS AND DISCUSSION

A. Classifier evaluation

Fig. 2 shows the distribution of classification performances obtained for online and pseudo-online sessions. Performance during online sessions was roughly as good as performance of pseudo-online sessions (0.88 ± 0.04 and 0.87 ± 0.03, respectively). The similar results indicate that pseudo-online data analysis confirm online performance.

The high performance obtained is also a result of the relatively loose restrictions on the label change point c, which could be as late as $-0.05\,\mathrm{s}$. Indeed, this interval limit was chosen for c on average in 41% of the movements for both session types. For the remaining movements c was on average $-0.3\,\mathrm{s}$.

B. Application oriented evaluation

In Table I different metrics that characterize the systems performance during application are summarized. Again, metric values for online and pseudo-online sessions were similar.

TABLE I

APPLICATION ORIENTED METRICS FOR ONLINE AND PSEUDO-ONLINE SESSIONS IN TERMS OF TP AND FP CHARACTERISTICS.

		Sessions	
		online	pseudo-online
TPR (%) at	$-0.00\,\mathrm{s}$	72.01 ± 6.02	72.09 ± 10.78
	$-0.05\,\mathrm{s}$	65.35 ± 10.40	65.30 ± 11.84
	$-0.10\,\mathrm{s}$	56.51 ± 13.13	54.88 ± 14.85
FPR (%)		10.23 ± 3.89	10.08 ± 2.30
time between 2 FPs (s)		1.16 ± 0.35	1.50 ± 0.37
FP duration (s)		0.15 ± 0.03	0.17 ± 0.05

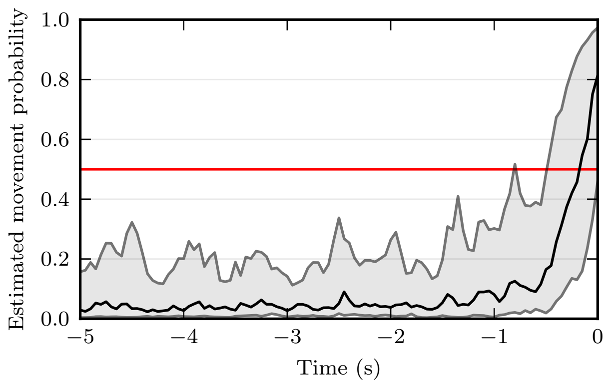

Fig. 3. Estimated movement probability over time t depicted as median (solid line) and 25/75 %-quantiles (shaded area) for all movements of the online sessions ($n = 80$). The probability estimation crosses 0.5 (red horizontal line, classification threshold) around -0.17 s and has its maximum 0.81 at $t = 0$.

On average approximately two out of three movements were predicted just before movement onset (time point -0.05 s). However, when all predictions within the interval $[-1$ s, -0.05 s$]$ were considered on average 89.05 % of the movements could be predicted. This indicates that although TPR at a specific time point might be low, it can be adjusted according to the application requirements by using more than one prediction outcome.

The median movement probability time course for all movements of the online sessions is depicted in Fig. 3. At time point -0.05 s the median estimated movement probability was 0.75. In light of our previous results [5], where we showed that a simulated probability of 0.75 has a significant effect on the contributed interaction force of the operator on the exoskeleton, the data here confirm that the comfort of the system can be improved by movement prediction based on EEG single trials.

During online sessions on average every 1.16 s FPs of 0.15 s duration occurred (see Table I). None of these FPs led to an unwanted lock-out, since the release mechanism was backed up by a force threshold (see Sec. II and [5]).

V. CONCLUSION

With the presented study we illustrate that it is indeed possible to use online movement prediction from EEG data within an application that has much fewer limitations than classical paradigms. Within the teleoperation task, subjects can, e.g., blink, swallow and change their position. Moreover, they have to execute more than one task in this scenario, and even when in resting position they additionally have to monitor warnings of the system. Still, we can record and classify EEG data and use it to make predictions of upcoming movements. When the movement is predicted successfully, robotic systems as the one used here, can use this information for improvements, such as a more intuitive man-machine interaction. In case of prediction errors, which occur and are always possible, the system is just unmodified *as is* and will in the worst case not facilitate execution of the user's movement. Performance evaluations of the movement predictions show that our TPRs are slightly lower than what has been reported in existing more controlled scenarios, which is presumably attributed to higher noise levels in the data due to a less controlled environment. It will be part of future work to handle these noise levels by a more elaborated signal processing. To this end, presented results are encouraging to transfer movement prediction systems as the one illustrated here to even more challenging real world applications.

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