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ONLINE DETECTION OF HAND OPEN VS PALMAR GRASP ATTEMPTS IN A PERSON WITH SPINAL CORD INJURY

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ABSTRACT: In a case study with a person with high cervical spinal cord injury, we show a first proof-of-concept on how to detect and classify different movement attempts of the same upper limb. The lesion was complete (AIS A) at level C4 and no hand function was preserved. We detected in a self-paced online setup hand open and palmar grasp with an accuracy of 68.4 % (chance level 50%).

INTRODUCTION

A brain-computer interface (BCI) can detect various intentionally modulated brain signals and use them as a control signal or as a communication channel [15]. Persons with cervical spinal cord injury (SCI) may profit from a BCI combined with functional electrical stimulation (FES) [26], a so called motor neuroprosthesis. The BCI detects the user's movement intention, and transforms the movement intention into a real movement via FES. It is a technical bypass of the lesion in the spinal cord. So far, several attempts have been shown to restore grasp function in persons with SCI using a BCI with FES [16, 22, 24]. Non-invasive BCI/FES neuroprostheses often exploit modulations of brain oscillations in the mu or beta band accompanying movement imaginations (MIs) [21]. However, these BCIs have also a downside. Despite using brain signals to control motor functions, the mental strategy used to modulate the brain signals is often not similar to the intended movement. For example, [16, 20, 22] used a repetitive foot MI or contralateral hand MI to control the hand. Furthermore, details how the MI is performed are hardly accessible in EEG brain oscillations. EEG brain oscillations rather allow to detect the state of performing repetitive MI, i.e. *that* one moves the limb but not *how* it is moved [1]. However, there is evidence that source imaging can be used to classify more complex MI [6].

Instead of brain oscillations, we exploit another brain signal called movement related cortical potentials (MRCPs) [28]. MRCPs were shown to encode, e.g. force [10] or reaching directions/targets [7, 13, 29], and were furthermore used to detect movements [18]. MRCPs could provide a non-invasive control signal which allows for a more natural neuroprosthesis control compared to EEG brain oscillations. A BCI based on MRCPs could detect movement attempts in persons with SCI like hand open, palmar grasp, pronation, supination, etc., and use these detections for neuroprosthesis control. In that context, we have shown that single movements of the same upper limb as well as grasps can be classified from MRCPs in healthy persons [19, 27]. However, a classification of self-paced attempted movements in the ongoing EEG of a person with SCI is lacking. We therefore propose in this work an MRCPs-based asynchronous online classifier, and show a proof-of-concept (without FES) of detecting hand open and palmar grasp in a person with SCI.

Table 1: ISNCSCI motor scores of the right upper limb

motor key muscles		score
elbow flexors	C5	4
wrist extensors	C6	1
elbow extensors	C7	0
finger flexors	C8	0
finger abductors	T1	0

MATERIALS AND METHODS

Participant: We recruited a right-handed male participant of age 55 with a chronic cervical SCI. The SCI has been sustained 6 years ago with a neurological level of injury of C4 and AIS A classification, i.e. complete SCI. No hand function is preserved, see Table 1 for ISNCSCI motor scores. Written informed consent was obtained.

Paradigm: We measured two sessions with the participant. He sat in his wheelchair in front of a computer screen and carried out instructions given on the computer screen. A *training paradigm* and a *test paradigm* were used to evaluate the asynchronous online classifier.

The training paradigm comprised of two types of trials: movement and rest. Movement trials were used to record hand open and palmar grasp. A movement trial started with a beep and a class cue which indicated either hand open or palmar grasp, see Figure 1. At second 2, the ready cue appeared and replaced the class cue. The ready cue was a green circle with a smaller inner white circle. 0.5 s to 1 s after the appearance of the ready cue, the green circle started to shrink within 2 s to 4 s to the size of the inner white circle. We instructed the participant to attempt the movement when the outer circle hit the inner circle. We refer to this moment as go cue. In session 1, we instructed the participant to attempt to open or grasp, and deliberately hold the position until the end

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of the trial, i.e. attempt a sustained movement. In session 2, we gave the instruction not to hold the position, but to make a short single movement attempt. Two seconds after the go cue, the trial ended and the screen turned black. During the movement trials, a cross was shown in the middle of the screen to fixate the gaze. Trials were spaced by a 2 s to 3 s time interval. In rest trials, a cross was shown for 70 s, and we instructed the participant to avoid any movement during this period. We recorded 5 movement runs and 4 rest runs. A movement run comprised of 30 movement trials, and a rest run comprised of 1 rest trial. In total we recorded 150 movement trials (75 trials per movement class) and 4 rest trials. We epoched then the 70 s long rest trials at random positions so that we had 150 rest trials.
The test paradigm is shown in Figure 2. The class cue (hand open, palmar grasp, rest), a beep, and a fixation cross were presented at the trial start. After 5 s, the class cue disappeared and only the fixation cross remained on the screen for 60 s. We instructed the participant to attempt several self-paced movements of the respective class during this 60 s period, or avoid any movement if it was a rest class. The participant was instructed to wait at least 5 s between movement attempts, and to report every movement attempt 2 s later by a soft speech sound. However, due to a misunderstanding, the participant reported movement attempts immediately afterwards in session 1 (but not session 2). When the participant reported a movement attempt, the experimenter pressed a button on the computer to log the time point of the movement event. The online classifier was constantly active and showed the respective movement icon (i.e. hand open or palmar grasp) for 2s whenever a movement attempt was detected. Thus, it was a closed-loop classification as feedback was provided. We recorded 6 runs in session 1 and 5 runs in session 2. Each run comprised of 4 movement trials and 1 rest trial.

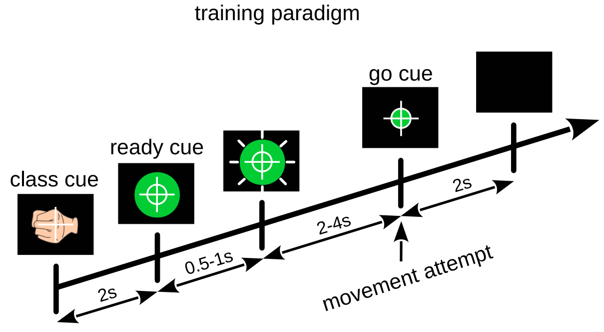

Figure 1: Training paradigm. A green filled circle shrunk at random speed. The participant attempted a hand open movement or palmar grasp when the green circle hit the inner white circle (the go cue).

Recording: We measured EEG with 61 electrodes covering frontal, central, parietal, and temporal areas. Reference was placed on the left earlobe and ground on AFF2h. Signals were sampled with 256 Hz with four 16-channel biosignal amplifiers and an active electrode system (g.tec

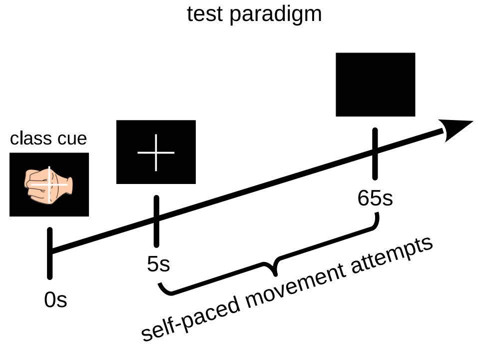

Figure 2: Test paradigm. The participant attempted several single self-paced movements.

medical engineering GmbH, Austria). A notch filter at 50 Hz and a band-pass filter with 0.01 Hz to 100 Hz (8th order Chebyshev filter) were used.

Preprocessing: We excluded channel AFz, and re-referenced the remaining channels to a common average reference (CAR). Next, we filtered signals with a causal 4th order Butterworth filter with 0.3 Hz to 3 Hz to extract low-frequency signals. In the training paradigm, artifact contaminated trials were removed with a statistical outlier rejection method like in [19].

Classifier and Detector: We classified the EEG from the training paradigm with a multi-class shrinkage linear discriminant analysis (sLDA) [3]. The input features to the sLDA classifier were the preprocessed EEG data, which were extracted from a causal time-window of length 1.4 s (feature extraction window). To find the optimal training time point, we time-locked to the go cue and calculated offline classification accuracies with a 10-fold cross-validation. For this purpose, we shifted the right corner of the feature extraction window from 1 s to 2 s relative to the go cue, and calculated for each time point the classification accuracy. The time point with the highest classification accuracy was then found as t_{train} (t_{train} = 1.875s in training session 1, and t_{train} = 1.625s in training session 2). The output of the classifier was subjected to a softmax transformation to obtain class probabilities.
The classifier included two additional classes: a pre and a post class. MRCPs have a duration of more than 2 s, and the pre and post classes are supposed to detect the early and late phases of MRCPs (irrespective of hand open or palmar grasp). These MRCPs phases could otherwise increase the chance of detecting a wrong movement class if the MRCPs are not yet (or are no longer) fully covered by the feature extraction window during online operation. We grouped therefore the movement classes (hand open and palmar grasp) at $t_{train} - 500\,\text{ms}$ and $t_{train} + 500\,\text{ms}$ to pre and post classes, respectively. The final online classifier was then trained on hand open, palmar grasp and rest classes at t_{train}, and on the time shifted pre and post classes, yielding in fact a 5-class classifier. See Figure 3 for an explanation how the trial-averaged classifier output looks like when applied on the training paradigm and time-locked to the go cue. An attempted movement

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should lead to a peak of the pre class probability, followed 500ms later by a peak of the hand open or palmar grasp class probability, and another 500ms later by a peak of the post class probability.
We build then a detector which detected attempted movements based on the time-sequences of the classifier outputs. This detector employed 3 time windows specified relative to t_0, see Figure 4. A movement was detected if the 3 peaks of the pre class, movement class, and post class fell within these 3 windows. The pre window was centered at $t_0 - 500$ ms, the movement window at t_0, and the post window at $t_0 + 500$ ms. Pre and post windows had a length of 300 ms, the movement window had a length of 100 ms. To detect a movement, the pre class probability had to be above 0.7 for at least half of the pre window (and analog for the post probability and window), and hand open class or palmar grasp class probabilities had to be above 0.9 for at least the full movement window. If all conditions were fulfilled, the movement class with the highest probability in the movement window (i.e. hand open or palmar grasp) was then eventually detected. A refractory period of 2 s followed every detection.

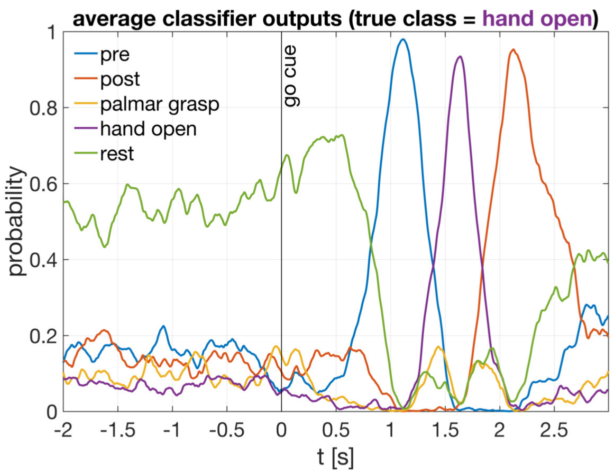

Figure 3: Trial-averaged output of the classifier for hand open trials in the training paradigm. The plot is time-locked to the go cue (0 s). One can see the peak of the hand open class, and preceding and subsequent peaks of the pre and post classes, respectively.

Detection delay: Several factors caused a delay between the onset of the movement attempt and the detection. As we do not know the true onset of the movement attempt we have to make some assumptions to estimate the delay. First, we assume that the onset of the movement attempt coincided with the go cue. Second, the average post class probability was maximal 500 ms after t_{train} and symmetric. There is a first delay between the onset of the movement attempt and the classifier training time point, found as t_{train}. This delay is due to the filter delay and the length of the feature extraction window. Furthermore, there is a second delay due to the detection logic based on pre and post classes. We can only provide a conservative estimation of this delay, i.e. the average maximum delay. We presume that the average post class

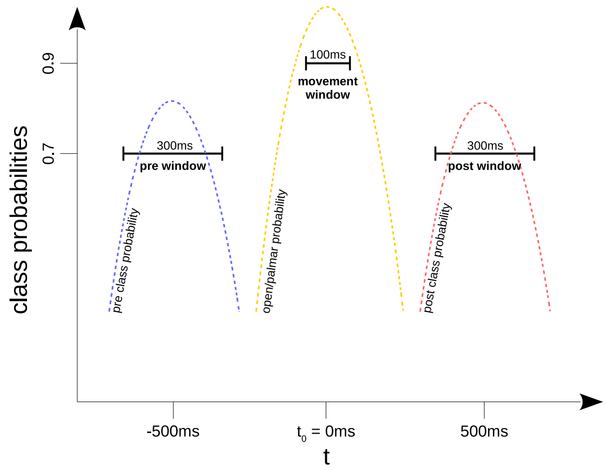

Figure 4: Illustration of the pre, movement and post windows of the detector. All windows had to be crossed for a certain amount of time by their respective probability to cause a movement detection.

probability crosses the post window probability-threshold (0.7) for exactly the length of the time-threshold (150ms, half the post window size). Shorter crossings do not cause a detection, and longer crossings cause an earlier detection. This second delay is the time from t_{train} to the point when the post class probability falls below the post window probability, which would be (under the second assumption) 500 ms + 75 ms after t_{train}. Thus, the maximum detection delay is then on average t_{train} + 500 ms + 75 ms.

Definition of the true-positive window:
We defined a true positive window to evaluate the online classifier. Every detected movement onset within the true positive window was counted as a true positive (TP), irrespective if it was a hand open or palmar grasp class. Every detection outside this window was a false positive (FP_{win}). The length of the TP window was set to 2 s which allowed for not more than one detection per window due to the refractory period of the detector. The center of the TP window was set with an offset to the logged movement onset, and accounted for the detection delay. Thus, the center should correspond to the assumed movement onset (i.e. the detection time point corrected by the detection delay). To find the offset between the TP window center and the logged movement onsets, it was necessary to compensate for the response time of the participant and the reaction time of the experimenter during reporting. As the average response and reaction times were unknown, we used a systematic approach to determine the offset. We iterated the offset from 0 s to 5 s and calculated the TP/FP_{win} ratio for each offset. The offset with the maximal TP/FP_{win} ratio was then determined as the final offset (the offset was 2.2 s in session 1, and 4.2 s in session 2).

RESULTS

We present our results separately for detection and clas-

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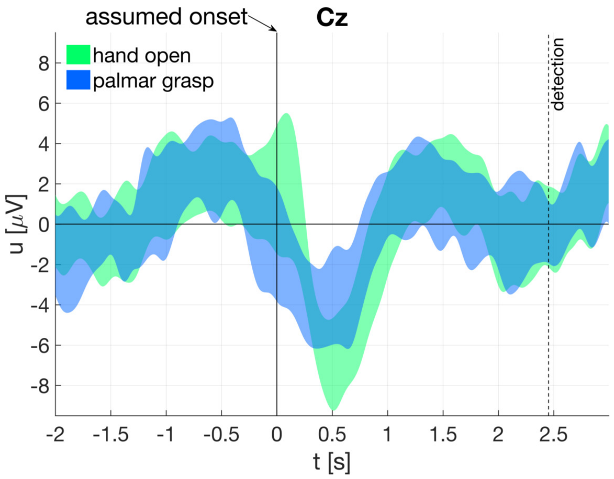

Figure 5: Electrode potentials of the test paradigm in session 1. Shown are the 95% confidence intervals at electrode Cz time locked to the assumed movement onset. The detection time point and the assumed onset are shown (i.e. the detection time point corrected by the detection delay).

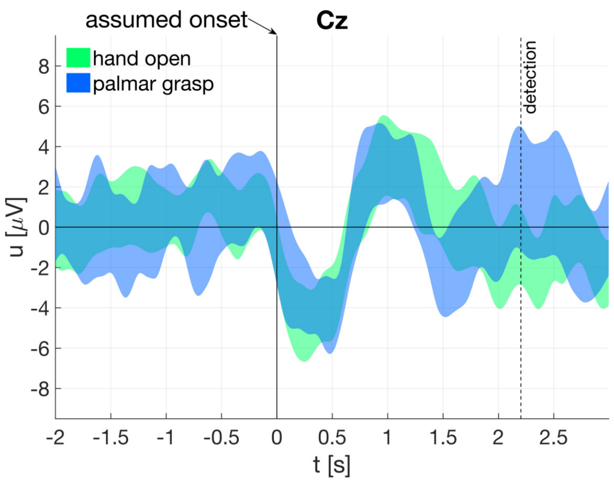

Figure 6: Electrode potentials of the test paradigm in session 2. Shown are the 95% confidence intervals at electrode Cz time locked to the assumed movement onset. The detection time point and the assumed onset are shown (i.e. the detection time point corrected by the detection delay).

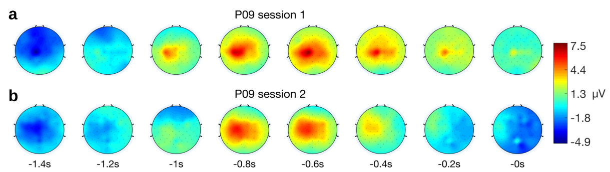

Figure 7: Test paradigm topoplots. The time lags are the input to the classifier when a movement was detected (the topoplots are time-locked to true positive movement detections, second 0 corresponds to t_{train}). **a:** Topoplots from session 1. **b:** Topoplots from session 2.

Table 2: Detection and classification results of both sessions. TPR and FP/min were calculated independent of the movement class. Accuracy was calculated on TPs.

sess.	TPR [%]	FP/min	acc. [%]	sig. level [%]
1	26.6	3.2	66.0	62.4
2	36.9	3.6	70.8	65.3

sification. Detection refers to the identification of any movement class in the ongoing EEG, regardless if it was hand open or palmar grasp. Here, the detection performance is quantified with true positive ratio (TPR) and false positives per minute (FP/min). TPs were all detections within the TP window, FPs were all detections during the 70 s rest trials (not to be confused with FP_{win}). Classification refers to the identification of the movement class itself and considers only TPs. Thus, detections outside the true positive window were ignored. The classification performance is quantified with the classification accuracy. The results of both sessions are shown in Table 2; the significance levels were determined with an adjusted wald interval [2, 17] with $\alpha = 0.05$. When averaging over both sessions, we obtained a TPR of 31.8 and 3.4 FP/min, with an accuracy of 68.4 %.
We also analyzed if the classification in the test paradigm is based on plausible brain signals. The electrode potentials on Cz are therefore shown in Figure 5 (session 1) and Figure 6 (session 2) for both movement classes. We considered only TP, and aligned to the assumed movement onset, i.e. the detection time point minus the detection delay. The detection delay was 2.5s in session 1 and 2.2s in session 2. The plots include 95% confidence intervals based on a t-distribution over trials. Both plots show around movement onset the characteristic negative deflection present in MRCPs. Noteworthy, the EEG signal in Figure 5 and Figure 6 are non-causally filtered to avoid phase distortion and ease the interpretation.
Furthermore we show in Figure 7 the topoplots of the trial-averaged time lags used as input to the classifier when a movement was detected (i.e. the feature extraction window). The topoplots indicate that the classifier used brain signals originating from lateral and central motor areas.

DISCUSSION

We show a first proof-of-concept on how to detect and classify attempted hand open and palmar grasp movements in a closed-loop. Noteworthy, the participant suffered from a complete SCI at level C4 and was not able to execute any movements with his hand.
The motivation of detecting movements online is to connect a BCI with a motor neuroprosthesis and restore movements in persons with SCI. We did another step towards that goal with an online detection in a closed-loop in a person with SCI. However, the performance is modest and at the moment not sufficient to control a motor neuroprosthesis in daily life activities. Most of all, the FP rate is not acceptable. Other movement detectors were shown to achieve better performances [10, 18]. Reasons

may be that those studies did not test participants with SCI, and furthermore relied on lower limb movements which produce larger amplitude MRCPs than upper limb movements [14]. The brain is adaptive and user training could therefore improve the performance, as seen in oscillation-based BCIs [8]. However, there is evidence that such a training is of limited benefit [11], and – if possible at all – novel training strategies need to be found.

We chose hand open and palmar grasp as movement classes because the participant was not able to execute these movements. We have shown in healthy participants that MRCPs encode other movements like pronation, supination, or different grasps [19, 27]. We expect therefore that the detection and classification is not limited to hand open and palmar grasp and generalizes also to other movements.

The externally-cued MRCPs elicited in the training paradigm should be similar to the MRCPs elicited in the self-paced test paradigm. Otherwise the classifier would haven been trained with improper data. We can expect that this is the case as MRCPs preceding self-paced and regular-cued movements are similar in shape and topography [5, 9]. Furthermore, we employed a training paradigm with no sudden appearance of any visual or auditory stimulus around the go cue. With that strategy we avoided any evoked potential related to low-level stimulus processing in the brain. However, we can not exclude that our training paradigm was contaminated with contingent negative variation (CNV) potentials [30]. CNVs can be elicited with a warning and an imperative (i.e. go) stimulus, which is also the basic structure of our training paradigm. CNVs comprise of two main components: one after the warning stimulus and one before the imperative stimulus. The latter component could form a potential complex with the Bereitschaftspotential (BP) [12]. However, with longer intervals between the warning and imperative stimulus (in the second range), the second component of the CNV becomes similar to the late BP in time course and scalp distribution [4, 23, 25], and therefore should not have strongly affected the classifier calibration.

We show that the source signals originate from the brain and are not residual movement artifacts for example. The topoplots indicate that the classifier mainly exploited a lateralized positivity for movement classification (preceded by a broad but centralized negativity). This positive deflection followed the typical negative peak of MRCPs [28] (c.f. Figure 5 and Figure 6).

The offset of the true positive window was chosen systematically to avoid any subjective influence on the classification accuracy. As the offset was chosen to maximize the TP/FP_{win} ratio of the movement trials, we may have made an overoptimistic estimation of the TPR (the FP measure is not affected as FP were counted on the rest trials). Nevertheless, the main result of this work is the classification of hand open vs palmar grasp in a closed-loop. A suboptimal choice of the true positive window would have led to a suboptimal estimation of the true classification accuracy, as the estimation would then consider more false positives and/or less true positives.

CONCLUSION

We introduce a proof-of-concept on how to detect and classify attempted hand opening and palmar grasp movements based on MRCPs. We tested our proof-of-concept on a person with a complete cervical SCI without any preserved hand function. We achieved a significant classification accuracy but also a high number of false positive detections. Thus, attempted hand movements can be non-invasively decoded from EEG, even if no hand function has been preserved. If the detection and classification performances can be improved, this may provide a control option for future neuroprostheses.

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