Decoding of continuous movement attempt in 2-dimensions from non-invasive low frequency brain signals*

Gernot R. Müller-Putz, *Member, IEEE*, Valeria Mondini, Víctor Martínez-Cagigal, Reinmar J. Kobler, Joana Pereira, Catarina Lopes Dias, Lea Hehenberger, Andreea I. Sburlea

Abstract—**Decoding intended movements from individuals with spinal cord injury (SCI) has been a central topic in brain-computer interface research for decades. Recent works, relying on neural spiking activity, demonstrated that the kinematics of intended movements can be detected in neural spiking activity and used by individuals with SCI to control end-effectors. Whether, and to which degree this approach translates to EEG remains an open question. In this work, we summarize our attempts towards realizing an EEG-based movement decoder. We summarize our efforts to address this topic from various perspectives, and we present results of a single case study with a non-disabled participant, where we decoded the intended movement trajectories, while the participant's arm was fixed.**

I. Introduction

'Making the paralyzed move' is a dream for many researchers but even more for people suffering from a spinal cord injury (SCI) or other diseases leading to non-functional limbs and therefore a dramatic decrease in quality of life. While walking is always the first function an independent observer thinks is most critical, affected people usually have other wishes [1]. The higher the lesion in the spinal cord, the less important is walking. While very high SCI lesions in the cervical vertebra lead to dysfunction of breathing and all motoric and sensory functions are lost, a lesion in the lower cervical levels lead to restricted hand and arm movements, while breathing, speaking and head movements are not so problematic [2].

The restoration of hand and arm function has been a research topic since the late 90s. Relatively soon, a vision came out which is of "reading" the intention of movement from brain activity and transferring it into real movement.

Analysing brain signals, i.e., neuronal activity from motor cortex and related areas first done in non-human primates [3] and later in humans led to first full (robotic) arm controlled systems [4, 5, 6]. Also neuroprosthetic devices, based on functional electrical stimulation, applied to the upper limb of tetraplegic participants could be successfully controlled by applying this invasive methodology [7, 8]. Recently, using the less invasive electrocorticogram (ECoG) technique motor control in tetraplegics was reported [9, 10].

Almost parallel to the developments in the invasive field, a first application of a non-invasive BCI to control the lost hand function of a high spinal cord injured male was presented in 2000 [11]. Introducing functional electrical stimulation and neuroprosthetics lead to more meaningful control [12, 13]. Improvements through hybrid BCIs [14, 15] and coding of brain patterns [16] were also reported [17]. However, a non-invasive natural control of a full arm movement was out of reach so far.

In a project granted form the European Research Council (ERC) we are working towards this vision. In the current work we want to give a brief overview of our findings so far. Additionally, we are presenting preliminary results from free non-invasive online decoding of 2-d movement attempts in one non-disabled participant.

II. Methods & Results

The main idea of the project is to combine several cortical brain patterns and mechanisms, which allow to detect goal directed movement intention, decode movement trajectories, detect errors, and provide kinesthetic sensory feedback related to movement.

A. Goal-directed movement detection

Movement-related cortical potentials (MRCPs) are neural correlates of movement planning which are typically revealed by time-locking to the movement onset. These potentials are modulated by several kinematic [18,19] and kinetic [20] aspects of movement, and also by the presence of motor goals [21]. The detection of movement in an asynchronous manner would be useful to trigger trajectory decoders (e.g., for robotic arm control) or discrete movement classifiers (e.g., for neuroprostheses control). The continuous detection of upper-limb movements from MRCPs is challenging, but in principle possible also in SCI [22]. In higher SCI lesions, without residual upper limb function, MRCPs cannot be revealed by time-locking to a movement onset, and thus labelling the data for calibrating movement detectors is a challenge. The use of "go"-cues is also not a solution, as other event-related potentials might be elicited and mask or alter the MRCPs. We have explored new paradigms which can overcome this challenge: in [23] we have shown that the detection of self-initiated reach-and-grasp movement imaginations is possible

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G.R.M-P. is with Institute of Neural Engineering, Graz University of Technology and BioTechMed, Graz Austria (gernot.mueller@tugraz.at).

V.M., R.J.K, J.P., C.L-D., L.H., A.I.S. are with the Institute of Neural Engineering, Graz University of Technology, 8010 Graz, Stremayrgasse 16/4, Austria.

V.M-C. is with the Biomedical Engineering Group, University of Valladolid, Valladolid, and with the 'Centro de Investigación Biomédica en Red' in Bioingenieering, Biomaterials and Nanomedicine (CIBER-BBN), Spain.

on an asynchronous offline scenario. In [24], we have shown that natural reach-and-grasp movements can be detected in an asynchronous (and online) BCI. The features used were not limited to MRCPs, as additional low-frequency time-domain activity generated from parietal and occipital areas was also observed. In this task, participants were allowed to shift their gaze towards the movement target (which is undoubtedly more intuitive than in state-of-the-art paradigms). The results were additionally compared with a control oculomotor task (i.e., exclusively saccades performed towards the target).

B. Grasp representation

To better understand the neural and behavioral mechanisms involved in grasping, we investigated the relationship between the broadband EEG representation of observing and executing a large variety of hand-object interactions and the muscle and kinematic representations associated with the grasping execution. Furthermore, we investigated the similarity of the neural representations with categorical models that encode grip and object properties [25]. We found that the EEG representation during the observation phase was correlated with the muscle representation during the execution most strongly in the movement holding phase. Furthermore, we found similarities with the categorical model that reflects the shape and the size of the object. Object properties and grasp types can be decoded significantly above chance level during the planning and execution of the movement and we could decode properties of the objects already from the observation stage, while the grasp type could also be accurately decoded at the object release stage [26]. With these findings we gain a joint understanding of the relation between neural and behavioral representations of grasping and make a step forward towards an intuitive control of neuroprostheses in motor impaired individuals.

C. Error detection during continuous movement

One important aspect for a smoother robotic arm control is to identify when the decoder does not work properly or the occurrence of large or abrupt deviations from the expected trajectory. We started by investigating the asynchronous detection of ErrPs in an offline scenario [27]. Afterwards, we carried out a study with non-disabled participants, in which we showed that it is possible to reliably detect ErrPs during the continuous control of a robotic arm, using an asynchronous online BCI [28]. Furthermore, we developed a generic ErrP detector by transferring ErrPs across participants [29]. Recently, we published a study with participants with a spinal cord injury, in which we applied this generic ErrP classifier to detect ErrPs during the continuous control of a robot, in an asynchronous online BCI [30]. The participants with an SCI presented a non-homogeneous ErrP morphology. Nevertheless, this study showed that when participants presented clear ErrP signals, the generic could be successfully used. Our results show that ErrPs can be transferred from non-disabled participants to participants with a SCI and that the asynchronous detection of ErrPs during continuous movement can be applied to potential end-users of BCIs.

D. Kinesthetic feedback

Usually, all BCIs for motor restoration rely on visual feedback. To overcome this, we have implemented a vibrotactile stimulation system to project movement sensations to the skin of the shoulder blade. In order to test the feasibility of employing it in conjunction with a BCI based on movement-related features, we conducted an initial study investigating several movement-related parameters during the execution of planar center-out movements. Movement trials could be classified against rest with accuracies significantly exceeding chance level, regardless of whether vibrotactile feedback was provided, in classification based on low-frequency amplitude features, as well as spectral mu and beta features. Classification between the movement directions only narrowly exceeded the significance threshold above chance level [31]. Currently, we investigate movement imagery of the same center-out tasks, with and without vibrotactile guidance.

E. Movement decoding for continuous robot control

Recent studies have shown the possibility to infer hand positions and velocities from the low-frequency (LF) electroencephalographic (EEG) activity [32, 33]. So far, this has only been performed offline. Here, we present two studies showing online control of a robotic arm by means of continuously decoded movements from LF-EEG.

Study 1 [34]: Ten healthy subjects took part in the study. The paradigm implemented a pursuit tracking task [33], where participants had to follow a target on the screen with a robotic arm. The participants' two-dimensional right-hand movement, EEG, and electrooculographic signals were simultaneously recorded. In the first part of the experiment, the participants performed calibration runs with the robot controlled by their hand movements. After the EEG decoding model was fitted to the hand movements, the robotic arm control was gradually switched from manual to EEG control, first with 33%, then 66%, up to the final condition of 100% EEG control.

The EEG processing pipeline included filtering (0.18-1.5Hz), eye artefact [35] and pop/drift [36] attenuation, partial least squares (PLS) regression, and Kalman filtering. In the first study, a linear Kalman filter estimated positions, velocities and accelerations. Grand average correlations between real and decoded trajectories were r=[0.30, 0.32, 0.29, 0.26] (for 0, 33, 66 and 100% EEG control conditions). The observed correlations were significantly (α=.05) higher than chance level (rchance=[0.13, 0.12, 0.11, 0.11]) and the ones of a PLS-based Wiener filter (WF) (r=[0.25, 0.26, 0.22, 0.20]), used in a previous study [33]. Both linear decoders exhibited a mismatch in amplitudes between the real and decoded trajectories (amplitude ratio 0.4). This mismatch can be overcome by integrating non-directional kinematic information (e.g., speed) with a non-linear decoder [38].

Study 2 [37]: Five participants were included in this pilot study. We used a nonlinear square-root unscented Kalman filter to integrate positions, velocities, and speed [38]. Grand average correlations were r=[0.43, 0.34, 0.27, 0.23] and the amplitude ratio between real and decoded movements was 1.07.

In our studies the KFs imporved the correlation upon WFs. Integration of speed in the second study additionally adjusted the amplitude of decoded trajectories, suggesting an informative role. Parieto-occipital and sensorimotor cortex activations are in line with the task type (visuomotor) and offline studies [33].

F. Decoding of movement attempt: preliminary results

Following the experiments in Section II.E we further adapted the experimental setup and performed an experiment in one male participant. Following the setup where non-human primates were controlling a robotic device with their arms fixed in small tubes, we were fixing the participants right arm and hand on the chair arm rest. This constraint prevents the participant from moving his arm and hand, therefore mimicking attempted movement. Clearly, the participant was allowed to activate muscles – just no movement was possible. Additionally, eye movements were tracked by a wearable eye-tracking system (Pupil Labs, Berlin). So, the attempted 'movement' trajectories were available from eye movements. The signal processing chain was the same as described above in study 2 [37] with the addition of distance and speed in the decoder [38]. The procedure of the experiment was divided into three parts: (i) Calibration of the movement decoder (50 trials) and eye-artifact removal algorithm [35]. (ii) Feedback runs with 33% (1 run, 10 trials), 66% (1 run, 10 trials) and 100% (2 runs, 20 trials). (iii) Free runs. Here, the participant was free to decide how to move the feedback ball. One trials lasted 23 s and was similar in the structure as described in section II.E.

In Table I the results of the calibration as well as the feedback runs are visible. It is clearly visible that the decoder had correlation around 0.2 for position and velocity which was higher than the α=0.05 chance level (obtained with a shuffling approach), with x-components a bit lower than y-components. During the pure EEG decoding (0% snake), it is more evident that y-component was mostly contributing to the decoding and especially in the 33% and 100% EEG (0% snake) the x-component was random.

TABLE I. POSITION (POS) AND VELOCITY (VEL) CORRELATION OF DECODER (UKF). FIRST COLUMN SHOWS MEDIAN OF THE CALIBRATION DATA (CROSSVALIDATION LEAF ONE OUT). REMAINING COLUMNS SHOW CORRELATION BASED ON ONLINE RESULTS.

	100% snake (loo_cv, 50 trials)*	**66% snake (10 trials)**	**33% snake (10 trials)**	**0% snake (20 trials)**
pos_x	0.22	0.36	-0.13	0.00
vel_x	0.16	0.32	-0.15	-0.01
pos_y	0.23	0.13	0.31	0.11
vel_y	0.23	0.11	0.30	0.11

The content of Figure 1 is twofold. First (Figure 1A) it shows qualitatively decoder results from the calibration runs. Both, position and velocity components are displayed on a randomly selected section. In Figure 1B a sketch of the participant the experimental setting can be seen. Figure 1C shows three trials representing all three task the participant chose to move the curser with 100% EEG control. In total 12 trials were recorded where the participant repeated in the order given in the figure for four times: move the cursor along a diagonal left '\', diagonal right '/', and make an circle 'o'. With the trajectories recorded from this data we calculated the 1st (blue) and 2nd (green) principal component (PC) to show the main orientation of the decoded trajectory. The proportion of variance explained by each principal component in each movement category (\, /, o) averaged over 4 trials each can be seen in Table II.

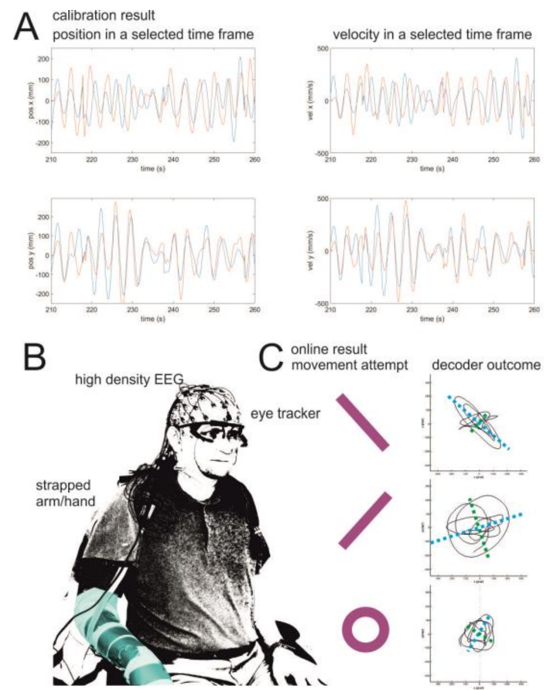

Figure 1. 2-dimensional decoding results. A) Calibration results. Shown are selected time frames covering about 3 trials (out of 50). In blue are the target trajectories, in red are the decoded trajectories. B) Experimental setup. Participant's forearm and hand were strapped to the arm rest. C) Participant choose to try to perform left diagonal, right diagonal and circular movements of the curser. Selected trials (out of 12), each for one of the chosen movement patterns. Blue dashed line shows the 1st principal component, the green one the 2nd PC.

TABLE II. AVERAGE TRAJECTORIE ORIENTATION MAIN COMPONENTS DURING FREE CONTROL.

Movement intention	\	/	o
var 1st PC | 2nd PC in [%]	78,79 | 21,20	65,13 | 34,87	63,04 | 36,96|

III. DISCUSSION

In this work, we gave an overview on how we plan to allow a person with a high cervical spinal cord injury to control an artificial robotic arm with a non-invasive EEG-based BCI. We briefly discussed asynchronous goal-directed movement detection (in healthies) and error-potential detection during continuous movement. We found insights of neural representation of grasp and gave first insights in how to apply kinesthetic feedback. The main part, however, discusses our findings in continuous 2-dimensional online decoding of arm movement as well as first preliminary results of free decoding of continuous arm movement attempts in non-disabled participants.

We achieved continuous low frequency EEG-based movement decoding for the online control of a robotic arm. Two (linear and nonlinear) Kalman approaches to integrate decoding information were introduced. Furthermore, we applied the findings described above [36, 37] and included distance and speed [38] in a new setup. The participant while having the forearm and hand fixed was attempting to move the cursor on a screen, first in a shared control setting and finally with 100% EEG control. Three different movement patterns were freely attempted by the participant for several repetitions. From the preliminary results presented and from the experience of the participant we can learn the following: (i) free control was possible to some extent. Since the correlations were relatively low, and mainly the y-axis, it was not possible to control circular movements. (ii) After the trial started, it took several seconds until the movement attempt was kind of reflected in the feedback cursor. (iii) It is not clear what contribution user learning can bring, we are convinced however that this will increase the decoder performance.

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