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LEARNING EFFECTS IN 2D TRAJECTORY INFERENCE FROM LOW-FREQUENCY EEG SIGNALS OVER MULTIPLE FEEDBACK SESSIONS

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Abstract— *Recent research from our group has shown that non-invasive continuous online decoding of executed movement from non-invasive low-frequency brain signals is feasible. In order to cater the setup to actual end users, we proposed a new paradigm based on attempted movement and after conducting a pilot study, we hypothesize that user control in this setup may be improved by learning over multiple sessions. Over three sessions within five days, we acquired 60-channel electroencephalographic (EEG) signals from nine able-bodied participants while having them track a moving target / trace depicted shapes on a screen. Though no global learning effect could be identified, increases in correlations between target and decoded trajectories for approximately half of the participants could be observed.*

Keywords— *Electroencephalography, trajectory decoding, learning effects.*

Introduction

Brain-computer interfaces (BCIs) [1, 2] are characterized by offering a user direct control over an interface without prior muscular activity. For years, a goal of our group has been the restoration of arm and hand movement respectively in people with cervical spinal cord injury (SCI) [3, 4, 5]. Through a BCI, these persons should be enabled to control an end-effector, e.g., a neuroprosthesis or a robotic limb. Starting from identifying different movement directions [6, 7, 8], the focus has advanced to continuous movement decoding.

Recently, it was shown that movement information (positions and velocities) in a plane is contained in low-frequency EEG signals, making it possible to infer executed movement trajectories in an online target tracking task with correlations between decoded and actual trajectories well above chance [9, 10]. However, the used paradigms were tailored to able-bodied participants, making their application to end users with limited motor output impossible.

As a possible solution to this, we conducted a pilot study based [11] on attempted instead of executed movement [12]. Feedback from the participant on the perceived level of control at the beginning and the end of the experiment lead to the assumption that the decoder accuracy may be improved through training. This implies that the decoding performance may not only be optimized through utilization of increasingly powerful signal processing and machine learning algorithms, but also via neuroplasticity with respect to the BCI users themselves. Considering this assessment, we hypothesized that any visible learning effects would take place within a short time span already. For this reason, we chose to investigate possible increases in BCI user performance over three sessions within five days. This timeframe was selected to keep the experience fresh in the participants' minds while allowing them to recuperate from the mental workload between the sessions.

In this work, we evaluate the two different paradigms we presented the participants with regarding an increase in performance over the sessions. Further, we evaluate whether neuroplasticity can play a role in 2D trajectory inference.

Methods

Participants and setup— EEG of nine able-bodied participants (24.2 ± 5.0ys) have been recorded three times each within five days. The participants sat in front of a TV screen with their dominant arm strapped to the chair (see Fig. 1, C), enabling minimal movement but largely restricting the motor output in order to mimic attempted movement [12]. Each participant (four female, five male) was assessed as right-handed according to the Edinburgh Handedness Inventory [13] and had normal or corrected-to-normal vision. Data of one specific participant was excluded from further analysis due to erroneous marker-labelling during the recording. The experiment was conducted as part of the Feel Your Reach project and as such was approved by the ethics committee of the Medical University of Graz.

Paradigm— In each of the three sessions, the participant was presented with two different paradigms: the *snakeruns* (Fig. 1, A) and the *freeruns* (Fig. 1, B). For the snakeruns, a target (called '*snake*') was shown on the screen, moving according to specifically designed trajectories that ensured decorrelation between x and y coordinate. The participant was asked to visually track the snake while attempting movement with the strapped lower arm and hand as if wielding a cursor.

In the freeruns, three different static shapes were shown on the screen: two diagonals (from top or bottom left, respectively), and a circle. In this paradigm, the participants had to trace the shape following their own pace without stopping, again visually as well as with attempted movement.

Each session was roughly divided into an offline calibration and an online feedback part.

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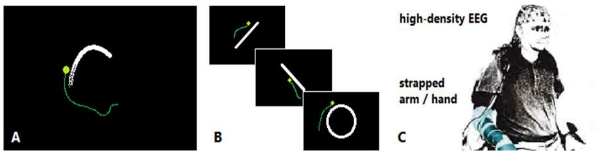

Figure 1: Experimental setup and paradigm. A) depicted moving target (snake, white) with green feedback dot, B) freerun shapes **/**, **** and O to be followed at the participant's own pace, C) experimental setup with the participant's dominant hand/arm strapped to the chair.

During the calibration phase, two *eyeruns* (including resting gaze, blinks, horizontal and vertical eye movement) and four snakeruns (12 trials of 23s each) were recorded. For the calibration snakeruns, fake feedback in form of a green dot corresponding to the delayed snake trajectory was shown on the screen to accustom the participants to the additional visual information. After recording the data for the calibration, the eye data were used to train our sparse generalized eye artifact subspace subtraction (SGEYESUB) algorithm [14], while the snakeruns were used to fit the partial least squares regression unscented Kalman filter (PLSUKF) decoder discussed in [10].
In the online phase, the feedback condition was successively increased first to 50% EEG feedback, corresponding to the mean between actual and decoded snake position (three snakeruns: 36 trials of 23s duration), and then to 100% EEG decoded feedback (three snakeruns, three freeruns: 36 trials of 23s duration each).

Recording and preprocessing— Data from 64 channels was recorded, corresponding to a 60 channel EEG according to the 10-10 system and four electrooculographic (EOG) electrodes placed at the outer canthi of both eyes as well as above and below the left eye. Ground and reference electrodes were placed at Fpz and the right mastoid. The initial sampling rate of 200Hz was first reduced to 100Hz after high pass filtering at 0.18Hz and anti-aliasing filtering at 25Hz; the bad channels were then interpolated, the eye artifacts attenuated using the SGEYESUB algorithm [14], and the EOG and AF channels were removed. The data were then re-referenced to common average reference, and pops and drifts in the signals were attenuated using the HEAR algorithm [15]. After low pass filtering at 3Hz and further downsampling to 20Hz, the signals were fed to the PLSUKF decoder [10, 16], yielding the feedback output shown as a green dot on screen.

Results

Snakeruns—An accurate assessment of the decoder performance was accomplished by evaluating the Pearson's correlation coefficient *r* between actual snake trajectory (ground truth) and decoded EEG signals for each trial. The correlations for each feedback condition (50% and 100% EEG), directional movement parameters (pos_x, vel_x, pos_y, vel_y), session and participant are presented in Fig. 2. The correlations for single trials (36 per session and condition, notwithstanding trial rejection) are displayed as small dots, mean and 25th resp. 75th percentiles as big dots and whiskers. For each session, the chance levels were calculated using a shuffling approach [9], in which EEG data and corresponding snake trajectories were randomly interchanged, a new PLS model fitted, and *r* evaluated, for 100 times. The upper confidence intervals of the chance level correlations (with alpha = 0.05) were then found as the 95th percentile of the correlation moduli and are depicted as horizontal lines. For all participants, sessions and feedback conditions, mean correlations (approx. 0.3) lie well above chance levels (approx. 0.15).

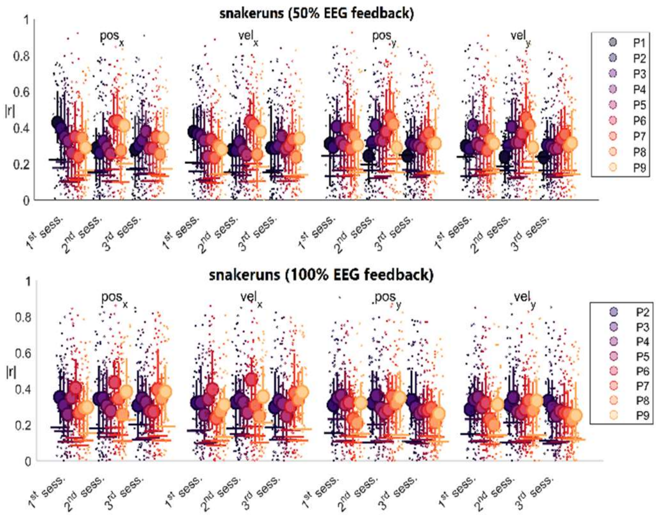

Figure 2: Correlations for all trials (small dots) with mean (big dots), 25th and 75th percentiles (whiskers) and chance levels (horizontal lines, see [9]) for each participant, directional movement parameter (pos_x, vel_x, pos_y, vel_y), session and feedback condition (top: 50% EEG, bottom: 100% EEG).

After evaluating the data of the first participant (P1), the initial recording sequence of three 50% EEG snakeruns and three 100% EEG freeruns was adapted, and snakeruns with 100% EEG feedback condition were added for quantitative performance analysis due to the lack of a ground truth for the self-paced freeruns. As a result, P1 could not be included in the 100% EEG feedback snakerun analysis (Fig. 2, bottom).
For both feedback conditions, single trial correlations are found to be spread over the whole range (0,1), with no global trend for the means over each session. A downward tendency from first to third session for approximately half of the participants can be observed, while the other half improved, often accompanied with a performance peak in the second session. Further, improvements in performance in one movement direction (x or y) are not necessarily seen in the other direction as well, implying varying decoder performance across movement directions over multiple sessions. Further measurements with additional participants will

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allow for statistical evaluation of the correlations over all individuals.

Freeruns— Because of the self-paced character of the freerun task, target positions as in the snakeruns are not available as a ground truth in the freeruns. As a workaround, the expected target position on screen at each point in time was assumed as the point the participant was visually focusing on. The ground truth trajectories were inferred via horizontal and vertical bipolar derivates of the EOG signals. After lowpass filtering at 3Hz and downsampling to 20Hz of the raw EOG data, the correlation between the trajectory inferred via horizontal and vertical EOG derivates and the decoded trajectory was used as an evaluation metric.

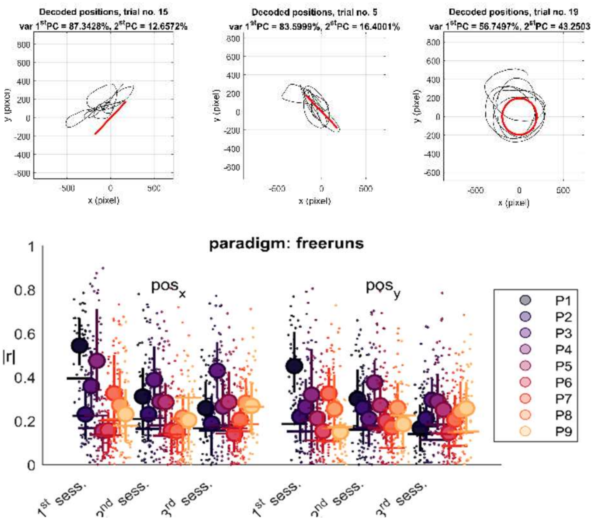

Figure 3: *Top*— Depicted shapes (red) and three corresponding EEG-decoded freerun trajectories (black) from P4, session 2. *Bottom*— Correlation between EOG-inferred and decoded trajectory for each trial (small dots), with mean (big dot), 25th resp. 75th percentiles (whiskers) and chance levels (horizontal lines) for each participant and session.

Three single freerun trials taken from P4, session 2 are shown in Fig. 3 for demonstration. The static shape shown to the participant on the screen is depicted in red, the EEG-decoded trajectory corresponding to the tracing task is overlaid in black. Pearson's correlation r between EOG-inferred trajectory (ground truth) and decoded trajectory for each participant, session and trial is shown in Fig. 3 (bottom). Small dots correspond to single trials, big dots and whiskers again to mean and 25th/75th percentiles of the correlations in each session. No distinction between the different depicted shapes (/, \, O) was made yet. The chance levels were again calculated using a shuffling approach.
As can be seen, the mean correlation lies below chance level for some sessions in contrast to the mean correlations during the snakeruns. Again, no global trend can be observed in terms of improvement or degradation of performance over all participants. However, a steady increase in performance can be observed in approximately half of the participants. Additionally, any trend from first to third session observed in one movement direction can be also seen in the other direction in two thirds of the participants, in contrast to the correlations in the snakeruns.

Discussion

Over three consecutive sessions in nine participants, no global learning effect could be observed for both presented paradigms (snakeruns, freeruns).
For each feedback condition, participant and session, the mean correlation in the snakeruns lay above chance level, though different decoding accuracies in x and y direction could be observed, implying a favored decoding direction. Approximately half of the participants showed an increase in performance from first to third session, which was often paired with a performance peak during the second session, while the other half exhibited a steady decrease in performance. Following a preliminary assessment, this does not directly correlate with the decoder performances observed on the calibration data. This implies underlying causes that are not strictly related to the varying decoder performance from session to session, even though the decoder was fitted anew for each session. Decreasing motivation and engagement of the participants due to the long experiment (3-4 hours per session) must be mentioned as influencing factors, along with a varying frustration tolerance between the participants. Although we did not ask the participants to fill a questionnaire, there seemed to be a consensus that higher learning rates were expected. This may have led to frustration and can explain the decrease in correlations from second to third session in participants with a performance peak in the second session.
For the freeruns, approximately half of the participants showed improvement from first to third session, whereas the performance decreased for the other half. Mean correlations did not lie above chance for all sessions, which in part can be attributed to the EOG trajectories that were used as a ground truth in the freeruns. In part, this may also imply that the self-paced freerun task was harder to fulfill than the tracking task during the snakeruns. Detailed investigations on correlations per specific shape (/, \, O), as well as on changes in correlation from session to session, remain to be done.
Detailed analysis regarding the grand average over all participants remains to be done and cannot be presented within the preliminary results yet.

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References

[1] G. Müller-Putz und S. Wriessnegger, Neuroprosthetics and Brain-Computer Interfaces in Spinal Cord Injury, A Guide for Clinicians and End Users, Chapter 3: Electroencephalography and Brain-Computer Interfaces, Springer, 2021.

[2] J. d. R. Millán, Introduction to Neural Engineering for Motor Rehabilitation, Chapter 12: Brain-Computer Interfaces, Wiley-IEEE Press, 2013.

[3] G. Müller-Putz, J. Pereira, P. Ofner, A. Schwarz, C. L. Dias, R. Kobler, L. Hehenberger und A. I. Sburlea, „Towards non-invasive brain-computer interface for hand/arm-control in users with high spinal cord injury," in *In Proceedings of the 6th International Winter Conference on Brain-Computer Interface (BCI 2018)*, South Korea, 2018.

[4] G. Müller-Putz, P. Ofner, A.Schwarz, J. Pereira, A. Pinegger, C. Lopes-Dias, L. Hehenberger, R. Kobler und A. Sburlea, „Towards non-invasive EEG-based arm/handcontrol in users with spinal cord injury," in *5th International Winter Conference on Brain-Computer Interfaces*, 2017.

[5] A. Schwarz, P. Ofner, J. Pereira, A. Sburlea und G. Müller-Putz, „Decoding natural reach-and-grasp actions from human EEG," *Journal of Neural Engineering,* Bd. 15, Nr. 1, 2018.

[6] J.-S. Woo, K.-R. Müller und S.-W. Lee, „Classifying directions in continuous arm movements from EEG signals," *Conference Paper, The 3rd International Winter Conference on Brain-Computer Interface, IEEE,* 2015.

[7] Y. Li, Y. Sun, F. Taya, H. Yu, N. Thakor und A. Bezerianos, „Single Trial EEG Classification of lower-limb Movements Using Improved Regularized Common Spatial Pattern," *Conference Paper, IEEE EMBS Conference on Neural Engineering,* 2015.

[8] N. Robinson und A. Vinod, „Noninvasive Brain-Computer Interface: Decoding Arm Movement Kinematics and Motor Control," *IEEE Systems, Man & Cybernetics Magazine,* Oct. 2016.

[9] V. Mondini, R. Kobler, A. Sburlea und G. Müller-Putz, „Continuous low-frequency EEG decoding of arm movement for closed-loop, natural control of a robotic arm," *Journal of Neural Engineering, vol. 17, 046031,* 2020.

[10] R. Kobler, A. Sburlea, V. Mondini, M. Hirata und G. Müller-Putz, „Distance- and speed-informed kinematics decoding improves M/EEG based upper-limb movement decoder accuracy," *Journal of Neural Engineering, vol. 17, 056027,* 2020.

[11] G. Müller-Putz, V. Mondini, V. Martínez-Cagigal, R. Kobler, J. Pereira, C. Lopes-Dias, L. Hehenberger und A. Sburlea, „Decoding of continuous movement attempt in 2-dimensions from non-invasive low frequency brain signals," *Conference paper, IEEE EMBS Conference on Neural Engineering,* 2021.

[12] P. Ofner, A. Schwarz, J. Pereira, D. Wyss, R. Wildburger und G. Müller-Putz, „Attempted Arm and Hand Movements can be Decoded from Low-Frequency EEG from Persons with Spinal Cord Injury," *Scientific Reports, vol. 9,* 2019.

[13] R. Oldfield, „The assessment and analysis of handedness: The Edinburgh inventory," *Neuropsychologia, vol. 9/I,* pp. 97-113, 1971.

[14] R. Kobler, A. Sburlea, C. Lopes-Dias, A. Schwarz, M. Hirata und G. Müller-Putz, „Corneo-retinal-dipole and eyelid-related eye artifacts can be corrected offline and online in electroencephalographic and magnetoencephalographic signals," *NeuroImage, vol. 218, 117000,* 2020.

[15] R. Kobler, A. Sburlea, V. Mondini und G. Müller-Putz, „HEAR to remove pops and drifts: the high-variance electrode artifact removal (HEAR) algorithm," *Conference paper, IEEE EMBC,* 2019.

[16] V. Martínez-Cagigal und e. al., „Non-linear online low-frequency EEG decoding of arm movements during a pursuit tracking task," in *42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). IEEE*, 2020.