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VISUAL INPUT AFFECTS THE DECODING OF IMAGINED MOVEMENTS OF THE SAME LIMB

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ABSTRACT: A better understanding how movements are encoded in electroencephalography (EEG) signals is required to develop a more natural control for motor neuroprostheses. We decoded imagined hand close and supination movements from seven healthy subjects and investigated the influence of the visual input. We found that motor imagination of these movements can be decoded from low-frequency time-domain EEG signals with a maximum average classification accuracy of $57.3 \pm 5.0\%$. The simultaneous observation of congruent hand movements increased the classification accuracy to $64.1 \pm 8.3\%$. Furthermore, the sole observation of hand movements yielded discriminable brain patterns ($61.9 \pm 5.5\%$). These findings show that for low-frequency time-domain EEG signals, the type of visual input during classifier training affects the performance and has to be considered in future studies.

INTRODUCTION

Understanding the encoding of movements in the human brain is paramount for the development of a new and more intuitive control of motor neuroprostheses. Our group already restored movement function in persons with spinal cord injury (SCI) with motor neuroprostheses [1, 2, 3, 4] based on functional electrical stimulation (FES) [5, 6]. However, the control of FES via a non-invasive brain-computer interface (BCI) is in general unintuitive and unnatural. The BCI requires subjects to learn the expression of brain patterns which can be unrelated to the actual restored movement (e.g. imagination of foot movement to control the hand). Furthermore, the imagined movements are usually repetitive movements and not single movements. These BCIs are usually based on sensorimotor rhythms (SMR) extracted from electroencephalography (EEG) signals. However, newer research suggests that more details of movements can be decoded from low-frequency EEG signals [7, 8, 9, 10]. Furthermore, our group decoded six single movements (elbow extension/flexion, pronation/supination, hand open/close) of the upper limb from low-frequency time-domain signals [11]. This is of special interest in the context of neuroprosthesis control as, e.g., persons with SCI may then imagine or attempt one of these single movements to control a motor neuroprosthesis more naturally. However, as there are no overt movements causing a change in the sensory feedback, the visual input (here: movement observation) becomes potentially more important and may have an impact on the decoding performance. In fact, a sole observation of another movement is known to interfere with the execution of a movement [12], and affects brain rhythms [13, 14]. Furthermore, the visual system can partly substitute the somatosensory system [15]. This point is of special interest because we speculate that the decoding of movements from EEG may depend on a closed loop between the motor cortex and the spinal cord, i.e. proprioceptive feedback may partly be responsible for the modulation of low-frequency EEG signals which is then decoded with a BCI. In this work, we analysed if the lack of varying sensory feedback during motor imagination (MI) can be partly substituted by visual input which in turn may improve the classification accuracy. We hypothesize that the simultaneous observation of hand movements which correspond to imagined movements improves the classification accuracy. As a control condition, we used abstract visuals.

MATERIALS AND METHODS

Subjects: Seven healthy and right-handed subjects participated in the study. They were aged between 20 and 28 years. Three of them were female. The subjects received payment for their participation.

Paradigm:
The subjects sat in a comfortable chair in front of a horizontal computer screen which was used to give instructions and visual input to the subjects. The right arm was positioned under the computer screen (see Fig. 1). We instructed the subjects to perform kinesthetic motor imagery (MI) [14] of closing the right hand (CLOSE) or rotating the right arm (SUPINATION) while observing a movie showing a congruent realistic or an abstract movement. The realistic visual input (RVI) was pre-recorded from a human arm performing the movements while the abstract visual input (AVI) was an animation of a circle turning into an ellipse (see Fig. 2). The circle narrowed either from the top and bottom corresponding to CLOSE or from the left and right side corresponding to SUPINATION. Additionally to CLOSE and SUPINATION, we recorded a REST condition where we showed a picture (realistic or abstract) instead of a movie. In

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REST subject were instructed to not perform any MI. However, REST was not further analysed in this work. To disentangle the effect of MI and the observation of visual input, we employed a movement observation condition. In this condition, subjects were instructed to omit any MI while observing the movie (OBS). Thus, we had three types of conditions: CLOSE/SUPINATION/REST (movement condition), AVI/RVI (visual input condition) and MI/OBS (mental task condition) (see Fig. 3). Fig. 4 shows the sequence of one trial. At the beginning of one trial, the subjects were informed on a computer screen whether MI has to be performed synchronously to the upcoming movie or whether the movie should only be observed. When the movie appeared, it immediately started to play for 2 seconds, paused then and finally disappeared at the end of the trial, i.e. every MI or observation lasted 2 seconds. The movie was either an RVI or AVI type and the movement shown was either CLOSE, SUPINATION or REST. The initial frames of the movies were exactly the same (AVI) or indistinguishable (RVI). After the movie stopped playing, a 1.5 s long idle period followed and then the trial ended. Subsequent to one trial, an inter-trial interval with a random duration of 1.5 - 2.5 s followed. We used a block design to record the trials and runs. Each block exclusively comprised 3 AVI or 3 RVI runs and the blocks where arranged as follows: RVI/AVI/AVI/RVI. Before the first RVI and AVI run, respectively, we additionally recorded a training run. This two training runs were used to familiarize the subjects with the paradigm and were not further evaluated. At the beginning, middle and end of a recording, we also recorded runs in which subjects performed eye movements or rested. However, those runs were not further used in this work. Each run comprised 11 trials per CLOSE/SUPINATION class and 5 trials per REST class. Thus, in total we recorded 66 trials (CLOSE/SUPINATION) and 30 trials (REST) for each RVI/AVI and MI/OBS condition.

Figure 1: Subjects observed or performed MI according to real visual input or abstract visual input. The right hand was under the computer screen.

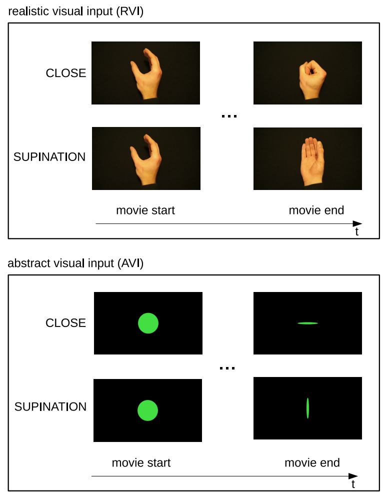

Figure 2: Subjects observed movements or performed MI with real visual input or abstract visual input.

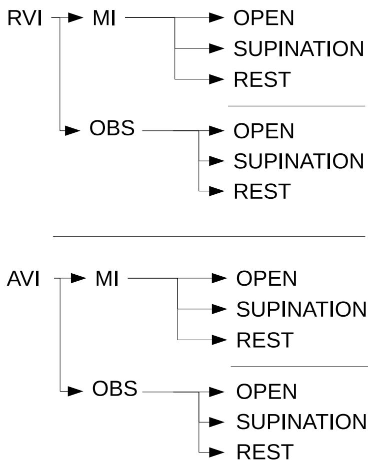

Figure 3: Types of conditions. Subjects perceived real (RVI) or abstract visual input (AVI). They performed MI of CLOSE/SUPINATION/REST or observed (OBS) CLOSE/SUPINATION/REST.

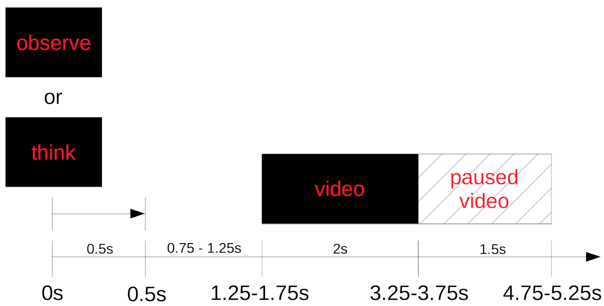

Figure 4: Trial sequence. An instruction was shown at second 0 for 500 ms to inform the subject if a MI has to be performed synchronously to the upcoming movie ("think") or if the movie should only be observed ("observe"). Subsequently, a movie appeared after a random interval and started to play.

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Recording: We recorded 61 EEG channels covering frontal, central, parietal and temporal areas of the head as well as 3 EOG channels placed above the nasion and the outer canthi of the eyes. Signals were recorded with active electrodes and biosignal amplifiers (g.tec medical engineering GmbH, Austria) with the reference placed on the right mastoid and ground on AFz. We applied an 8th-order Chebyshev bandpass filter from 0.01 Hz to 200 Hz and sampled the signals at 512 Hz. Furthermore, a notch filter at 50 Hz suppressed line noise.

Preprocessing: First, EEG channels were visually inspected and noisy or defective channels were removed. To prepare the data for an independent component analysis (ICA), we band-pass filtered with a zero-lag 4th-order Butterworth filter from 0.3 Hz to 70 Hz. Then we calculated the median absolute deviation (MAD) for each channel using data only from trials (i.e. not from inter-trial intervals) and marked EEG samples as artefact contaminated if they exceeded a threshold of 7.41 times the MAD (corresponding to 5 times the standard deviation for normally distributed data) of the respective channel. All samples which were not marked as artefact contaminated were subjected to an Extended Infomax ICA [16] implemented in EEGLAB [17] (which was applied using the first n principal components explaining 99 % of the variance of the data). ICA components corresponding to eye movements and muscle artefacts were marked as artefact contaminated. The above mentioned sample-based MAD method was solely used to detect transient artefacts which can impair an ICA. However, for the actual classification we used EEGLAB to detect artefact contaminated trials with: (1) amplitudes above/below -80 μV and 80 μV, respectively; (2) trials with abnormal joint probabilities; (3) trials with abnormal kurtosis. The methods (2) and (3) used 4 times the standard deviation of their respective statistic as a threshold to detect artefacts.
Finally, we applied a 0.3 Hz to 3 Hz zero-lag 4th-order Butterworth band-pass filter the original (unfiltered) EEG data to extract low-frequency time-domain features from the EEG, and removed independent components and trials previously marked as artefact contaminated.

Classification: We classified the two classes CLOSE and SUPINATION in each RVI/AVI and MI/OBS condition. We used a shrinkage linear discriminant analysis (sLDA) [18, 19] and a sliding window. In more detail, we used the time lags -200 ms to 200 ms in 100 ms time intervals relative to the center of the sliding window as an input to the sLDA classifier (i.e. 5 time lags). We moved this window over the trials (from -1 s to 3 s in 62.5 ms time steps relative to the start of the movie) and report the classification accuracies associated to the center point of the sliding window. The classification results were validated with a 10x10-fold cross-validation at each classification time step.

Topoplots: To calculate the topoplots, we first interpolated removed channels. Then, we calculated the difference between the average scalp potentials (monopolar) of CLOSE and SUPINATION for each RVI/AVI and MI/OBS condition at each time point within a trial (using a time resolution of 62.5 ms). Afterwards, we took the absolute value of each channel value and time averaged over the movie period of 2 s. Finally, we averaged over subjects.

RESULTS

Classification Accuracies: Fig. 5 shows the classification accuracies of CLOSE vs SUPINATION for all conditions. Classification accuracies were calculated from -1 s to 3 s relative to movie start with a time resolution of 1/16 s. The significance level with respect to a single subject is 64 % ($\alpha = 0.05$, adjusted Wald interval [20, 21], Bonferroni corrected for the time duration in Fig. 5). Five subjects exceeded the significance level between 0 s and 2 s in the RVI-MI condition, 6 in RVI-OBS, 4 subjects in AVI-MI, and no subject in AVI-OBS. RVI yielded higher classification accuracies than AVI, and MI yielded higher classification accuracies than OBS, c.f. Table 1. We conducted a two-way repeated measure ANOVA with 2 factors - RVI/AVI (visual input) and MI/OBS (mental task) - and compared the classification accuracies at the time point of maximal average classification accuracy. The visual input main effect was significant ($F(1, 6) = 8.25$, $p = 0.03$), i.e. the classification accuracy increase between AVI and RVI was significant. The mental task main effect ($F(1, 6) = 0.79$, $p = 0.41$) and the interaction effect ($F(1, 6) = 0.04$, $p = 0.84$) were not significant. The sphericity assumption was tested with Mauchly's test and was not violated ($p = 0.57$).

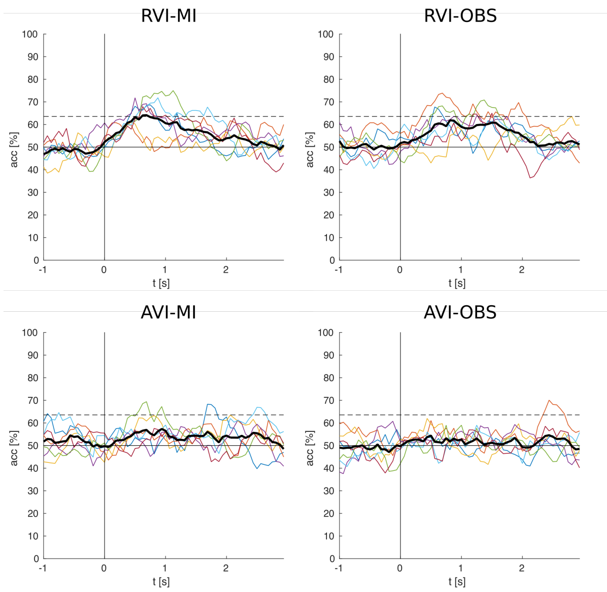

Figure 5: Classification accuracies for RVI/AVI and MI/OBS conditions. Shown are the individual subjects' accuracies and the grand average in bold. At second 0 the movie started to play for 2 seconds. The horizontal solid line is the chance level, the dashed line is the significance level on a single subject basis.

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Table 1: Maximum average classification accuracies with standard deviations and times relative to the movie start

	RVI-MI	RVI-OBS	AVI-MI	AVI-OBS
max acc [%]	64.1	61.9	57.3	54.4
std dev [%]	8.3	5.5	5.0	4.3
time [t]	0.69	0.81	0.94	0.50

We also analysed the classification accuracy of MI vs OBS with RVI. For this purpose, we aggregated CLOSE and SUPINATION trials in the RVI-MI and RVI-OBS conditions and classified these two conditions, see Fig. 6. The significance level with respect to a single subject is 60 %.

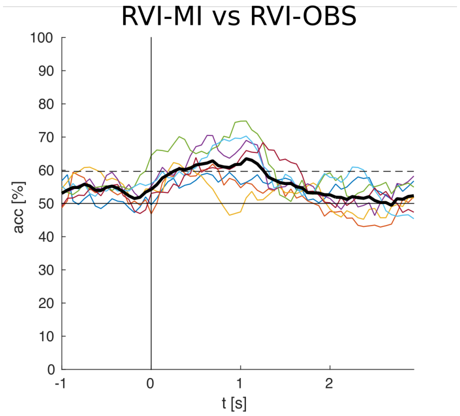

Figure 6: Classification accuracy of MI vs OBS with RVI. Shown are the individual subjects' accuracies, the grand average in bold, the chance level (horizontal solid line), and the significance level (dashed line).

Topoplots: Fig. 7 shows the topoplots where a prominent central pattern is observable for motor imagery during real visual input (RVI-MI).

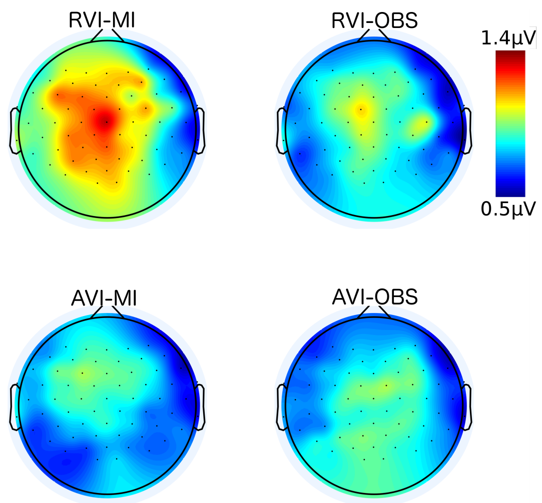

Figure 7: Topoplots. Shown are subject averaged absolute differences between the CLOSE and SUPINATION scalp potential maps. All plots have the same scale (blue is the minimum, red the maximum).

DISCUSSION

We showed the classification of two MIs from the same upper limb based on low-frequency time-domain EEG signals. Importantly, the MIs were not repetitive as in classical SMR-based BCIs but single ones, which are closer to ordinary movements. Furthermore, the MIs corresponded closely to movements which currently could be restored with a motor neuroprosthesis [6]. Some subjects reached a significant classification accuracy when observing abstract visual input. This indicates that the analysed imagined movements can be decoded even in the absence of any realistic visual input. This is in line with [22, 23], where imagined hand movements were decoded from the frequency-domain of EEG. Furthermore, consistent with our initial hypothesis, the results show that the classification accuracy can be increased when serving realistic visual input. Perhaps by substituting the somatosensory feedback at the somatosensory cortex with forwarded input from the visual system as in [15]. However, in our experiment there was no dedicated phase to incorporate the observed hand in ones own body schema.

In a practical setup, we cannot simply present realistic visual input to improve the classification accuracy because that would require knowledge about the indented movement before it was classified. The idea is rather to bootstrap the classification, i.e. presenting realistic visual input in the initial training of the classifier when no feedback is provided yet (open-loop). If the classifier performance is on an acceptable performance level, the subject can then be trained with actual feedback (closed-loop). A principle which has been applied in invasive studies [24, 25] with a robotic arm. However, their the idea was rather to obtain kinematic data for decoder calibration than observing human movements. A robotic arm is different to a human arm, however the boundary between abstract and realistic visual feedback is probably not sharp but continuous and the robotic arm may have been perceived similar to an human arm. Further studies could investigate if the presentation of a human hand is advantageous to a robotic arm in the open-loop classifier training. However, in the context of motor neuroprostheses, movement function is restored without using a robotic arm and this question does not arise.

Most surprisingly, the sole observation of hand movements yielded classification accuracies comparable to MI (c.f. RVI-MI and RVI-OBS). Movement observation has been reported to modulate brain rhythms [13, 14] (with respect to a no-movement condition). In this work, we show for the first time (to the best of our knowledge) that the observation of different movements of the same limb can be decoded from low-frequency time-domain EEG signals. In the context of motor neuroprosthesis control,

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this raises the question if the discriminability in RVI-MI is solely due to the simultaneously observed movement. The classification accuracies in AVI-MI indicate that a classification is basically possible, regardless of the visual input. Furthermore, the results show that MI and movement observation are discriminable during real visual input. However, it can not be answered in this study whether the classification accuracy *increase* is (1) solely due to movement observation or (2) whether the neural correlate of MI is modulated by the movement observation in a way which increases the discriminable information or (3) a combination of both. Nevertheless, the open-loop/closed-loop training approach may still work even when the increase of classification accuracy is solely due to the movement observation. Thus, the impact of this finding on the open-loop/closed-loop training has to be investigated in forthcoming studies. If the observation of movements has activated the mirror neuron system which in turn facilitated the classification is debatable. Mirror neurons fire only when observing meaningful movements. However, in our study no interaction of the movement with the environment was given, i.e. the observed movements were non-goal-directed and should not have activated the mirror neuron system.

The amount of discriminative information in the 4 different conditions is also reflected in the topoplots. The RVI-MI topoplot shows the largest amplitude differences between CLOSE and SUPINATION, followed by RVI-OBS and then the two AVI conditions. The observed RVI patterns are widespread. However, central motor areas are pronounced the most, showing that the discriminative information is indeed encoded in brain signals. Interesting is that RVI-MI has a more amplified pattern than RVI-OBS but similar classification accuracies. This may be due to a more stable pattern during the video sequence (topoplots are averaged over the whole movie period as opposed to the classification accuracies). This indicates that the discriminative information is encoded differently between MI and movement observation.

CONCLUSION

We show the classification of two imagined movements of the same upper limb and show that the classification accuracy can be increased if the movement is simultaneously observed in a video. Furthermore, we show that also the sole observation of movement videos yields discriminable brain patterns.

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