PLEASE REPEAT - CLASSIFICATION OF 3D REACH TARGETS FROM ELECTROENCEPHALOGRAPHIC SIGNALS IS ENHANCED BY REPETITION

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Introduction

The advent of high quality multi-channel EEG recording systems and the significant advance in the field of machine learning enabled decoding complex motion features, such as the direction of hand movement in real (Waldert et al. 2008) and imaginary conditions (Ofner and Muller-Putz 2015). These decoding algorithms usually use classifiers like linear discriminant analysis (LDA) and support vector machine (SVM) on signal features to decode classes of movements, while other algorithms such as multivariate regression (MVR) are used to decode hand movement trajectories (Rickert et al. 2005). Currently, the discrimination of actual or imagined pointing movements to different targets with the same limb is modest. This is due to the fact that these motor tasks activate essentially the same motor-related neural networks for all targets, thus, the discrimination between different actual or imagined movements has to rely more heavily on differences in temporal and spectral features of the neural activity rather than on differences in spatial activation patterns. In this

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study, we suggest that forming a distinct, target-specific neural activation pattern can be enhanced by segregating the internal representation of the different conditions (targets) and that this may be pursued by forming a strong recollection of each of the hand movements (muscle/kinesthetic memory) (Krakauer and, Shadmehr 2006). As kinesthetic memory involves consolidating a specific motor task into memory through repetition (Karni et al. 1995, Shadmehr and Holcomb 1997), a block design task was utilized in which each target is pointed at for several times consecutively.

Methods

Subject and Paradigm Fifteen healthy subjects (15 males, aged 25-46 years) gave informed consent and participated in the study, which was approved by the Wolfson Medical Center Helsinki committee. The subjects sat 1.5 m in front of a motion sensing device (Microsoft Kinect) and were instructed not to move their head or talk throughout the entire experiment. The experimental design consisted of five targets; target 1, 2 and 3 lay in the shoulder horizontal plane forming 45°, 67.5° and 90°, respectively, relative to a horizontal axis passing through the torso and shoulder, whereas target 4 and 5 lay 45° below and above the shoulder sagittal plane, respectively, relative to a sagittal axis aligned with the shoulder. The subjects were informed that they should make, or imagine making repetitive pointing movements with their right dominant arm to one of the five targets distributed in the workspace and return to the home position ('H') in synchrony with an auditory cue (2 kHz and 1 kHz tone for a forward and backward movement, respectively). Six subjects practiced a block design task aimed at testing the model generalization to different motion velocities (slow and fast) and trial types (actual and imagery). Nine subjects practiced both block design and non-block design aimed at testing the effect of the type of design on decoding accuracy. In order to avoid eye movements/blinks artifacts, the subjects were instructed to gaze at the aimed target (not to track their moving arm) and try to avoid eye blinks. Figure 1 illustrates the experimental setup.

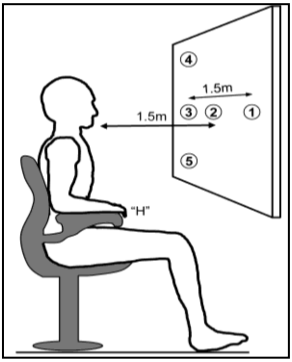

Fig. 1

Experimental setup

Targets positions. Target 1, 2 and 3 lay in the shoulder plane forming 45°, 67.5° and 90°, respectively, relative to a horizontal axis passing through the torso and shoulder, whereas target 4 and 5 lay 45° below and above the shoulder plane, relative to a sagittal axis aligned with the shoulder. The home position ('H') was a foam pad glued to the chair right armrest.

Data Recording We acquired parallel recorded electroencephalogram (EEG), electromyogram (EMG) and kinematic data in two computers connected by serial communication (RS232). The EEG and kinematic data were synchronized using timestamps. EEG signals were recorded from 62 active channels (with gel) and from one EOG electrode that was attached inferiorly to the orbital fossa of the left eye (g. HIamp80, g.tec medical engineering GmbH, Schiedlberg, Austria). We recorded surface EMG from the right arm biceps (BPMP150MW, BIOPAC systems, Inc., Goleta, CA, USA). Kinematic data were recorded from the right dominant hand, elbow and shoulder at 30 frames per second (FPS) using a 3D Microsoft Kinect camera system.

Preprocessing The EMG was amplified (gain: 2000), filtered (1-500Hz), sampled (A/D resolution: 16 bits, sampling rate: 2000 samples/s), rectified and averaged (time window = 30 ms) in order to capture the "envelope" of the signal for later rejecting arm biceps artifacts (including mechanical artifacts) from the EEG signal using Independent Component Analysis (ICA) (denoising). Next, the average rectified (AVR) EMG data was resampled at 1200Hz to match the sampling rate of the EEG and EOG. EEG data were passband filtered using an equiripple filter between 4–30 Hz in order to discard low band (e.g., baseline drift and motion artifacts) and high band (e.g., EMG) artifacts. The channels were analyzed for artifacts and any contaminated channels were interpolated. Next, the data were referenced to the average of all scalp electrodes and ICA was performed on the dataset. The resulting ICs were analyzed for artifacts and contaminated ICs were subtracted from the dataset. In order to extract the movement and imagery epochs, the data were cut around the auditory cue onset - from 0 ms to 800 ms, for the slow movements, and 0 to 500 ms, for the fast movements. The epochs were analyzed for artifacts and any contaminated epochs were removed from the dataset. Finally, the baseline (whole epoch mean) was removed from each epoch.

Feature Extraction Multi-class Common Spatial Pattern (CSP) filters were computed to extract discriminant information from multiple classes of EEG signals. First, a covariance matrix was computed for each of the five target classes. Next, the five covariance matrices were used to compute a joint approximate diagonalization (JAD). Finally, the independent components (ICs) that approximately maximized mutual information of class labels and extracted EEG components were computed. We then used four CSP filters as features, wherein each filter is the log of the weighted variance calculated on the multi-channel data.

Computing chance level To assess statistical significance of the classification performance, the distribution of chance classification in the case of finite number of test trials should be considered. To that end, we calculated the probability of getting k correct classifications by chance, which is given by:

$$P(K) = C(n,k) \times P^k \times (1 - P)^{n-k}$$

wherein C(n, k) is the number of k combinations out of n test trials and P is the probability of classifying a target in each trial (1/5 = 0.2).

Results

First, we visually inspected the EMG and kinematic data to verify that the arm was moving vs. idle during actual movements and imagery trials, respectively, that subjects generated stereotypical point-to-point trajectories to each of the five targets and that the preprocessed EEG data was clean of non-physiological and physiological artifacts (Fig. 2). Next, we tested for movement time differences across targets. No significant difference between movement times (forward and backward) was found across the five targets for each of the subjects for both the slow (n=30, p>0.07, F<2.4) and fast (n=48, p>0.07, F<2.3) actual movements (one-way ANOVA). Finally, we tested for a correlation between EOG and kinematics (tangential velocity). The coefficient of determination between the two descriptors was very low (r^2<0.04) for all subjects (mean ± SD = 0.02 ± 0.02, median=0.02).

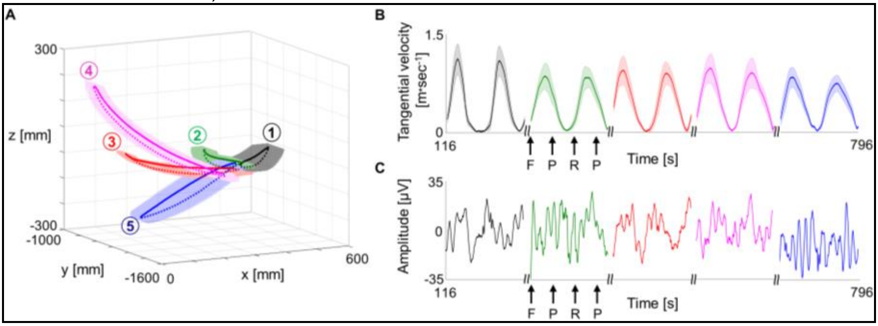

Fig. 2

__A__ Mean (SD) path to each target during Fast Actual Movements of a representative subject (#1). __B__ Mean (SD) tangential velocity to each target. The arrows indicate the timing of a trigger cue for forward (F), pause (P) and backward (B) movement. __C__ Mean EEG waveform of FC3h electrode, positioned over the left sensorimotor area, to each target. The subject generated roughly straight point-to-point trajectories with bell-shaped velocity profile. The corresponding EEG signal was clean of non-physiological and physiological artifacts.

In order to test the model accuracy for decoding target location, the model was trained and tested on a five class training and testing dataset, respectively. The analysis was performed separately for the two trial types (actual / imagery) and motion speeds (slow / fast). Next, a confusion matrix for each of the four datasets and six subjects was computed. Averaging across subjects, the decoder accuracy for the trained target was significantly higher than chance level for all the four combinations of trial type and speed (84±15%, 84±17%, 77±25% and 79±21% for slow actual, slow imagery, fast actual and fast imagery of movements, respectively; $p<0.001$). The average target decoding accuracy for both the 'Pause at Home' and 'Pause at Target' epoch was 67±27%, suggesting that both of the rest periods included discriminative neural patterns, probably due to ongoing movement planning processes. Finally, in order to test the model accuracy for decoding target location, irrespective of trial type, all the data were pooled across all conditions for each subject and used to train and test the model. Averaging across subjects, the decoding rate reached 75±22 (72±30%, 74±39%, 77±11%, 62±15%, 81±15 and 84±15 for subject 1 to 6, respectively). Overall, these findings indicate that neural features during both response (actual or imagined) and rest epochs can be used to decode target location.

To study whether decoding a target location is dependent on trial type (actual / imagery) and motion speed (slow / rapid), the model was trained on slow actual movements to one of the targets and was tested on imagery of slow movements to the *same* target, i.e., testing data preceded training data by one sub block (48 seconds). Averaging across subjects, the model decoded target location with 61±11% accuracy, which is significantly higher than chance level ($p<0.001$). Decoding rate was also significantly higher than chance level when the training data were exchanged with the testing data, i.e., the model was trained on imagery of slow movements and tested on slow actual movements to the same target (57±19%) or the model was trained on fast actual movements and tested on imagery of fast movements to the same target (63±16%), and vice versa (64±14%) ($p<0.001$ for all three tests). Overall, these findings indicate that the model generalized well to different trial types (actual / imagery) than those used for training.

It was found that when imagery of fast movements to a given target followed actual movements to the same target by three sub blocks, the vote of the model for that target was greatest and significantly higher than chance level (55±5%, 63±16% and 64±7%, respectively; $p<0.01$ for all tests) and also significantly higher than the vote for the target lastly visited ($p<0.01$ for all tests), suggesting that short-term, target-specific kinesthetic memory has an enhancing effect on decoding accuracy. However, it was found that when imagery of fast movements to a given target followed actual movements to the same target by ten sub blocks, the model did not vote for that target (i.e., 0%) and the vote was greater for the target lastly visited (70±7%), suggesting that time proximity has a major effect on decoding accuracy.

Next, we aimed at studying whether the high decoding rate was tied with the generation of repetitive movements (block design) to each of the targets, we asked nine naïve subjects to generate both repetitive and non-repetitive, randomized pointing movements to each of the targets. Averaging across subjects, the decoder accuracy for the trained target was significantly higher than chance level when the target was aimed at repeatedly (48±18%, $p=0.01$). When a sequence of movements, one for each target, was generated repeatedly, the decoding rate of target position was low (30±19%) and not significantly different than chance level ($p>0.1$). These findings suggest that block design enhances decoding accuracy by time proximity between consecutive trials, possibly due to similar brain state conditions and the consolidation of target-specific motor memory.

Finally, in order to detect the electrodes which activity mostly changed across conditions (targets) and thus are preferentially used by the model for discriminating between the five targets, we generated a 2-D topoplot map of the most important (first) CSP filter for each of the six subjects practicing the block design task, trial type (actual or imagery), motion speed (slow or fast) and pause epoch (pause-at-home or pause-at-target). The contribution of each electrode corresponds to its absolute weight averaged across the different training and testing datasets. The six topoplots exhibited a similar topography pattern wherein the most discriminative features were extracted from electrodes positioned over the contralateral sensorimotor area (electrode C3h), the ipsilateral prefrontal cortex (electrode F2) and the ipsilateral sensorimotor or somatosensory cortex (electrode CCP4h) (Fig. 3). These findings suggest that for all actual and imagery movements or resting epochs, decoding of target location relied mostly on changes in the spectro-temporal activation pattern in these electrodes rather than on a change in the spatial activation pattern.

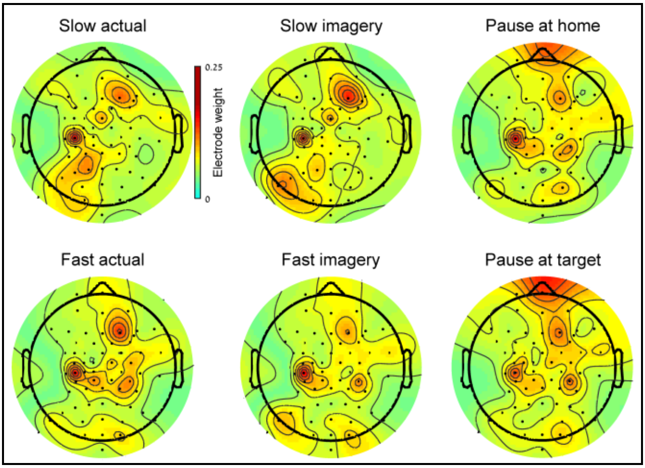

Fig. 3

2-D topoplots, averaged across the six subjects, of the most important CSP filter (i.e., explaining the largest variance of activation between the five targets) for each movement trial (actual or imagery, slow or fast) and rest period (Pause at home and pause at target). Color bar - electrode weight.

Conclusions

Overall, our findings suggest that block design enhances the decoding accuracy of target location and that the high decoding rate is generalized to different trial types. Deciphering the mechanisms underlying the enhanced decoding accuracy found for the block design and the effect of motor memory on decoding performance can ultimately be used in more general settings wherein movements are not executed in blocks.

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A detailed description of the experimental paradigm and results can be found in:

Sosnik R, Tadipatri VA, Tewfik AH, Pellizzer G(2016), Block design enhances classification of 3D reach targets from EEG signals. Neuroscience 329: 201-212.