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FINDING THE OPTIMAL SIX: DECODING FROM A LARGE SET OF HAND GESTURES WITH 7T FMRI FOR IMPROVED BCI CONTROL

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ABSTRACT: Decoding movements from the human sensorimotor cortex has been of great interest for brain-computer interfaces (BCIs). To establish the possibility of increasing the degrees of freedom of a sensorimotor-driven BCI, we investigated the decodability of 20 hand gestures using 7-Tesla fMRI and narrowed it down to a set of six best distinguishable gestures. Six able-bodied volunteers performed gestures from the American Sign Language alphabet and single-digit movements. Results indicated significant classification accuracies across all 20 gestures ($mean = 46\%,\ range\ = 39.5\% - 51.5\%,\ chancelevel = 5\%$), with some differences in decodability across gestures. Subsequently, optimal sets of six gestures were identified by establishing classification performance for all possible permutations, and applying the identified set in a leave-one-subject-out cross-validation scheme. The results showed a near-optimal classification in five out of six subjects. Our findings contribute to the understanding of the generalizability of gesture decoding performance and offer insights for refining BCI control strategies to enhance communication for individuals with motor impairments.

INTRODUCTION

Fully implantable brain-computer interfaces (BCIs) intend to establish a communication pathway between signals directly measured from the surface of the brain and a computer [1]. This can be of great use for individuals with locked-in syndrome, a condition that can result from Amyotrophic Lateral Sclerosis (ALS) or brainstem stroke [2]. A common target for BCI-readout is the sensorimotor cortex due to its well-established topographic representations and the fact that it shows activity during attempted movement even years after paralysis, despite the absence of the actual movement [3, 4]. For BCI control, different attempted movements need to be classified and coupled to intended commands. However, if the cortical activity related to the selected movements is not distinct enough, the BCI may misclassify the intended action – resulting in outcomes that are not desired by the user. Thus, it is crucial to ensure that the command-coupled movements are well-decodable and not easily confused by the BCI.
While fully implanted electrocorticography (ECoG)-BCIs used at home have shown considerable success [5], their degrees of freedom have been limited so far (i.e., opening and closing the hand to produce a 'brain-click'). Expanding the range of BCI control signals could significantly speed up communication, thereby improving their usability. A substantial increase in the degree of control in a home-use ECoG-BCI could be provided by the ability to decode six different movements, each corresponding to a specific command (i.e., "up", "down", "left", "right", "select", and "escape"). These six commands would be produced through six different attempted movements with the hand. Particular sets of attempted movements may be more or less suitable for this purpose based on the similarity of the elicited cortical activity patterns. To optimize the performance of such BCI, we require a set of hand movements that is maximally distinct based on brain activity patterns in the sensorimotor cortex. As there is potentially a huge number of possible movements, the options need to be narrowed down at the outset.
Functional magnetic resonance imaging (fMRI) allows us to measure the representations of different hand movements in the sensorimotor cortex non-invasively and with high spatial resolution. This method provides the opportunity to explore activity in the sensorimotor cortex for various movements and across multiple individuals. Using fMRI, it is feasible to distinguish individual finger movements [6, 7], but also hand gestures consisting of the flexion and extension of multiple fingers [8, 9], even for attempted movements without an actual motor output [10]. Furthermore, fMRI results can be extrapolated to an implanted BCI as previous work has shown that fMRI activity patterns map consistently to the gamma band of ECoG recordings [11–13], for review, see [14].
Here, we investigate the decodability of 20 unimanual hand gestures in six healthy individuals, using 7-Tesla fMRI. From these 20 gestures, we identify the set of six that results in the most accurate classification. Furthermore, we explore the consistency of classification performance across individuals and look at the potential compromise of choosing hand movements based on group averages as opposed to individual results. These in-

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sights can serve as a starting point to predict which hand movements can be well-decoded from the sensorimotor cortex.

MATERIALS AND METHODS

Participants: Six healthy, able-bodied volunteers (age: $mean = 23$ *years*, $SD = 1.8$; 4 females; all right-handed) performed a hand gesture task during the acquisition of functional scans in a 7-Tesla MRI scanner. All participants gave written informed consent to participate, which was approved by the Medical Research Ethics Committee according to the Declaration of Helsinki (2013).

Data acquisition: MRI data were recorded using a Philips Achieva 7-T MRI system with a 32-channel head coil. Functional data were recorded using an EPI sequence (TR/TE = 1400/29 ms, FA = 60°, multiband factor 2, voxel size = 1.5 x 1.5 x 1.5 mm^3, in-plane resolution = 200 x 200 mm^2, 40 slices). A high-resolution anatomical T1-weighted MP2RAGE [15] was acquired for anatomical reference.

Experimental task: Participants performed a gesture task with their right hand. The movements were a sub-selection of 15 gestures from the American Sign Language alphabet based on ease of execution. In addition, we included individual flexion of each finger, resulting in a total of 20 gestures (Fig. 1). Participants practiced the hand gestures at home during the week prior to scanning to ensure familiarity with the movements.

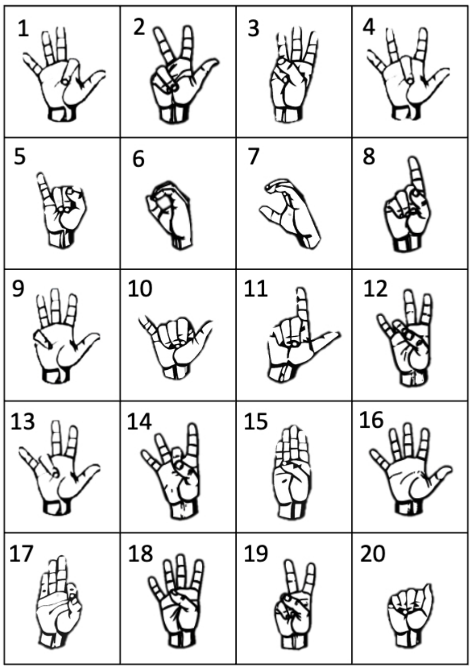

Figure 1: The task contained 20 right-hand gestures, including single-finger flexions (gestures “1”, “4”, “9”, “13”, “18”) and gestures from the American Sign Language alphabet.

During the scan, the stimuli were projected onto a screen that was visible to the participants through a mirror and prism glasses. Each trial consisted of three different images, illustrating either the preparation phase, execution phase, or resting phase of the gestures to be performed (Fig. 2). After the preparation phase (2 s), the participant was instructed to execute the presented gesture and hold it for 6 s (execution phase) before returning the hand to the baseline position (hand relaxed, fingers slightly bent, palm face up; resting phase). The resting phase lasted for 8.8 s, to prevent blood-oxygen-level-dependent (BOLD) responses to bias the activity estimates of the subsequent trial. The stimuli were presented in a pseudo-random order.

Each gesture was performed once per run. Participants completed 10 runs in total, split across two scanning sessions on separate days (5 runs/session). This yielded a total of 10 repetitions per gesture for each participant. MRI-compatible data gloves (5 DT Inc, Irvine, USA) were worn during the task on both hands to record kinematic data. The data glove measurements were visually inspected for correct bending of the fingers and the absence of additional movements.

Figure 2: Trial schematic. An image of a gesture inside a red rectangle signaled the onset of a preparation phase, which was included to minimize error in the execution of the movement. The change of the rectangle’s color to green indicated to the participant to make the displayed gesture and hold it for the duration that the gesture was presented. After returning the hand position to baseline, there was an 8.8 s pause until the onset of the next stimulus.

Data preprocessing: Functional scans from the Gesture Task were preprocessed using SPM12 (http://www.fil.ion.ucl.ac.uk/spm/) and custom MATLAB (https://www.mathworks.com) scripts. Scans from both sessions were aligned with each other and coregistered with the T1-weighted image. A General Linear Model was created including factors for each gesture. T-maps were computed for each gesture type while using a leave-one-run-out procedure, resulting in a total of 200 t-maps (20 gestures x 10 run-combinations).

Region of Interest: The left precentral and postcentral gyrus were defined as regions of interest through the Freesurfer surface reconstruction pipeline (https://surfer.nmr.mgh.harvard.edu), based on the Desikan-Killiany atlas.

Gesture classification: To assess the discriminability of hand gestures in the contralateral sensorimotor cortex, we used a support vector machine (SVM). The 500 voxels with the highest absolute t-values across gestures were selected as features. The BOLD signal in these voxels was detrended and transformed into z-scores for each run separately. For each trial, the peak signal in the 5th,

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6th, and 7th volume after trial onset was extracted, which corresponds to the amplitude of the peak of the BOLD signal.
The SVM was run with a linear kernel and constraint parameter C = 1. A leave-one-run-out cross-validation scheme was used, meaning that with each iteration, one run was left out for training the model, and the left-out run was subsequently used to test the model. For each training/test set, the classification accuracy was calculated as the proportion of correctly classified gestures. These classification scores were then averaged across iterations, resulting in a single classification score per participant.
Classification performance was further evaluated using confusion matrices, which contain the details on correct and incorrect classifications. Confusion matrices were computed per subject and subsequently averaged (Fig. 3).

Choosing an optimal set of six gestures: For maximizing the performance of a BCI, we aim to select the six best distinguishable gestures and estimate if the performance of this set is generalizable across subjects. For this, we created SVMs for all possible combinations of a set of six out of the 20 gestures (in total 38760). This resulted in 38760 classification accuracies for each participant, containing the classification accuracy per possible gesture set. The optimal sets were selected based on the mean accuracy across participants. These sets were then evaluated using a leave-one-subject-out cross-validation, by testing their performance relative to that of all other combinations.

RESULTS

Classification performance of 20 gestures: The classification accuracy for all gestures across all participants ($mean = 46\%$; $range = 39.5\% - 51.5\%$) was significantly above the 5% chance level ($t(5) = 19.8$, $p < 0.001$) (Fig. 3). Visual inspection of the confusion matrix revealed that the decoder often confused gesture “18” with “15” ($mean = 31.7\%$), and gesture “9” with “2” ($mean = 28.3\%$).

Gesture set selection: With the aim of finding the set of six gestures that are maximally decodable, we ran the SVM for each of the possible 38760 combinations of six out of 20 gestures. The gesture sets with the, on average, highest classification performance are shown in Fig. 4, in addition to the set with the highest mean ranking.

Next, to estimate the extent to which group-mean performances of optimal gesture sets are generalizable to different participants, we chose a gesture set based on a group-average result (leave-one-subject-out cross-validation) and checked the performance of this set in an individual. A summary of the results can be seen in Tab. 1. The difference in classification accuracy between the chosen gesture set and the set with maximum classification in the left-out subject ranged from 8.33% to 20.00%. The percentile scores of the chosen set in the distribution of all sets ranged between 95.01% to 98.86%

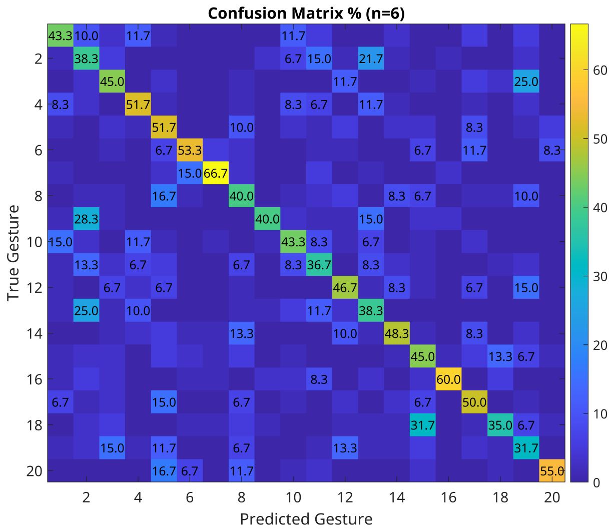

Figure 3: Average group classification in % for all 20 gestures ($chancelevel = 5\%$). The numbers inside the squares correspond to the accuracy values assigned to the classified gesture (for values > 5%).

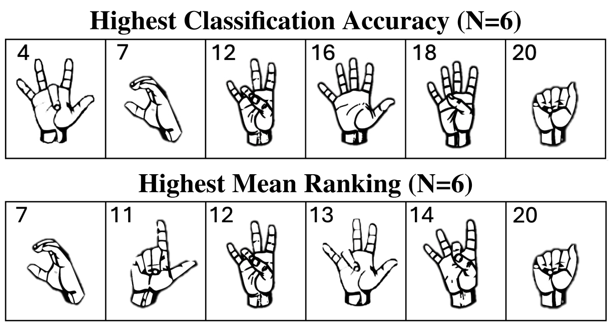

Figure 4: The overall best decodable set of six gestures, based on average classification accuracy (top row; $mean = 87.22\%$, $SD = 4.91\%$) and on average ranking scores (bottom row; $mean = 76.38\%$, $SD = 6.94\%$) of all participants ($chance\ level = 16.67\%$).

for five subjects, one subject’s (sub006) percentile score was 82.15% (Fig. 5). Some gestures were consistently present in the best-performing sets from the group average, with gesture "7", "16", and "20" being selected 100% of the time (Tab. 2). The highest performing subject-specific gesture sets were more varied, however, gesture "7" and "16" were still present in 66.67% of the sets (the highest observed percentage for subject-specific sets), and "20" in 50% of the cases. Gestures "10", "11", and "15" were never present among the highest performing gestures.

DISCUSSION

In this study, we examined which sets of gestures are consistently well-decodable across individuals with 7-Tesla fMRI. For this, we first demonstrated the classification performance of 20 gestures and then created subsets of six gestures with the highest classi-

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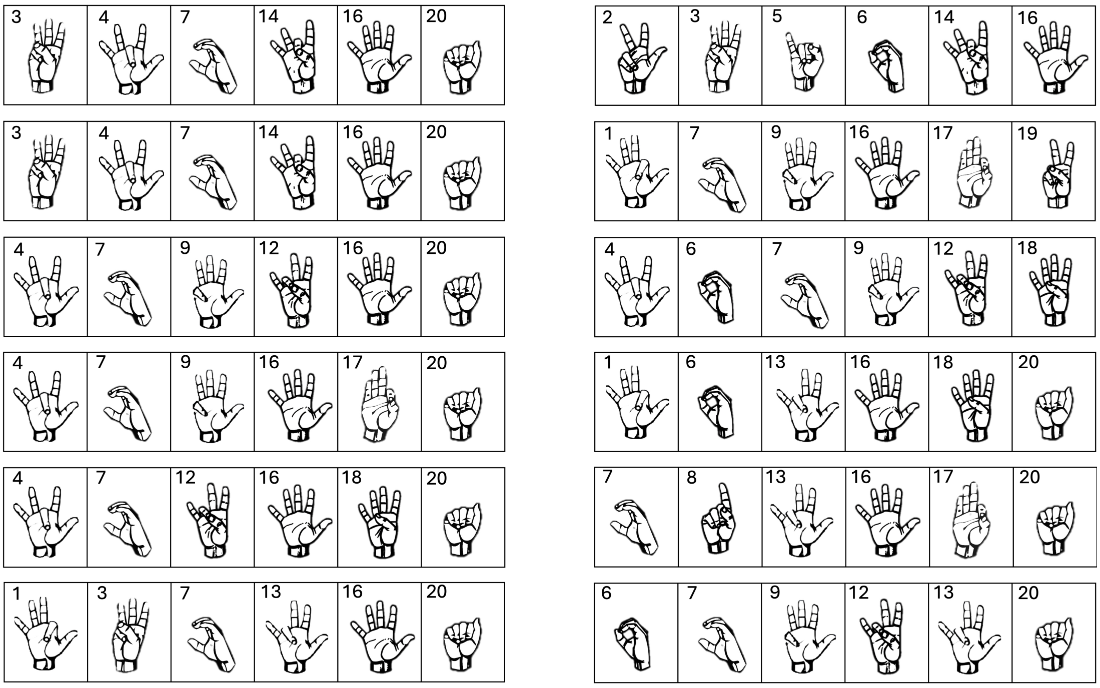
Table 1: Results for leave-one-subject-out gesture set selection. From left to right: Accuracy of the best-performing gesture set for five subjects ("GS Acc. leave-one-out"); accuracy of the selected gesture set for the left-out subject ("GS Acc. sub"); highest accuracy of subject's best-performing gesture set ("Max Acc. sub"); the difference between selected gesture set and subject's best-performing gesture set ("Diff"); subject's average classification performance of all possible gesture sets ("Overall Mean sub").

	GS Acc. leave-one-out (n=5)	**GS Acc. sub**	**Max Acc. sub**	**Diff (Max Acc. sub – GS Acc. sub)**	**Overall Mean sub**
sub001	86.67%	88.33%	100.00%	11.67%	76.40%
sub002	86.67%	88.33%	98.33%	10.00%	76.13%
sub003	88.33%	81.67%	90.00%	8.33%	68.37%
sub004	86.67%	88.33%	96.67%	8.33%	73.08%
sub005	87.67%	85.00%	96.67%	11.67%	68.68%
sub006	89.00%	71.67%	91.67%	20.00%	63.35%

Table 2: Comparison of the selected gestures based on group average performance (left column) and the best-performing gestures based on the left-out subject's classification accuracy (right column).



	Highest gesture set leave-one-out (n=5)	**Highest gesture set sub**
sub001	3, 4, 7, 14, 16, 20	2, 3, 5, 6, 14, 16
sub002	3, 4, 7, 14, 16, 20	1, 7, 9, 16, 17, 19
sub003	4, 7, 9, 12, 16, 20	4, 6, 7, 9, 12, 18
sub004	4, 7, 9, 16, 17, 20	1, 6, 13, 16, 18, 20
sub005	4, 7, 12, 16, 18, 20	7, 8, 13, 16, 17, 20
sub006	1, 3, 7, 13, 16, 20	6, 7, 9, 12, 13, 20

fication performance across participants. Our findings demonstrate the feasibility of decoding a large set of gestures across able-bodied individuals. Twenty gestures could be decoded from sensorimotor activity with, on average, 46% accuracy. Furthermore, we evaluated the generalizability of optimal gesture sets across individuals. By selecting optimal gesture sets based on a group average and testing their performance in individual participants, we demonstrated that those sets still have a well above-average classification accuracy in the respective individual compared to those of all other sets (percentile ranks higher than 95% for five out of six subjects). This suggests that movements identified through group-level analysis are likely to generalize to individuals. One participant showed a relatively low classification accuracy for the group-selected set (percentile rank at 82%). However, it was still higher than the subject's average classification score across all possible sets. Furthermore, we noticed that the general classification performance in this subject was lower than in the other participants and that some trials contained ambiguous movements. Further investigation is needed to assess if the performance improves upon the exclusion of wrong trials.

Visual inspection of the successful gestures indicated that distinct digit combinations and wrist movements can be best distinguished from each other. In contrast to that, gestures that were especially prone to confusion were "18" (fingers spread, thumb flexed) with "15" (fingers together, thumb flexed); and "9" (pinky flexed) with "2" (pinky and ring finger flexed). Interestingly, this was not the case for gestures "6" (wrist rotation, thumb, and other fingers touch) and "7" (wrist rotation, thumb, and other fingers bend, not touching), which were consistently among the best decodable gestures with a low confusion score with each other. This may be due to the difference in sensory feedback, which can be checked by decoding from the primary motor and somatosensory

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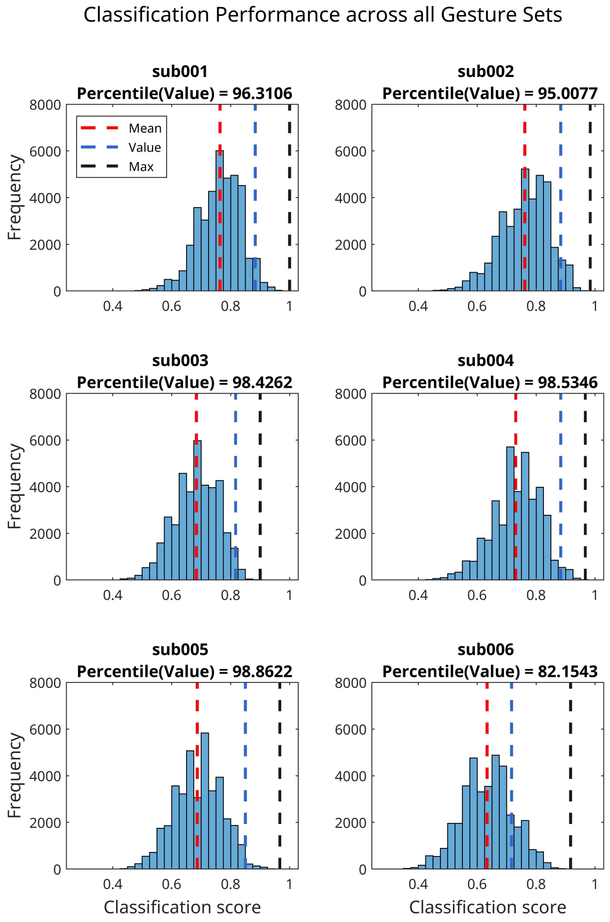

Figure 5: Distribution of the classification accuracies across all possible gesture sets of 6 (38760 combinations) for each participant. The red line ("Mean") indicates the average classification accuracy across all possible sets. The blue line ("Value") shows the accuracy of the selected gesture set based on the highest performance in the other five subjects. The black line ("Max") shows the highest classification score of the respective subject.

cortex separately. In general, gestures that have only subtle movement differences are also more difficult to discriminate.

Partly, this result might not seem very surprising considering the topography of the sensorimotor homunculus containing representations of individual fingers [16, 17]. Thus, a gesture consisting of thumb flexion should be well distinguishable from a pinky flexion gesture. However, previous research has also observed that the activation of complex coordinated finger movements is not a mere linear combination of the activation of individual finger movements [18–21]. The exact nature of movement representation in the sensorimotor cortex and what makes some movements better decodable than others is thus still to be fully elucidated.

Limitations: One main limitation of our study is the small sample size. We assume that the predictions can be improved with higher sample sizes, making the compromise between the group and an individual's optimal result even lower. Additionally, the limitation of only ten repetitions per gesture may have led to sub-optimal accuracy results, thus, increasing the repetition count could yield higher scores. Furthermore, at the study's current state, a direct translation to ECoG-BCIs is not possible, as our features were selected from the entire sensorimotor cortex which is not fully accessible by surface recordings. A more restrictive feature selection that overlaps with the recording of an ECoG grid can benefit the translation. We also acknowledge that the acquired data is from able-bodied participants who produced overt motor output. Even though the sensorimotor cortex of paralyzed patients still shows activity [22], potential BCI users might vary more widely in how well they can induce similar activity patterns when attempting certain hand movements. Thus, current results may not apply to every BCI user.

Future directions: Some gestures showed high decodability, while others were prone to confusion. However, the exact neuronal mechanisms underlying these variations are still unknown. Future work directed towards understanding which parameters are driving distinct representations in the sensorimotor cortex would not only provide valuable information for optimizing decoding algorithms for BCIs but would also enhance our basic understanding of the nature of movement representations in the sensorimotor cortex.

CONCLUSION

In this paper, we investigated the decodability and consistency of sets of six gestures extracted from 20 different gestures. Our findings show potential gestures that exhibit robust decodability across individuals. The consistent variations in classification performance across gestures indicate substantial underlying similarity in sensorimotor representation patterns across individuals that makes some gestures more easily decodable than others. The findings highlight the potential for improving BCI control through optimized gesture selection.

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