

Give Me a Sign: Studies on the Decodability of Hand Gestures Using Activity of the Sensorimotor Cortex as a Potential Control Signal for Implanted Brain Computer Interfaces

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The major driving force behind the development of brain computer interfaces (BCI) has been the desire to re-establish communication for severely paralyzed or even locked-in patients. As a consequence, different strategies have been developed to provide a direct link between a still-functional brain and the outside world, bypassing the non-functional muscle system (Wolpaw et al. 2002). The first BCIs used the P300 evoked potential (Farwell and Donchin 1988) and slow cortical potentials (Birbaumer et al. 1999), as they can be measured by electroencephalography (EEG).

In the ideal case, a BCI would enable its user, previously incapable of any communication, to participate in a conversation at the same speed and with the same expressiveness as a non-paralyzed person would. However, the use of electroencephalography (EEG) as the primary recording method has to date limited the potential to decode brain activity, due to its low spatial resolution and signal-to-noise ratio. EEG can only detect prominent changes in brain activity and often has to integrate information over time in order to detect a certain activity pattern. These limitations reduce the speed and flexibility of any communication based on EEG BCI.

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In recent years, an alternative to the EEG-based BCIs has emerged that is based on invasive recording techniques such as single-cell/multi-unit recordings (Collinger et al. 2012; Guenther et al. 2009; Hochberg et al. 2012) and electrocorticography (ECoG) (Leuthardt et al. 2004; Vansteensel et al. 2010; Wang et al. 2013). These methods provide a much higher spatial resolution and have a superior signal-to-noise ratio compared to EEG, and provide the potential to differentiate between a greater number of cognitive states and at a faster rate.

The primary objective of invasive BCI research has been the control of artificial limbs using the activity from neurons of the primary motor cortex. Using the combined activity of individual neurons (Hochberg et al. 2012), or larger populations of neurons (Wang et al. 2013), allows tetraplegic patients to control artificial arms and hands with a promising degree of accuracy, enabling them to grasp objects, for example.

Our hands, however, are not only suitable for manipulating objects but also for communication. In sign languages, for example, different hand gestures represent the letters of the alphabet. Sign languages are full-fledged languages that allow anything to be conveyed in the same way that any other language can. With the help of the hands, face and even the entire body, words and meanings are expressed as complex signs. To spell words or names for which no specific signs are available, sign languages also contain a fingerspelling alphabet. For each letter of the alphabet, there exists a specific gesture that can be formed with one hand (see Fig. 1).

The muscles of our body, hands and fingers are controlled by a network of cortical and subcortical structures involving, among others, the cerebellum, the basal ganglia and the primary motor cortex. The topographic representation of body parts in primary motor cortex (Penfield and Rasmussen 1950) makes it easy to differentiate between the movements of the different body parts (legs and arms)

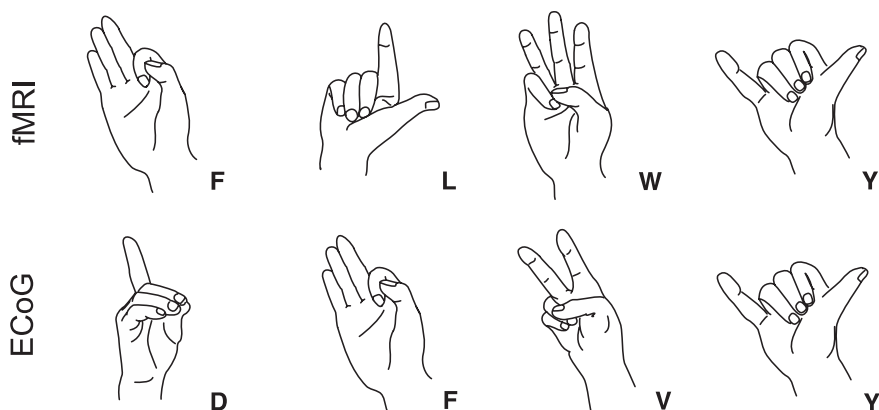


Fig. 1 Participants had to execute one of four hand gestures taken from the American sign language alphabet. For the fMRI study, the gestures ‘L’, ‘F’, ‘W’ and ‘Y’ and for the ECoG study ‘D’, ‘F’, ‘V’ and ‘Y’ were used

based on neuronal activity, and this topographic representation is also present for individual fingers. The hands and fingers are known to be extensively represented on the sensorimotor cortex at a specific anatomical landmark, the so-called hand knob (Yousry et al. 1997). Moreover, it has been shown that the movement of individual fingers (Kubánek et al. 2009; Miller et al. 2009) and the coordinated movements of all fingers [e.g. during grasping (Chestek et al. 2013; Pistohl et al. 2012)] can be discriminated based on the neuronal activity of the sensorimotor cortex. Consequently it should also be possible to decode communicative hand gestures.

The confined representation of the hand makes it a very interesting target region to extract control states for a permanent BCI using implanted electrodes. Nevertheless, permanent BCIs based on needle or surface electrodes require surgical intervention for the electrode placement. Every surgery comes with a certain risk for the patient, which is especially the case for people with locked-in syndrome. The required surgery should therefore be as short and limited as possible. The hand knob area would be such a region. It is located on the gyrus ‘at the cross point between the pre-central sulcus and the central sulcus, and is therefore also visible on the cortical surface’ (Yousry et al. 1997), and is also confined to a small area. This makes it surgically comparatively easy to access and therefore only requires a small surgical intervention.

We propose using communicative hand gestures as the control signal for an ECoG based BCI with the purpose of re-establishing communication. If it were possible to decode multiple gestures from their activation pattern over the motor cortex, it would provide an interesting and powerful approach for the control of BCI, specifically aimed at reinstating communication. We therefore studied the feasibility of decoding communicative hand gestures using high-field fMRI and high-density ECoG.

1 fMRI

In a first step towards our goal of using hand gestures for BCI control, we studied the decodability of gestures using functional magnetic resonance imaging (fMRI). Although our objective is an implantable BCI using ECoG electrodes, the fMRI provides valuable information that is difficult to acquire by other means. The primary advantage of using fMRI (compared to invasive recording techniques) is that it allows larger groups of people to be studied. The obtained results are therefore generalizable to the population. fMRI provides a good spatial resolution which, at 7 T field strength, is comparable to what can be measured with high-density ECoG electrodes (1–2 mm inter electrode distance). Furthermore, it allows researchers to record from all parts of the brain (including deeper structures) at the same time. The rather good correspondence between the brain activity patterns on the cortex as measured by fMRI and by ECoG (Hermes et al. 2012; Siero et al. 2013; Vansteensel et al. 2010) makes it possible to use the fMRI results to inform our subsequent ECoG study.

The classification of individual gestures on a single trial basis requires a good signal-to-noise ratio, and the representations we were interested in are presumably rather fine-grained (Dechent and Frahm 2003) necessitating high spatial resolution. We therefore conducted our study using a Philips Achieva MRI 7 T system with a 32-channel head-coil. Given the superiority of 7 T fMRI over typical fMRI at lower field strength, in terms of signal strength and quality (van der Zwaag et al. 2009), we expected to be able to decode individual movements on a single trial basis.

Twelve young healthy right-handed volunteers participated in the study, in which they had to execute four hand gestures taken from the American Sign Language alphabet (corresponding to the letters 'F', 'L', 'W' and 'Y'; see Fig. 1) inside the scanner. The participants were naive to the meaning of the signs prior to the experiment. In a familiarization session, they practiced the gestures and learned the corresponding letters. The execution of the gestures inside the scanner was recorded by an MRI compatible data-glove (5 DT). This data-glove provides information about the flexion of each finger [for a more detailed description of this study, please see Bleichner et al. (2013)].

As we wanted to classify individual gestures, all participants performed two runs. The data from the first run (training run) was used to train a classifier, and the data of the second run (test run) was used to test whether we could predict which gesture was performed on a single trial basis. For this, we computed average activation maps on the training run for each type of gesture. The resulting four activation maps (one for each type of gesture) then served as prototypical templates. Furthermore, to reduce the amount of data, we selected a subgroup of voxels that was considered most informative (i.e. showing a high level of activation of any of the gestures). The individual trials from the test run were then compared with the four prototypes. Using a simple pattern correlation classification, we computed the Pearson correlation between the activity pattern of the individual trial and the activity patterns of the four prototypes. The individual trial was labeled according to the gesture type with which it had the highest correlation.

We found an average classification score for the four gestures of 63 % (range of 35–95 %). This was significantly above the chance level of 25 %, indicating that the gestures could be distinguished on a single trial basis. Noticeably, the classification accuracy varied considerably between participants from barely above chance level (35 %) to almost perfect classification (95 %; Fig. 2a shows the individual classification scores). This wide range of classification scores, however, could be explained by the consistency with which the gestures were executed. The data-glove provided information on the movement of the individual fingers, and allowed us to compute how consistently the gestures of the same type were executed. There was a significant negative correlation ($r = -0.62$, $p < 0.05$) between the classification accuracy and the variability of the gesture execution (Fig. 2b). The less variably the gestures were executed, the higher the classification accuracy. This indicates that the gestures can be classified with high accuracy provided that the gestures are consistently executed.

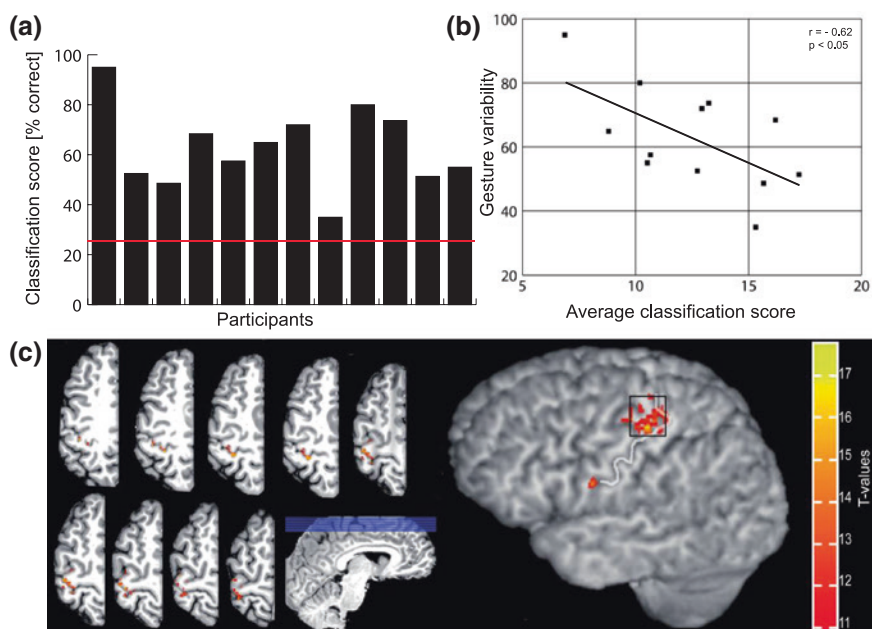


Fig. 2 fMRI results: **a** classification accuracy given as percentage correct for each individual. The *red line* indicates the 25 % chance level. **b** There was a significant negative correlation between the classification accuracy and the variability with which the gestures were executed. Participants who executed the gestures more consistently had a higher classification score. **c** (*Left*) Location of the most informative voxels shown on the axial slices for one participant. The majority of informative voxels are located at the hand knob area. The informative voxels follow the characteristic Epsilon shape of the hand knob. (*Right*) Most informative voxels as projection to the cortex. The *white line* indicates the central sulcus, and the *black square* indicates the possible location of a high density—EcoG grid (2×2 cm)

The most informative voxels were confined to a small patch of cortex surrounding the hand-knob area (Fig. 2c). The axial slices show nicely that the informative voxels cluster around the hand knob being partly located within the sulcus as well as on the gyrus.

Unlike fMRI, which provides a complete sample of the entire brain including deeper cortical structures, ECoG electrodes, which are located on the cortical surface, cannot measure from tissue in the sulcus. The ECoG electrodes are most sensitive to the neuronal activity of the tissue directly underneath the electrode, and probably cannot measure much from within the sulcus. To make our fMRI results comparable to the situation with ECoG electrodes, we restricted our voxel selection to those voxels that were located in the upper 6 mm of the cortical surface and we restricted the analysis to a patch of cortex of 2×2 cm (centered on the most active voxels). This corresponds to the area that could be covered by a high-density 8×8 electrode grid (Fig. 2c: right side, black square).

Using this restriction, we achieved an average classification accuracy of 53 % (range 32.5–92.5 %), which, though significantly lower than the values obtained using all voxels ($p < 0.05$), was still significantly above chance level ($p < 0.01$). For the best participant, that is, the person who performed the gestures most consistently, the classification accuracy was still 92.5 %, which would allow very good BCI control.

These results indicate that it is possible to distinguish different gestures, based on their single trial activation pattern, using a confined area of cortical tissue around the hand-knob region. Consistent execution of the gestures is essential for effectively discriminating the gestures.

2 ECoG

From the fMRI experiment, we learned that the four hand gestures could be classified with a comparably high accuracy using only a small patch of cortex (on the gyrus) that would also be accessible by ECoG surface grids.

In a subsequent study, we had the opportunity to test whether the gestures could also be discriminated using high-density ECoG. In the intensive epilepsy monitoring unit of the University Medical Centre Utrecht/The Netherlands, we recorded from five patients undergoing ECoG monitoring prior to surgery for epilepsy focus detection and functional mapping.

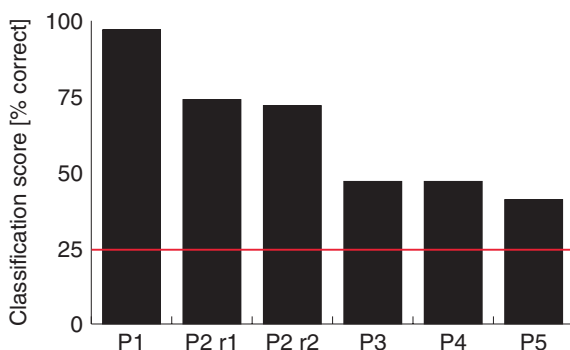
The grids, with an inter-electrode distance of 3 mm, contained 9 times more electrodes than the standard clinical grid (inter electrode distance of 1 cm). The grids contained either 4×8 or 8×8 electrodes and covered the hand-knob region to varying degrees. Only for one patient was the grid optimally located on the hand-knob.

As in the fMRI experiment, we asked participants to perform four hand gestures: ‘D’, ‘F’, ‘V’, ‘Y’ (see Fig. 1). Participants, who were naïve to the meaning of the gestures, underwent a short familiarization period. Due to the limited time we had with the patients, we could only record 40–80 trials in total per patient. To control for the accurate execution of the gestures, the hand movements were recorded using the data-glove as in the fMRI study.

After the normal pre-processing steps of filtering for line noise, and then re-referencing to the common average reference (comprised of all electrodes on the high density grid), the data was epoched into segments of 3 s (1 s before and 2 s after movement onset as determined based on the data-glove recording). For each epoch and electrode, the average power was computed for the frequency range of 70–125 Hz. Based on the literature, this frequency range was expected to be most informative for distinguishing the movements of individual fingers.

In a leave-one-out cross-validation scheme, we performed classification using pattern-correlation. All trials of each condition (excluding one) were used to compute the average activation pattern, leaving us with four averages (one per condition). The excluded trial was then compared with the four averages and classified

Fig. 3 ECoG classification results shown for each participant. The y-axis presents “classification scores” as percentage correct. The chance level of 25 % is indicated by the *red horizontal line*. Patient 2 (P2) did two sessions

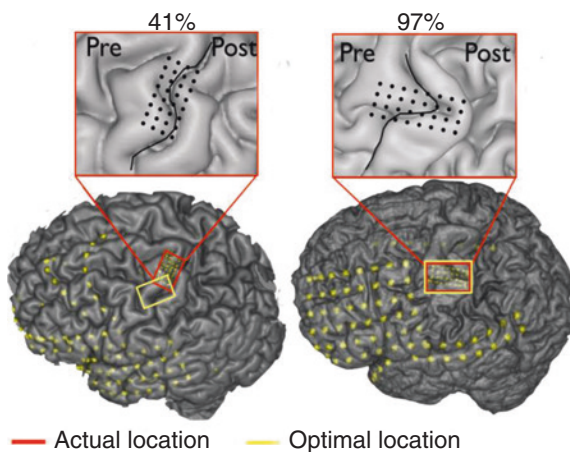


as the condition with which it had the highest similarity (as computed by Pearson correlation).

The classification accuracy varied considerably between participants, ranging from 40 to 97 % (see Fig. 3). These large differences are primarily due to the location of the grid. In the fMRI study, we have already seen that the most active voxels cluster around the hand-knob region, being confined to a small area. For patients where the electrode grids did not sufficiently cover the hand-knob, the classification accuracy was low.

The participant with the best classification accuracy had the best coverage (see Fig. 4), which was also confirmed by the 7 T fMRI data we had from this patient. The second best patient also had a sufficiently good coverage, though the electrodes were located primarily on the post-central area. The reason for the lower classification accuracy for this participant was the poor execution of one of the gestures. In both runs (this was the only participant with two runs) the execution of the ‘D’ gesture entailed considerable problems, leading to hesitation and superfluous movements.

Fig. 4 Electrode locations (yellow dots) rendered on the individual anatomy for the worst (41 %) and best (97 %) performing participants. The *red rectangles* indicate the actual location of the high-density grids. The *yellow rectangles* indicate the anatomical location of the hand knob which can be considered optimal



These results show that classification of executed gestures is also possible using high-density surface electrode grids. Our data also suggest that the location of the grid is essential for good classification results. It appeared that high classification accuracy would also have been possible with a sub-selection of electrodes, which could allow the placement of fewer electrodes. Unfortunately, we did not have sufficient data to test this hypothesis.

3 Discussion

The two studies provide converging evidence that hand gestures, as used in the finger spelling alphabet, can be decoded from a small patch (several cm²) of cortical surface. Using high-density electrode grids, it was possible to achieve almost perfect classification. We take this as evidence that hand gestures are in principle suitable for BCI control.

The small area from which the informative activation was recorded provides an optimal target for subdural grid placement. The burden and risk for the patient should therefore be limited.

The high correspondence between our fMRI and ECoG results provides some interesting opportunities. While this relationship has to be studied in more detail, our results suggest that high-field fMRI can help to pre-localize the optimal location for the electrode grid prior to surgery. The hope is that it will be possible in the future to individually tailor the exact placement of an electrode grid based on the individual cortical representations. Furthermore, a good pre-surgical localisation of the optimal implantation position will increase the chance of success for a patient. This will be especially important for patients with severe paralysis, where the cortical representation might deviate from normal anatomy, due head trauma, tumours or cortical reorganisation after extended periods of paralysis.

Another advantage of this correspondence is the potential to check prior to implantation whether the patient is able to control a BCI using this strategy inside the scanner, by examining the discriminability of the different patterns of activation. This could prevent unnecessary surgical procedures in cases where the chances of success are small. The signal quality allows for realtime feedback of the classifier (Andersson et al. 2012), allowing for presurgical testing.

Using hand gestures to control a BCI has a number of beneficial features. To provide a natural communication speed, BCIs have to be able to discriminate a large number of control signals in a short time. From the user's perspective, it should be possible to generate different control signals effortlessly in fast succession. However, many BCI control strategies require the user to switch between different mental tasks. For example, the fMRI based speller from Sorger et al. (2012) requires the users to switch between three different tasks (e.g. motor imagery, mental calculation and inner speech). This constant task switching, however, is tiring for the user. Using different hand gestures does not require such constant task switching and can be highly automated. Furthermore, the different control signals are just variations of

the same task (i.e. the execution of a gesture), so additional control signals can be introduced by using more gestures. Our approach should therefore be extendable to a larger number of control signals without additional effort for the user.

An important limitation in our experiments is that we studied executed movements in able-bodied participants, while the target group for such BCIs is patients with severe paralysis capable of attempted movements only. We have previously shown that imagined movements, assuming an adequate proxy for an inability to move in paralysis, in abled participants does not activate the primary motor cortex (M1), as measured with fMRI (Hermes et al. 2011). We instead postulate that executed movements are a better proxy for attempted movements in paralyzed people. There are studies that support this notion. Hotz-Boendermaker et al. (2008) have reported that paraplegics showed activation of the primary motor cortex during attempted movements that was comparable to the executed movements in healthy controls. Moreover, Hochberg et al. (2012), Collinger et al. (2012) and Wang et al. (2013) have shown that the sensorimotor cortex in paralyzed people provides sufficient information during attempted movements that allows for control of a robotic arm in several dimensions. Nevertheless, it remains to be shown that the complex hand gestures can also be discriminated during attempted movement and whether our approach is feasible for patients for actual BCI control.

Our approach allows an active BCI [as defined by Zander and Kothe (2011)] to be built. ‘The BCI derives its outputs from brain activity which is directly and consciously controlled by the user, independent of external events’ (Zander and Kothe 2011). Unlike the P300 speller where the user is dependent on external stimulation (i.e. the flashing of the letters), a gesture controlled BCI allows for self-paced control. The user can generate control signals whenever he wants, providing him with a larger degree of freedom and flexibility. It can also be an option for people that have problems (i.e. due to visual impairments) using the standard P300 speller (Brunner et al. 2010).

Finally, we expect that our approach would only interfere to a limited degree with other tasks. An often underestimated problem of BCI systems is the number of false alarms. BCIs are generally studied under well-controlled conditions in which the user is confronted with little distraction and has to perform a well-defined task (e.g. copy the spelling of a predetermined sentence). Under real circumstances, the control task (e.g. inner speech) might interfere with the task at hand (thinking about what to do), causing unintended reactions from the BCI system. We assume that this interference with general cognitive tasks should be minimal when using attempted movements.

Postulated advantages of using gestures for BCI control

- A small, confined area of cortex is sufficient to discriminate four different hand gestures. This confined area is an optimal target for subdural grid placement.
- The close correspondence between the fMRI and ECoG results suggests that it is possible to pre-localize the best grid position with fMRI prior

to implantation. Furthermore, it is possible to train the patient inside the scanner prior to implantation, using realtime classification feedback.

- Our approach does not require switching between different control tasks (e.g. motor imagery, mental calculation and inner speech), since it is possible to create different control signals by varying the same task (i.e. different gestures).
- Our approach is extendable. Though we have only differentiated between four gestures, it should be possible to differentiate a larger number of gestures.
- Increasing the number of gestures and thereby the number of control signals would not increase the time that is necessary for a selection.
- Our approach can be self-paced. Unlike a P300 speller, external stimulation is not necessary. This also makes it interesting for visually impaired patients.
- Interference effects with other cognitive tasks are expected to be minimal. This may have a positive effect on the false alarm rate.

4 Conclusion

The studies presented here provide a first indication that communicative hand gestures as they are used in the fingerspelling alphabet of sign languages can be distinguished based on their neuronal activity on a small patch of cortex. The hand-knob area, which is anatomically well defined, therefore provides an interesting target area for high-density electrode implantation. We conclude that hand gestures can provide an interesting possibility to control an ECoG based BCI for communication. As our results have been obtained in able-bodied people, considerable work has to be done before this approach can be used in an actual application for people with severe paralysis.

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Brain-Computer Interface Research

A State-of-the-Art Summary 3

Guger, C.; Vaughan, T.; Allison, B. (Eds.)

2014, VI, 137 p. 39 illus., 13 illus. in color., Softcover

ISBN: 978-3-319-09978-1