Real time decoding of hand grasping signals from macaque premotor and parietal cortex

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Abstract

A brain machine interface (BMI) for visually guided grasping would provide significant benefits for paralyzed patients, given the crucial role these movements play in our everyday life. We have developed a BMI to decode grasp shape in real-time in macaque monkeys. Neural activity was evaluated using chronically implanted electrodes in the anterior intraparietal cortex (AIP) and ventral premotor cortex (F5), areas that are known to be involved in the transformation of visual signals into hand grasping instructions. In a first study, we decoded two grasp types (power and precision grip) and three grasp orientations (target oriented vertically or tilted left or right) from the neural activity during movement planning with an accuracy of about 70%. These results are proof-of-concept for a BMI for visually guided grasping that could be extended for larger number of grip types and grip orientations, as needed for prosthetic applications in humans.

1 Introduction

1.1 Invasive brain-machine interfaces

Advancements in hardware and computer technology have made it possible to record simultaneously from many neurons in the brain and to use these signals for the control of a neural prosthesis. Such invasive brain-machine interfaces (BMIs) have been developed by several research groups, predominantly for arm reaching [1-4]. Our aim is to develop a similar system for the decoding of hand grasping movements (Fig. 1). Neural activity is recorded from AIP and F5 of macaque monkeys and interpreted in real time by computer software that makes a prediction of the intended hand movement. This is then fed back visually to the animal and used as a reward contingency.

1.2 Hand grasping signals in the brain

Hand movements are extremely versatile and span a wide range extending from powerful grips to extremely delicate and precise tool manipulations. Electrophysiological studies have identified the premotor and the parietal cortex as two high-level areas that are involved in the preparation of hand movements. These areas are distinct from the primary motor cortex that encodes low-level movement details like trajectories and muscle activity. In the parietal cortex, the group of Sakata has described neurons in the anterior intraparietal area (AIP) that encode the visual appearance of the object to be grasped or the grasping movement itself, and they highlighted the major role of this area for the transformation of visual information into high-level plans [5]. In the premotor cortex,

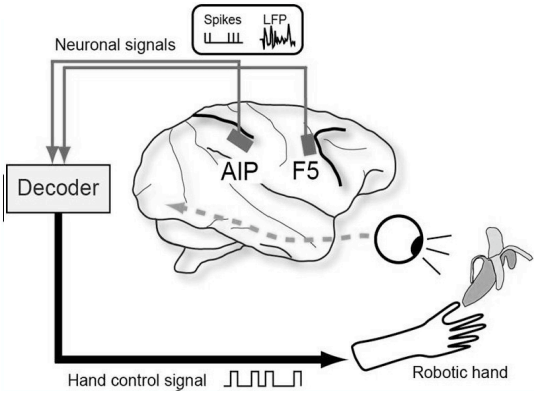

Fig. 1: Decoding hand grasping signals in AIP and F5 for controlling a robotic hand.

the group of Rizzolatti found similar grasping neurons that were specifically active for a particular grasp type or hand orientation [6]. They named this area 'frontal area 5' (F5) after histological examination. Anatomical tract tracing and reversible inactivation furthermore demonstrated that AIP and F5 are reciprocally connected and functionally relevant for hand grasping. In previous work, we have explored the coding of grip type and grip orientation in AIP and F5 during a delayed hand grasping task and could demonstrate the usefulness of these signals for the development of a BMI for hand grasping [7, 8].

2 Methods

2.1 Animal training

One juvenile macaque monkey (5.5 kg) was trained in a *delayed grasping task*, where it first placed its hands at rest and fixated a red LED before a grasping handle

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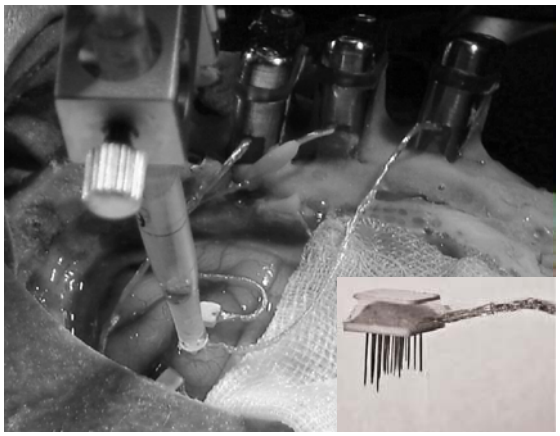

Fig. 2: Electrode implantation. Inset: 16 channel electrode array.

was presented in one of 5 different orientations. The color of an additional LED then instructed the animal to grasp the handle either with a power or precision grip, respectively. The animal then had to withhold movement execution until, after a short delay, the fixation LED dimmed. Correctly executed trials were rewarded with a small amount of juice. All procedures were in accordance with and approved by the Veterinary Office of the Canton of Zurich.

2.2 Electrode implantation

After successful training, 5 floating micro-electrode arrays (FMA; MicroProbe Inc, Gaithersburg, MD, USA) were implanted in AIP (2) and F5 (3) of the animal. Figure 2 shows a photograph taken during surgical implantation. Each array comprised 16 platinum-iridium electrodes (length 1.0-4.5mm, spacing 0.5 mm) and 2 reference electrodes (Fig. 2, inset). This configuration facilitated the recording of neuronal activity within cortical sulci, where the areas AIP and F5 are located.

2.3 Signal recording and decoding

Neural signals were sampled using a Cerebus (Cyberkinetics Inc, Foxborough, MA) Neural Signal Processor (NSP) and streamed to a dedicated decoding PC via UDP. Spike sorting was conducted online by manually setting time-amplitude discrimination windows. Decoding was implemented using maximum likelihood estimation. We benchmarked decoder performance offline before commencing BMI experiments by using a spike simulator tool capable of creating artificial Poisson-distributed spike trains as well as loading and replaying previous neuronal recordings. Both decoder and simulator were implemented in C++ including the Neuroshare library for reading files, the Cerebus UDP Network Protocol and a graphical user interface.

In *grasp decoding trials*, spike data were sampled during the planning phase and the planned grasp was decoded in real time using Maximum Likelihood Estimation. The decoded grasp was presented to the monkey with a still image during the grasp phase. If correct, the animal received a small juice reward.

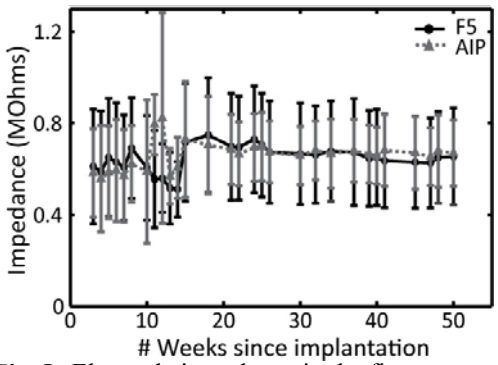

Fig. 3: Electrode impedance in the first year after implantation.

3 Results

3.1 Electrode stability

Electrode impedances remained stable during the course of almost a full year post-implantation (Fig. 3). The mean impedance across 50 weeks (±SD) was 0.64 MΩ (±0.06) for 43 electrodes implanted in F5 and 0.66 MΩ (±0.06) for 28 electrodes in AIP. Nine electrodes were non-operational according to the specifications of the manufacturer and are not included here.

3.2 Neural signals

From these permanently implanted electrodes, we recorded action potentials (spikes) from many individual neurons while the monkey performed the grasping task. Figure 4 shows the peristimulus time histogram of an example neuron that responded much more strongly when the animal was planning and executing a power grip than a precision grip movement. Other neurons were preferentially active for precision

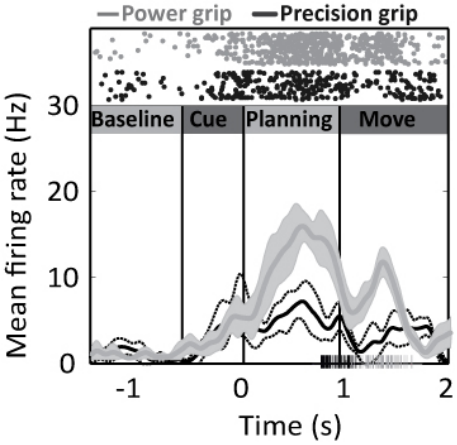

Fig. 4: Neural tuning for hand grasping. Example cell with spike rasters (on top) and mean firing rate (at bottom) for power and precision grips during the delayed grasping task.

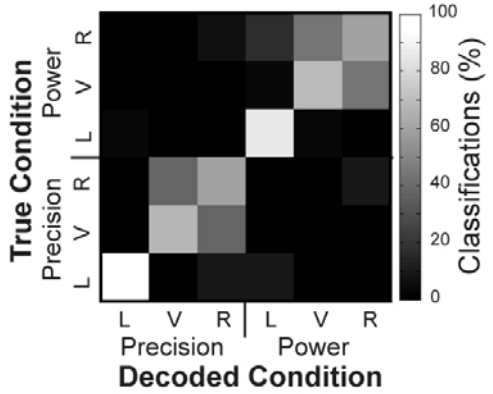

Fig. 5: Confusion matrix indicating the performance to decode the grip type (power and precision) and the grasp orientation (target tilted left, vertical or right).

grip and many cells also encoded the orientation of the object to be grasped (not shown). This diversity of tuning properties in the neural population allows the construction of decoding algorithms for the prediction of hand grasping movements in real time.

3.2 Real time decoding

We then explored the capability to decode the grip type and the grip orientation in real-time. For this, we first collected spiking activity from AIP and F5 while the monkey performed the delayed grasping task, to determine the distribution of spike counts for each of the possible grasping combinations. Then in *prosthetic grasping* trials, spike data were sampled online during the planning phase, and the planned grasp was decoded in real time. The decoded grasp was visually presented to the monkey during the grasp phase. If correct the animal received a small juice reward. In an initial experiment, we decoded grasp type (precision vs. power) with mean accuracy 94%. Following this, we simultaneously decoded grasp type and 2 grasp orientations (target tilted to left or right) achieving a mean accuracy of 91%. Finally we were able to decode 6 conditions (grasp type and 3 orientations, target tilted left, vertical or tilted right) with mean accuracy 72%. Figure 5 shows the decoding performance in this task. We found that grasp types were almost never confused, while errors in the grasp orientation occurred mainly to the neighboring conditions.

4 Discussion

Our findings show for the first time a working BMI for hand grasping that can distinguish between two different grasp types and various grasp orientations. It is clear however that further improvements are needed before such a BMI could help patients suffering from paralysis: for example, increased electrode longevity as well as the ability to decode a continuum of grip types and movement timing.

5 Conclusion

Our results are proof-of-concept that a BMI for visually guided hand grasping is possible from the high-order planning signals present in AIP and F5. This BMI could be extended for a larger number of grip types and orientations, and to include real time state decoding, as needed for prosthetic applications.

6 Acknowledgements

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7 References

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