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Decoding Grip Types from Premotor, Parietal, and Motor Cortex

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Abstract. Despite recent advances in developing neural interfaces for controlling prosthetic arms and grippers, the ability to decode and execute different grasping patterns remains a major challenge. Here we present a simple Bayesian decoder for classifying a wide range of different grip types. Simultaneously recorded multi and single unit activity from AIP, F5, and M1 was used to decode grip types performed on 50 different objects with an accuracy of 54% and 67% (2% chance level) during motor planning and execution, respectively. The results demonstrate the possibility of accurately decoding grip types well before movement execution.

Keywords: hand, grasping, decoding, grip type, parietal cortex, premotor cortex, motor cortex

1. Introduction

The complexity of the human hand, which can be controlled in more than 20 degrees of freedom, makes the decoding of hand and finger movements challenging [Hochberg et al., 2012; Collinger et al., 2013]. The use of neuronal activity from higher cortical areas that represent motor programs rather than individual finger movements might help reducing this dimensionality. Here we employed spiking activity from macaque anterior intraparietal cortex (AIP), ventral premotor cortex (F5), and the hand area of primary motor cortex (M1) to decode grip types performed on a wide range of objects.

2. Material and Methods

2.1 Experimental task and hand-tracking

A monkey was trained to grasp 50 different objects in a delayed grasping task. The animal first placed its hand at rest and fixated a red LED before a randomly selected object was presented (cue epoch). The animal then had to withhold movement execution until, after a short delay (planning), the fixation LED dimmed (start of execution). To find the grip types performed on the objects, the monkey was trained to wear a data glove based on electromagnetic sensors [Schaffelhofer and Scherberger, 2012] providing 27 degrees of freedom of the animal's hand and arm. The joint angles collected while holding the objects were used to classify the 15 most different grip types by applying hierarchical clustering based on the Euclidean distances between the joint angle vectors of individual trials.

2.2 Decoding

Simultaneously to the monkey's hand kinematics, we recorded neuronal activity from 6 floating microelectrode arrays (FMA; MicroProbes, Gaithersburg, MD, USA) chronically implanted in AIP, F5, and M1 (192 channels). We used spiking activity from the planning epoch as well as during motor execution to decode both the grip types performed on the objects as well as the 50 objects being grasped, using leave-one-out crossvalidation. The mean firing rates of all single and multiunits were measured and defined as the input parameters to a naive Bayesian decoder that has been shown to perform well for this kind of data [Subasi et al., 2010; Townsend et al., 2011].

3. Results

We predicted the grip types performed on the 50 objects from 10 different recording sessions. During the planning epoch, movement intentions could be decoded with an accuracy of 54% ± 4% (mean ± sd) using spiking activity from F5, AIP, and M1 together (chance level 2%). The highest decoding accuracy was achieved during motor execution (67% ± 5%, mean ± sd). An example recording session is illustrated in Fig. 1. Performing a neuron drop analysis for individual areas revealed that AIP and F5 (t-test, $p < 0.01$) achieved the highest decoding accuracy in the cue epoch (AIP: 47% ± 3; F5: 49% ± 4%; mean ± sd). During motor planning, F5 showed the exclusively best performance (46% ± 5%), whereas in M1 decoding was most accurate during motor execution (59 ± 8%).

Furthermore, hand kinematics recorded with the electro-magnetic tracking glove was used classify the 15 most different grips performed on the objects. These 15 grip types could then be decoded with an accuracy of 74% in the planning epoch and 87% in the execution epoch (see Fig. 2).

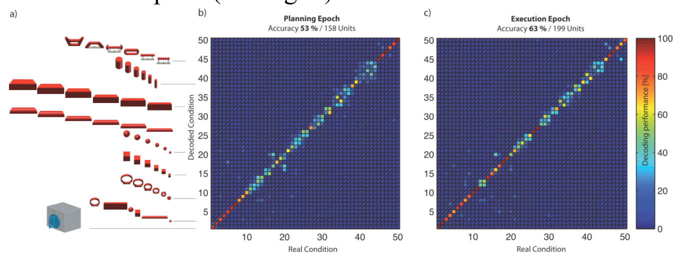

Figure 1. *Object decoding performance. (a) Set of 50 different objects being grasped. (b-c) Confusion matrices showing the grasp decoding accuracy using the combined spiking activity from AIP, F5 and M1 during movement planning and execution.*

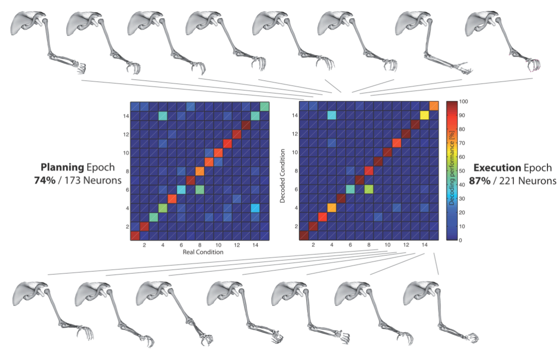

Figure 2. *Grip type-decoding performance. Using simultaneously recorded neurons from AIP, F5 and M1 allowed to accurately predict grip types during motor planning and execution.*

4. Discussion

These results clearly demonstrate the possibility of accurately decoding a wide range of different grip types from higher cortical areas related to hand grasping, like AIP and F5, well before movement execution, in addition to using the movement execution epoch for which primary motor cortex is particularly well suited. Furthermore, maximum likelihood classifiers, using signals from higher cortical areas, can be employed to predict discrete grip types instead of a large set of individual joint angles that would otherwise be necessary to describe the hand shape [Velliste et al., 2008; Vargas-Irvine et al., 2010]. Such a strategy can effectively reduce the dimensionality of the decoding problem in order to predict grip types rather than individual degrees of freedom of the hand.

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