

VISUAL TRAINING FOR POPULATION VECTOR BASED CORTICAL CONTROL

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Abstract—We have developed a method for training animals to control a variety of devices from cortical signals. In this report we describe a protocol to parameterize a cortical control algorithm without an animal having to move its arm. Instead, a highly motivated animal observes a computer cursor moving towards a set of targets once each in a center-out task. From the neuronal activity recorded in this *visual following* task, we compute the set of preferred directions for the neurons. We find that the quality of fit in this early set of trials is highly predictive of each neuron's contribution to the overall cortical control. *Copyright © 2005 IFAC*

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1. INTRODUCTION

Much of the effort in implementing cortical control of devices has been devoted to recording from as many neurons as possible (Nicoletis 2003, Nicoletis et al., 2003) and designing algorithms which extract the maximum information from those neurons (Schwartz et al., 2001). An assumption underlying this work is that if a subject's intention can be read out from cortical signals, the intention could be carried out with electronic systems. Recent estimates say that, at minimum, several hundred neurons will be needed to achieve a satisfactory performance (Camena et al., 2003, Wessberg et al., 2000).

This assumption limits the approaches one might take to designing signal processing for a neuroprosthetic system. Recent work has shown that by allowing a mapping from cortical activity to device motion to adapt to the ways in which a subject uses a neuroprosthetic system, high fidelity control can be implemented with a few tens of neurons (Serruya et al., 2002, Taylor et al., 2002). In this paper we describe one method for parameterizing a system with those properties. This will facilitate the

reduction in the number of neurons required for cortical control of neuroprosthetic devices and a systematic means to identify those high performance neurons.

2. METHODOLOGY

Briefly, in our experimental paradigm the animal views a 3D arena in a mirror, and manipulates objects in the arena either with arm movements behind the mirror (Schwartz et al., 2004, Reina et al., 2001), or with direct cortical signals (Helms Tillery et al., 2003, Taylor et al., 2003, Taylor et al., 2002). The core task consists of moving a cursor into targets in the 3D work space (Fig. 1). The targets are spheres placed at specific locations in the workspace, and the cursor is a sphere of a different color that is under control of the animal.

In the cortical control task, we use a *population vector* (Georgopoulos et al., 1986, Georgopoulos et al., 1984, Georgopoulos et al., 1983) to provide a mapping from neuronal activity to cursor motion (Taylor et al., 2002). The population vector treats the firing pattern of each neuron as representing a single vector in space, that neuron's *preferred direction* (PD). Each PD is scaled according to its

neuron's firing rate, and the set of PDs then summed to produce a single resultant vector, the population vector (PV).

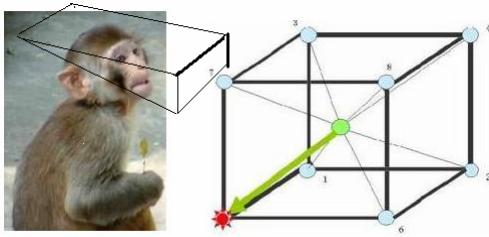


Fig. 1. Real-time 3D brain-control experimental setup. (A) A mirror in front of the monkey's face reflects a 3D stereo image of the moving cursor and static target projected from above. The 3D position of the cursor is determined by either the position sensor or by the movement predicted by the subject's cortical activity ("brain-control"). The cursor and target are shown with dotted outlines in the monkey's workspace, but do not physically exist. The monkey sees the cursor and target as being in the workspace but cannot see its own arm. (B) shows the approximate relative cube and target size during the hand-control task from the same observer view point as in (A).

Each neuron in this system requires determining the three parameters specifying a preferred direction and a fourth giving the background rate. In previous work, the firing patterns observed during arm movements are used to parameterize the mapping function (Taylor et al., 2002, Camena et al., 2003). Further improvements in performance were observed by allowing the parameters to adapt to reflect the firing patterns observed when the animal attempted to directly control a neuroprosthetic device (Taylor et al., 2002). In a separate experiment, the initial values for those parameters were assigned randomly to start the adaptation process for the cortical control. In this case, the system still converged onto a similar location in parameter space, suggesting that the parameter space used by a subject to control a cortically-controlled prosthetic system has a stable convergent set.

We have developed a *visual following task* in which we use a computer algorithm to drive the neuroprosthetic device directly while the device's movement is observed by a highly motivated subject (a primate working for its daily water rations). The animal does not perform any motor task during this phase. Under computer control, the cursor takes 1.5 seconds to move from the center to each target, and 12 seconds to perform the complete set of eight movements. After the animal watches this motion, we parameterize each neuron's PD from the activity recorded during that 12 seconds of pure visual task (see Fig. 2). Thereafter the animal controls the cursor movement using a population vector algorithm

that maps neuronal activity into instantaneous cursor motion.

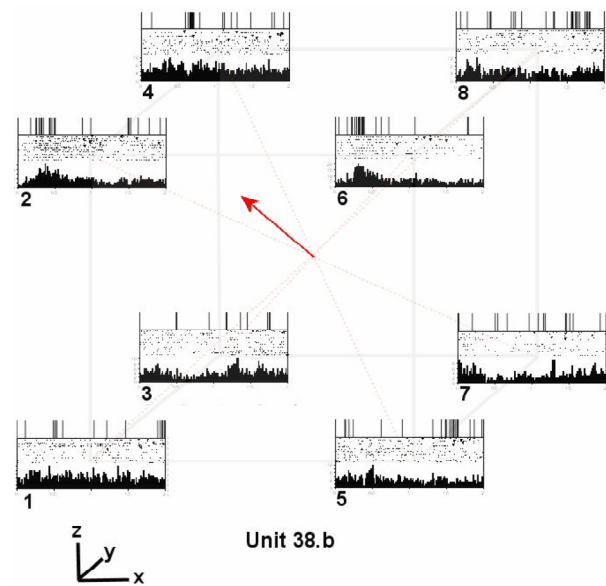


Fig. 2. *Visual following task and cortical control.* Each raster/histogram shows the activity of a neuron during cortically controlled movements to each of the eight target locations. On top of each raster is a single trial record from a set of single movements in the visual presentation. The firing observed in this task close to that expected from the preferred direction (red arrow).

Finally, we estimate each neuron's individual contribution to the cortical control algorithm by removing that neuron from the system and determining the change in the average angular error between the direction to the target and the direction of cortically controlled cursor motion. We call the resulting change in error the *Individual Removal Error (IRE)*. We performed the analysis over a period of 38 days. Only those cells recorded in all 38 days were included in the analysis. The data set contained a total of 63 neurons, 45 of which were recorded across all 38 days.

3. RESULTS

To begin analysis of the visual following task, we compared the preferred directions computed from the initial bout of visual following (12 seconds) with the preferred directions and system performance after 5 minutes of performance (Fig. 3). We found that, on average, the initial estimate of preferred direction across the cell was 60 degrees away from the final preferred direction. Second, the improvement in system performance, measured as the average angle between the estimates and the direction to the target (the right panel), paralleled the increasing accuracy of the preferred direction estimate (left panel). The rate of convergence and the performance improvement are affected little by removing a large

number of neurons from the calculation (more on this point later).

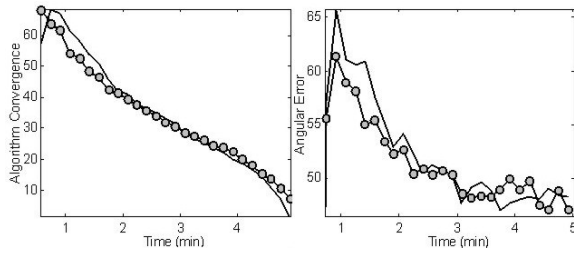


Fig. 3. Algorithm performance as a function of error reduction on time from the start of the visual tracking task. On the left is the mean error in estimates of the preferred directions, beginning with the start of the visual following. On the right is the average difference between target direction and movement direction over the same span. Solid lines show the same result computed when only 20 neurons were used for the prosthetic control.

In order to quantify the quality of the preferred directions estimated with this visual following task method, we split the data from the brain control period into segments of 12 seconds each. This is the length of the data from the visual following task used to compute the initial preferred direction. We calculated preferred directions for all the neurons over each 12 second interval, and then computed the average angle between the preferred direction calculated over the whole session and the preferred directions calculated from the smaller segments. Finally, we compared these differences to the difference between the PDs calculated from the visual following task and the PDs calculated over the entire day's data set.

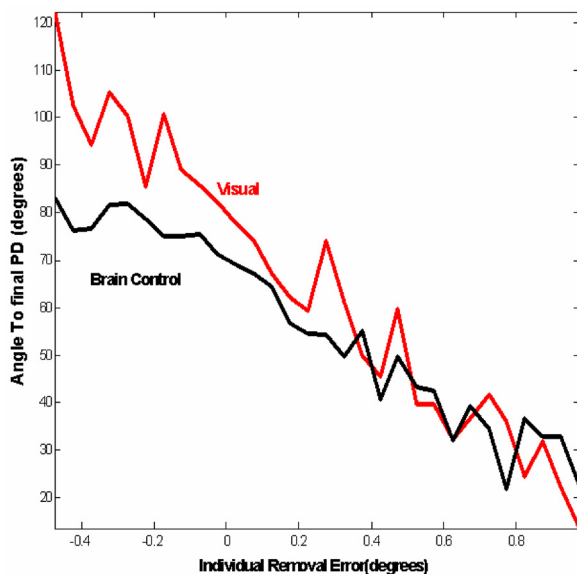


Fig. 4 The relationship between the initial estimate of preferred direction under the visual following task and the brain control task as a function of IRE.

The first step in our analysis of how each neuron's property contributes to the overall performance of the mapping algorithm is to determine the contribution of each cell to the variation in the performance of the mapping algorithm. For this purpose, we performed offline analysis of cortical data recorded during brain control. We first computed the Individual Removal Error for all of the cells, and then indexed the neurons according to the magnitude of their IREs, with smallest values first, increasing monotonically.

Fig. 4 shows the relation between the IRE and the accuracy of preferred direction estimated from small segments of data in visual following (red) and brain control (black) segments of data. Note the linear decrease between these angles between the overall PD and the PD estimated from random 12 second intervals of data.

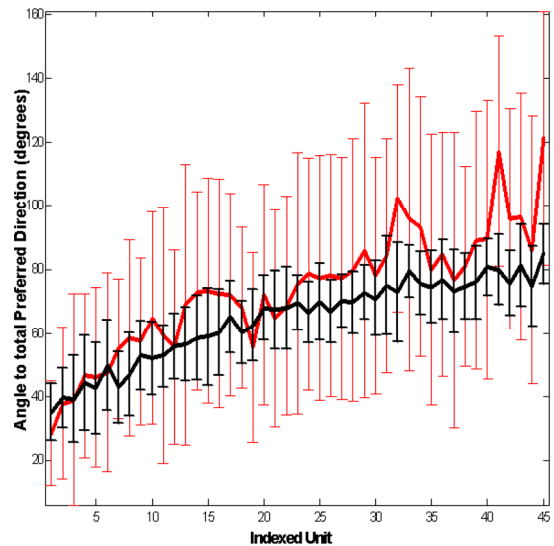


Fig 5. Reproducibility of fit for 12 second intervals of data estimated from either the visual observation or brain control task. For each neuron, we computed the mean angle between the PD computed from 12 seconds of data with the PD computed over the entire brain control epoch. The red trace shows mean and standard deviation of this value for the visual following task. Black shows the same value taken from 12 second windows of the brain control task.

For the main group of cells (index numbers 10-30), removing the neuron resulted in only a small change in the performance of the PV for brain control. For a small set (index > 30) their removal produced substantial decrements in the performance of the brain control, seen here as increases in the mean directional error. These are the neurons that have the greatest positive contribution to the brain control. For a third small set (index < 10), removing the cell from the PV improved the performance as indicated by a decrease in the mean directional error. The distribution of IREs is close to symmetric with a mean value of 0.06 (median 0.03).

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Fig. 5 shows the results obtained over a period of 38 days. On this plot, the units have been indexed according to their IRE, in decreasing order. Parameters characterizing directional tuning properties of units with a good quality (left hand side) can be estimated from small segments of data, furthermore, there is no significant difference in the visual following task and the brain control task. The standard deviation is higher for the visual following period, which might be explained by the fact that the animal is not always fully attentive at the start of the experiment.

4. DISCUSSION

We have found that in a highly motivated subject, we can identify the parameters necessary for computing a population vector by using a purely visual stimulus. We cannot say at this stage whether the tuning we see is in the *visual following task* related to visual responses, or if rather the animal is attempting to drive the cursor towards the target by thought. For our purposes, this distinction is not crucial, since the tuning that results from the visual following task is reliably close to the tuning that develops in the brain control task.

We also found that the ease with which we could compute the tuning of the neurons was closely related to their final contribution to the overall performance of the control algorithm. This characteristic could form one set of criteria in identifying subsets of recorded neurons that provide strong contributions to cortical control of neuroprostheses.

5. CONCLUSION

We have developed an algorithm which allows parameterization of a population vector for cortical control of a neuroprosthetic system using no arm movements. We have shown that the robustness of the fit for individual neurons is a reliable predictor of how those neurons contribute to the overall performance of the cortically controlled neuroprosthetic system.

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