

The general utility of a neuroprosthetic device under direct cortical control

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***Abstract* - We have described an adaptive signal processing method that allows fine graded control of a cursor in three-dimensions from cortical signals [1]. Here we describe application of the same signal processing method to direct cortical control of a robotic arm for a variety of tasks. Our subject was extensively trained in controlling a computer cursor in a 3D virtual environment. We applied the mapping between cortical activity and cursor motion to endpoint control of a robotic arm. This algorithm was refined further as the animal continued to make 3D point-to-point movements of the brain-controlled robot. The animal then used the cortically-controlled robot to retrieve food placed at arbitrary locations within the workspace and deliver the food to a hopper. Finally, the animal learned to use the cortically-controlled robot to deliver food directly to its mouth.**

***Keywords*—Neuroprosthetics, motor cortex, cortical control, robot, arm**

I. INTRODUCTION

Recent publications have shown the feasibility of using signals recorded simultaneously from modest numbers of neurons to generate a unitary control signal appropriate for directing the motion of prosthetic devices [1-6]. Early work in this field optimized signal extraction from limited sets of cortical implants [4,7-10]. Recent reports in which animals have had direct volitional control over a device instead concentrate on the brain's learning capacity to increase task performance[1,2,5,6]. These experiments are carried out in a closed-loop environment resulting in good control of external devices by means of a few tens of neurons.

We have previously described one such environment, in which animals learned to control the motion of a computer cursor in three dimensions by direct brain control [1]. A computer cursor, however, is a relatively simple device, being fully specified by a straightforward Cartesian coordinate system. The

real goal of motor neuroprosthetics is to control something much more complex, like an arm, that may have many more degrees of freedom organized in a totally different coordinate system. Here we describe success in teaching a primate to feed itself using a directly observed cortically controlled robotic arm.

II. METHODOLOGY

The approach used here to develop a control signal is identical to the method described previously [1]. We trained rhesus macaques to perform 3D movements of a brain-controlled cursor in a virtual environment while their arms were restrained. The task was a center-out task in which the animals moved a yellow cursor sphere from a central position to one of eight green target spheres located radially. Cursor movements were controlled in real time by the activity of about 40 primary motor and premotor cortical neurons recorded from intracortically implanted microwire arrays.

In the initial phase of each day's experiment, the cortical activity controlled the cursor movements directly via an adaptive algorithm. This algorithm used an iterative process to create a brain-to-cursor-motion decoding scheme based on how the neurons fire when different targets were presented. The form of the movement control algorithm is similar to a population vector in that movement at each time step is determined by a vector sum of the neurons' normalized firing rates multiplied by a set of linear coefficients.

We used random numbers for initial values of these coefficients, and then applied the iterative process to improve cursor control. In a traditional population vector, these X, Y, and Z coefficients would be a unit vector in each cell's preferred direction calculated from an initial set of baseline arm movements. Previously we have shown that cortical neurons' preferred directions in the brain-controlled cursor task are not well related to their preferred directions during arm movements. The coefficients determined by the adaptive process not only reflected the preferred directions under brain control, but also scaled and skewed the tuning profiles to emphasize

units which had better directional tuning or were tuned to under-represented areas of the workspace.

Each day, the initial cursor movements were not well controlled. However, after five to ten minutes, the coefficients had adapted enough to produce reasonably stable cursor motion, and the animal was switched to a robot control task for the final refinement of the control algorithm. The animal still watched the task in the virtual environment, and worked for fluid rewards, but from this point on the cortical signals were used to control the motion of a six-axis robotic arm (Zebra Zero, IMI Inc). The cursor in the VR environment tracked a position sensor (Optotrak, Northern Digital, Inc., Waterloo, ON) mounted on the end effector of the robot. Thus, the animal observed the motion in the familiar VR setting, but the control was directed to the robotic arm (see Fig. 1).

For the final stages, we attached various end-effectors to the Zebra-zero that allowed the animal to deliver food items. In one set of experiments we used a spoon, and the animal transported a piece of food from a target location to a central food hopper using the spoon (see Fig. 2). In another case we used a clipping device. We would place a food item in the clip, and the animal would drive the clip to its mouth under cortical control and retrieve the food item from the clip (Fig. 3).

All procedures described in this paper were performed under the approval of the University IACUC and in accordance with NIH guidelines.

III. RESULTS

Center Out Task

Once the adaptive control algorithm had converged, the animal was able to exert accurate graded control over the motion of the robot in the 3D center-out task, acquiring the targets with near 100% accuracy. Figure 1 shows the main layout of the initial cortically controlled robotic arm experiment. The cursor in the virtual environment tracked the motion of the cortically controlled robotic arm. In the lower two panels of Fig. 1 we show examples of robotic arm motion to each of the eight targets. In the VR environment, the task was by all appearances very familiar to the animal, and the animal was able easily to master direct cortical control of the robotic arm.

VR Self-feeding Task

After the animal had performed the center-out task for liquid rewards, we began to present food for retrieval within the animal's workspace (Fig 2). We

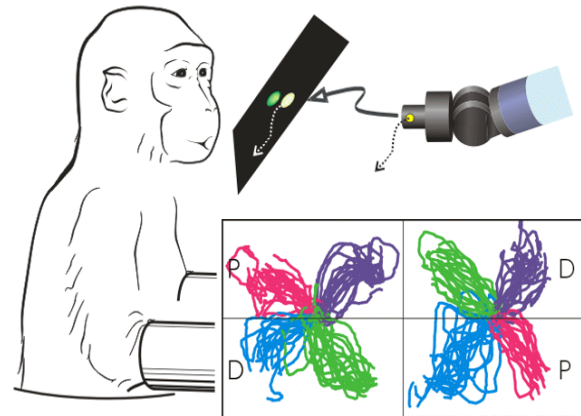


Fig. 1. Use of the virtual reality environment to teach a monkey direct cortical control over a robot arm. In the inset are robot trajectories for the 3d center->out task as viewed from the monkey's perspective. P = proximal, D = distal.

attached a position sensor to a pair of forceps that were used to manually present small food morsels within the workspace of the robot arm. We also added a spoon on an extension to the end-effector of the robotic arm. The extension was provided to extend the reach of the robot, and the spoon provided a means for transporting food items using the robotic arm. The VR target represented the food location and the cursor showed the spoon's position.

At the beginning of each trial, the spoon was located at a central start position. An experimenter then held a food item in an arbitrary location within the workspace of the robotic arm, and that location was presented as a target sphere in the VR. If the animal successfully moved the spoon to a location directly under the food, a tone would sound, signaling the experimenter to release the food into the spoon. Then a new target would appear in the VR, corresponding to the location of a delivery apparatus placed directly in front of the monkey's mouth (Fig 2). If the animal successfully moved the spoon into the delivery apparatus, the program inverted the spoon, dumping the food into the dispenser, which then pneumatically transported the food around the virtual reality screen to the monkey's mouth.

After a brief exposure to the new task, the animal was able to quickly move the robot arm to intercept food morsels from locations throughout the workspace and deliver that food to the dispenser. We show examples of movements to various target locations followed by deliveries once the food had been acquired in the lower panel of Fig. 2). In a typical session lasting 30 to 40 minutes, the animal would be

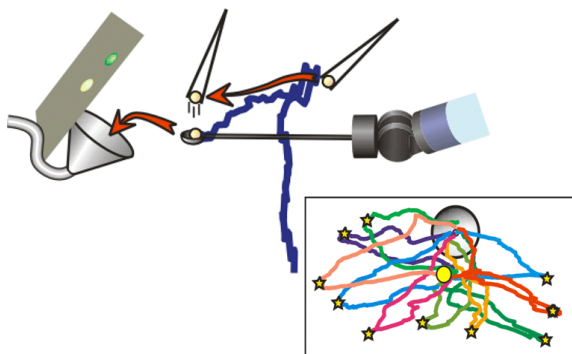


Fig. 2. Retrieving food items from arbitrary locations. The blue trace shows the path of the robot while “pursuing” a moving food item. The inset shows a set of movements from the home position (yellow circle) to food items (stars) and back to the delivery hopper.

able to capture about 100 food rewards in 140 food presentations. Most missed rewards were due to the virtual cursor going out of view when the infrared position sensor on the spoon got blocked by the food dispenser or the animal’s arm restraints

We also had the animal perform several trials of tracking in which the experimenter moved the food around the workspace. The animal was able to reliably pursue and capture these food morsels, and deliver those items successfully to the dispenser.

Directly Observed Self-feeding Task

As a final stage, we removed the VR display, and allowed the animal to directly observe the robotic arm, the end effector of which was now a clip. We attached a food item to the clip, typically a small piece of orange, and allowed the animal to eat the orange only if it could directly place the item into its mouth using the robotic arm (Fig. 3).

Initially, we created a home position approximately 2 inches in front of the animal, and started all movements from this location. As the animal’s performance improved (defined as the amount of time between successful food rewards), the home position was moved successively farther from the animal.

In the inset to Fig. 3, we show trajectories corresponding to approximately ten minutes of direct cortical control from a home position of 8". The bulk of the trajectories have a downward direction, reflecting a bias often present in the cortical control signals. When the animal shuffled, or attended to the robot, the motion would tend to follow a different path. The brain control signal was briefly turned off and the robotic arm re-homed if the arm was nearing

a boundary in the workspace.

The thicker red traces show 20 instances in which the clip was loaded with a small piece of orange. In all of the cases, the general trend of the motion is towards the animal. In 18 of the cases illustrated here, the restrained animal was able to directly retrieve the orange from the robotic arm by driving the arm close enough to its mouth.

IV. DISCUSSION

A number of devices might one day be controlled by neuroprosthetic systems, ranging from simple computer cursors, to transport vehicles requiring graded two-dimensional control, to prosthetic arms requiring graded control of many degrees of freedom. We have demonstrated here that the nervous system need not control all the degrees of freedom available in a controlled device in order to perform a useful task. Our robotic arm has six axes, and we generated movement by rotating around five of those. The control signal generated from the cortical arrays, however, was only three-dimensional. Because we were applying standard algorithms for robotic control, the monkey was able to concentrate on the core elements of the tasks – point-to-point movements of the end-effector – rather than the complex coordinated joint motions necessary to perform that task.

Performance of more sophisticated tasks, such as controlling a hand, or maneuvering an arm around obstacles, might require many more signals, but even this is not entirely clear. For example, even though a complete kinematic description of the hand requires as

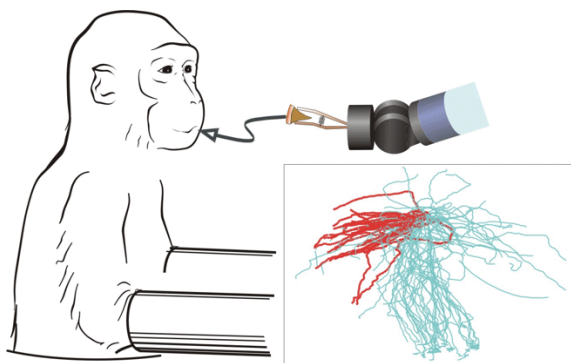


Fig. 3. Delivering food to the mouth using a cortically controlled robotic arm. The diagram outlines the arrangement, with a piece of orange clipped into the robot end effector. The inset diagram shows 10 minutes worth of cortical control trajectories from a central start location. Red traces show cortical control when orange piece is in robot.

many as 22 variables, in practice, both hand posture and hand force application can be largely described with as few as two or three independent variables [15, 16]. If this is the case, we could apply a control solution to the hand that is analogous to the endpoint solution used here, controlling hand motion with only 2 or 3 variables. As has been clearly shown here and elsewhere, fine graded control of two or three degrees of freedom can be readily accomplished with a few tens of neurons [1,2,3,6].

VI. CONCLUSION

It is possible to control a sophisticated device for a significant task using small numbers of neurons. There is a question of recording stability to address, but we note that at the time of these experiments, we had recorded stable signals from this convoluted cortex for over three years.

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REFERENCES

- [1] D.M. Taylor, S. I. Tillery and A. B. Schwartz, "Direct cortical control of 3D neuroprosthetic devices." *Science* Vol. 296, pp 1829-32, 2002
- [2] J.K. Chapin, K. A. Moxon, R. S. Markowitz and M. A. Nicolelis. "Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex." *Nat Neurosci*, vol. 2, no 7, pp 664-70. 1999.
- [3] P.R. Kennedy, R. A. Bakay, M. M. Moore, K. Adams and J. Goldwaith. "Direct control of a computer from the human central nervous system." *IEEE Trans Rehabil Eng*, vol 8, no 2, pp 198-202. 2000.
- [4] J.C. Wessberg, R. Stambaugh, J. D. Kralik, P. D. Beck, M. Laubach, J. K. Chapin, J. Kim, S. J. Biggs, M. A. Srinivasan and M. A. Nicolelis. "Real-time prediction of hand trajectory by ensembles of cortical neurons in primates." *Nature* vol 408, pp 361-5. 2000.
- [5] D.M. Taylor and A. B. Schwartz. "Using virtual reality to test the feasibility of controlling an upper limb FES-system directly from multi-unit activity in motor cortex." In *Proc 6th Ann Intrnl Functional Electrical Stimulation Soc*, Cleveland, Ohio, 2000.
- [6] M.D. Serruya, N. G. Hatsopoulos, L. Paninski, M. R. Fellows and J. P. Donoghue. "Brain-machine interface: instant neural control of a movement signal." *Nature* vol 416, pp 141-2. 2002.
- [7] H.S. Seung and H. Sompolinsky. "Simple models for reading neuronal population codes." *Proc Natl Acad Sci U S A*, vol 90, no 22, pp 10749-53. 1993.
- [8] E.M. Maynard, N. G. Hatsopoulos, C. L. Ojakangas, B. D. Acuna, J. N. Sanes, R. A. Normann and J. P. Donoghue. "Neuronal interactions improve cortical population coding of movement direction." *J Neurosci*, vol 19, no 18, pp 8083-93. 1999.
- [9] Isaacs, R. E., D. J. Weber and A. B. Schwartz. "Work toward real-time control of a cortical neural prosthesis." *IEEE Trans Rehabil Eng*, vol 8, no 2, pp 196-8. 2000.
- [10] A.B. Schwartz, D. M. Taylor and S. I. Tillery. "Extraction algorithms for cortical control of arm prosthetics." *Curr Opin Neurobiol*, vol 11, no 6, pp 701-7. 2001.
- [11] A.P. Georgopoulos., J. F. Kalaska, R. Caminiti and J. T. Massey. "On the relations between the direction of two-dimensional arm movements and cell discharge in primate motor cortex." *J Neurosci*, vol 2, pp 1527-1537. 1982.
- [12] A. P. Georgopoulos, J. F. Kalaska, M. D. Crutcher, R. Caminiti and J. T. Massey. "The representation of movement direction in the motor cortex: single cell and population studies." in *Dynamic Aspects of Neocortical Function*. G. M. Edelman, WE Gail and W. M. Cowan, Ed. New York, NY: J Wiley, 1984, pp 501-524.
- [13] A.P. Georgopoulos, A. B. Schwartz and R. E. Kettner. "Neuronal population coding of movement direction." *Science*, vol 233, pp. 1416-1419. 1986.
- [14] M. Santello, M. Flanders and J. F. Soechting. "Postural hand synergies for tool use." *J Neurosci*, vol 18, no 23, pp 10105-15. 1988.
- [15] M. Santello and J. F. Soechting. "Force synergies for multifingered grasping." *Exp Brain Res*, vol 133, no 4, pp. 457-67. 2000.