Closed-Loop Cortical Control of Direction Using Support Vector Machines

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***Abstract*—Motor neuroprosthetics research has focused on reproducing natural limb motions by correlating firing rates of cortical neurons to continuous movement parameters. We propose an alternative system where specific spatial-temporal spike patterns, emerging in tasks, allow detection of classes of behavior with the aid of sophisticated nonlinear classification algorithms. Specifically, we attempt to examine ensemble activity from motor cortical neurons, not to reproduce the action this neural activity normally precedes, but rather to predict an output supervisory command to potentially control a vehicle. To demonstrate the principle, this design approach was implemented in a discrete directional task taking a small number of motor cortical signals (8–10 single units) fed into a support vector machine (SVM) to produce the commands *Left* and *Right*. In this study, rats were placed in a conditioning chamber performing a binary paddle pressing task mimicking the control of a wheelchair turning left or right. Four animal subjects (male Sprague–Dawley rats) were able to use such a brain–machine interface (BMI) with an average accuracy of 78% on their first day of exposure. Additionally, one animal continued to use the interface for three consecutive days with an average accuracy over 90%.**

***Index Terms*—Brain–machine interface (BMI), cortical control, neural prosthetics, wheelchair control.**

I. Introduction

MODERN neuroscience has revealed that thousands of cortical neurons contribute to every aspect of even our most mundane movements. One cannot twitch a finger without first setting off a firestorm of activity in the cortex. While practical communication between cortical neurons and an external device dates back years before [1], [2], Georgopoulos' concept of cosine tuning in the primary motor cortex [3] and his later population vector algorithm [4] has shaped much of modern neuroprosthetics. Georgopoulos and his colleagues were able to serially record hundreds of neurons from the motor cortex of monkeys reaching for targets in two- and three-dimensional (2- and 3-D) spaces. They observed that a significant number of motor cortical neurons had preferred directions. When movements were executed in the preferred direction of the neuron, its firing rate increased while movements away from the preferred direction decreased the firing rate. This concept is commonly called cosine tuning since the most popular model used to explain the firing rate of a given neuron is one where the firing rate is proportional to the cosine of the angle between the movement direction and the preferred direction. By assuming the distribution of the preferred directions of the cells accessible is uniform throughout space, the population vector algorithm was developed. This algorithm reconstructed the movement direction by averaging the preferred directions of all the cells weighted by the normalized firing rate of the cell.

Many groups have since successfully regressed activity from large numbers of cortical neurons collected simultaneously on multielectrode arrays onto some aspect of future limb movement. This alone is impressive and has even allowed the functional replacement of natural limbs in simple laboratory reaching tasks [5]–[7]. To date, only a handful of neuroprosthetics results have been of a closed-loop nature [5]–[8]. Closed-loop brain–machine interface (BMI) systems allow users real-time interaction with a neuroprosthetic system where they can actuate an external device while receiving feedback to correct errors and plan for future use. Some widely accepted results in neuroprosthetics derive from open-loop system studies [9], [10]. That is, studies in which researchers gather sophisticated neural and kinematic data and later attempt to determine to what degree they can reconstruct the kinematic data given the neural data.

The first modern closed-loop BMI study was [8]. Here, rats were trained to depress a lever to move a water dripper arm and receive a water reward. Dozens (40–60) of microwires were implanted into the motor cortex and thalamus of 6 rats. Neural recordings were taken and synchronized to the position of the rat's response lever. Various algorithms (population rate, principal component analysis, recurrent neural networks) were then used to regress the lever position onto the neural recordings. The lever was then disconnected and the position of the dripper arm was instead controlled by the output of the regression algorithm. The authors claimed that four of the six rats could use the interface.

Serruya *et al.* [5] followed this with a study in which monkeys were able to control the position of a 2-D cursor. Initially trained using a planar manipulandum to control the position of a cursor on a screen, signals from tens (7–30) of motor neurons, recorded from Utah electrodes, were regressed against both position and velocity. One monkey was allowed to control the cursor using the neural control with time to target results similar to manipulandum control.

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Taylor *et al.* [6] demonstrated the feasibility of employing dozens (~ 40) of motor neurons when working in a closed-loop environment. Monkeys were trained to move a 3-D cursor in virtual reality by moving their wrist in a workspace. Parameters for a modified population vector algorithm could then be identified. Subsequently, the monkey's wrist was restrained and he was forced to use the signals from his motor cortex to direct the cursor position. The algorithm could also adapt parameters to better estimate the mapping between neural signals and 3-D velocity over time.

Carmena *et al.* [7] showed a study in which both the 2-D position and velocity of hand motions as well as a gripping force were regressed based on 30 min of data. The two monkeys in this study used the brain interface to control a robot arm, which was tracked and fed back to the animal as a cursor on a 2-D screen. Unlike most earlier studies that focused primarily on motor cortical areas, monkeys in this study had hundreds (96–320) of microwires implanted in many brain areas. In this and similar previous studies, the animals were placed in a laboratory environment to perform stereotypical tasks with a goal to regenerate a step-by-step movement trajectory of the arm movement.

Recently, Musallam *et al.* [11] published a study in which they used cognitive signals primarily from the parietal reach region to determine intended movement to one of 4–8 targets. Using from 200 to 1100 ms of data from 1–16 neurons during a prereach hold period, classification rates from 25.6% to 75.2% were reported. Additionally the expected size, type, and probability of reward could be determined to some degree.

In this and other relevant studies, neuroscientists seek to understand the motor system by examining the effect on motor behavior induced by cortical action. In the past two decades, studies of the motor cortex, especially those interested in BMIs have focused on generating mappings to determine an animal's limb movements from its motor cortical firing activities. While it is important to understand how the nervous system controls movement, we are interested primarily in devising a system that can practically move from initial studies of simple tasks to someday improving the quality of life for human patients.

Motivated by creating realistic devices that can provide patients with tangible increases in quality of life, we focus on a scenario of possibly controlling a vehicle that is not controlled from second-to-second by updating some 3-D trajectory, which many research groups aspire to, but rather is controlled by high level commands from the user. It is conceivably useful to tell a wheelchair to "Go Left," "Stop," or "Veer Right," and let sensors and actuators on the wheelchair work out the trajectory details, as opposed to constantly setting and resetting the trajectory of the wheelchair. This can be viewed as a series of simple asynchronous decisions. We view driving toward a goal a likely objective of such a device and seek to model such a situation using rats driving toward a lighted cue object. In this study, we use a driving surrogate task with paddle pressing in a conditioning box to mimic the trajectory of decisions needed to pilot a vehicle toward a cue.

Driving with supervisory commands requires deriving a discrete control signal. One of the objectives of this study is to explore if it is possible to devise such an abstract supervisory control command from the firing patterns in the motor and premotor regions. Specifically in this study, rats were trained to press paddles on the left and right sides of their conditioning chamber. We do not try to ask how the recorded neurons, individually or collectively, in the motor cortex are involved with the trajectory of the paw or shoulder, especially since we allow the rat to vary this trajectory at will. What is important is that some neurons are actively involved with movements that eventually lead to the manifestation of a high-level output like "press the left paddle" and that by computing with these neurons one can begin to detect the control signal corresponding to "press the left paddle." This is not a trivial problem if one only records from a small number of neurons in a single hemisphere. For example, there seems to be little difference in how an animal presses two identical paddles varying only in their spatial location by about 15 cm and presumably little difference in how the cortex controls certain aspects of limb movement. However, as shown in the data and analysis following, features do exist in the neural data that allow the determination of the rat's directional control signal.

The task of discriminating between *Left* and *Right* classes of responses by creating a mapping from neural activity to movement control signals is ideally suited to support vector machines (SVMs) [12]. The SVM is a classification algorithm that is rigorously posed so that few free parameters are needed to develop a robust classifier even for high-dimensional data. In fact, the evaluation of the decision function at the heart of the SVM is based on a subset of the training data. The support vector machine has successfully been applied to data sets from many fields often resulting in improvement over traditional methods.

In the following study, we devised a test system that allowed us to determine to what extent it is possible to derive supervisory commands for generating a correct paddle press control signal from a handful of electrode recordings spanning a broad sample of the motor cortex. We trained rats in a directional task within a conditioning chamber mimicking wheelchair driving control, allowing them to complete the task in any way they desired. We then examined cortical recordings preceding left and right paddle presses and used an SVM to create a closed-loop BMI system. This system functionally replaced the paddle pressing, allowing rats who had never interacted with such a system before to achieve an average accuracy of 78% on the first day of exposure to the interface. This accuracy was significantly better than that predicted by a naïve Bayesian algorithm. Further, the calibration of the SVM model and its parameters was based on less than 100 trials of real paddle press tasks where only the time when the rat was asked to press the paddle was noted and not any specifics of the path or timing of the motion.

II. METHODS

A. Surgical Implantation

Four male Sprague–Dawley rats were used in this research. The animals were implanted with 2×4 arrays of 50 μm tungsten wires coated with polyimide and spaced 500 μm apart for a total array size of approximately 1.5×0.5 mm. The surgical procedure is similar to that described in [13]. In brief, rats (weighing 250–400 g) were initially anesthetized with a mixture of ketamine (5 mg/kg), xylazine (0.5 mg/kg), and acepromaizine (0.1 mg/kg) and supplemented as needed

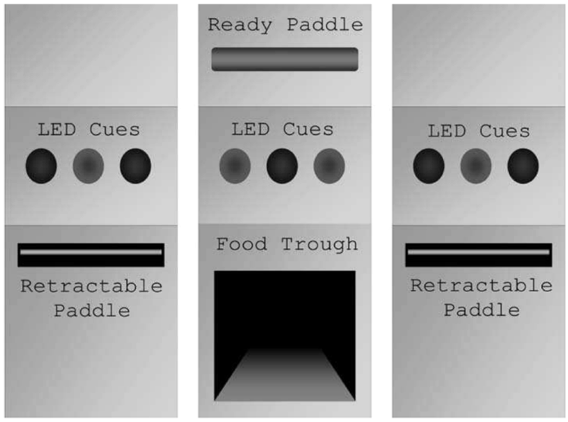

Fig. 1. Rat's view of the conditioning chamber.

to maintain areflexia. The physiological state of the animal was monitored for blood oxygen saturation and heart rate. The animal was placed in a stereotactic frame (Kopf Instruments, CA) and warmed with a water blanket maintained at 37 °C. The skin and fascia covering the surgical site was removed to the cranium and two stainless steel bone screws were placed on either side of the midline in the parietal plates to provide anchors for the dental acrylic. Another small craniotomy was opened to insert a stainless steel ground wire. The exposed craniotomies were then covered with GelFoam™ and the entire surgical site was sealed with dental acrylic. The electrode connector (Omnetics, MN) was also cemented in place with dental acrylic.[1]

The implant was centered +3 mm anterior, +2 mm lateral from bregma, and −2 mm ventral from the surface of the dura mater. The implant site was intended to broadly sample the motor cortical area [14] including neck, forepaw, and shoulder regions. The rat motor region is often referred to as having rostral (analogous to pre- or supplementary motor cortex) and caudal (analogous to primary motor cortex) regions. The implant site targets the rostral region for two reasons, first responses in the rostral region seem less tightly coupled (temporally) to movement initiation or cessation but remain highly correlated to kinematics, and amongst cells with large degrees of modulation, rostral cells favor premovement bursts over bursts later in the movement [15].

B. Animal Training and Behavioral Task

Rats were placed in an operant conditioning chamber (Med Associates, VT) equipped with retractable paddles on the left and right (Med Associates PN ENV-112CM) as well as a nonretractable paddle in the center panel, named the "ready paddle" (Med Associates PN ENV-110RM). A custom made food trough was placed in the center panel, under the center panel lights (Fig. 1). Three horizontally spaced red light-emitting diode (LED) indicators were installed on each of the three custom made panels. Of the three lights, only the noncenter LEDs on the left and right panels, and the center LED on the center panel were used. These LED indicators are referred to as outside left, inside left, center, inside right, and outside right for convenience.

During the training phase before the electrodes were implanted, the rat began a trial by pressing the nonretractable central ready paddle. One of the four cue LEDs on either the left or right panel was illuminated. Two seconds later the retractable paddles extended. With each press of the paddle, an audible sound was produced in addition to the light being shifted to the left or right one step corresponding to a left or right press, respectively. The rat was trained to move the light toward the center by properly pressing the paddles until the center light was illuminated. For example, if the outside left light was initially lit, the rat was expected to press the left paddle twice to turn on the light in the center. If the rat stopped responding once the center LED was on, he was rewarded with a food pellet (45 mg Noyes). Two behaviors could result in a brief time out: responses that moved the light out of the box (i.e., pressing the left paddle when the outside right light was illuminated) or lack of response within an allowed response window (i.e., 10 s without response). The light must remain in the center position for 1 s to receive a food reward. If the rat responded before this one second was up the light would move past the center. This could be corrected if the proper paddle was pressed within the allowed response window. During the entire task performance, the animal was free to move about the conditioning chamber and produce natural movements.

C. Neural Data

After an animal had achieved a task performance level in excess of 90% in training (90% of the trials ended in food rewards), microwire arrays were implanted into his right hemisphere motor cortical areas. While handedness was demonstrated in most animals, this was not taken into account when selecting the hemisphere to implant. This was due to two major observations: 1) the animal was freely moving during the task and thus free to implement any paddle pressing strategy, and 2) that the implanted electrodes covered a broad range of his motor cortex.

Implanted rats were then placed in the behavioral apparatus again where action potentials from the microwires were amplified and recorded using an NMAP system (Plexon Inc., TX). A custom interface was built to allow the paddle press, paddle extension, cue illumination, and start and end of trial signals to be utilized simultaneously by the Med Associates system and recorded by the digital inputs of the NMAP system.

Little preprocessing was done to the recorded data. Often visual inspection would suggest that activity from more than one neuron influenced the potential on a single electrode. When a clear distinction could be made amongst multiple waveform patterns they were treated as separate neural signals. Traditionally, such neural information has been treated as discrete events marked at times when extra-cellular potentials indicate an action potential has fired in a neuron close to the electrode. This leaves a list of times when action potentials, commonly called "spikes," are detected. This list of discrete events can be dealt with directly or transformed into a continuous variable. Most methods that perform this transformation are estimating the mean firing

[1]The Institutional Animal Care and Use Committee at Arizona State University approved the experimental protocol for this investigation.

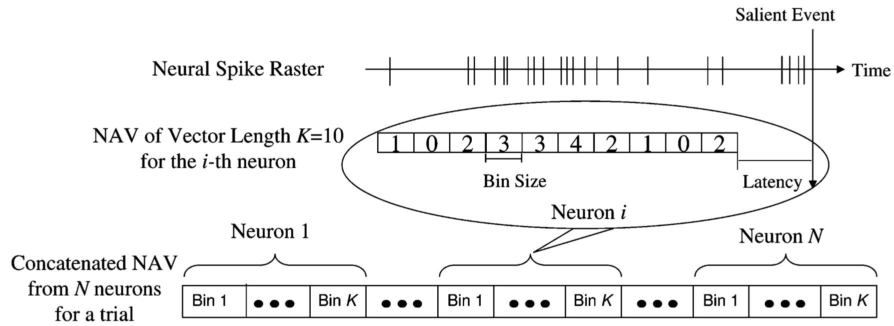

Fig. 2. Construction of an NAV.

rate of a neuron over a given time interval. In this study, temporal bins are formed and the number of events that take place in a given bin are counted to provide such an estimate.

Neural activity vectors (NAVs) were created from binned spike times. To bin the data into NAVs, three parameters must be selected: bin size, latency, and window size. Bin size refers to a period of time in which spike events are counted. A window, usually containing several bins, is the period of time under consideration in the classification algorithms. The vector length is the number of bins in a window. The last bin is aligned to some salient event (e.g., paddle press) with an offset called the latency. The convention adopted in this study aligns the last bin before an event if the latency is negative, and places the last bin after an event for positive latencies. In the following studies, NAVs refer to a vector of concatenated NAVs each formed from a separate neuronal signal. Such formulation aims at capturing the spatial-temporal nature of a neural representation and serves as inputs to a nonlinear mapping between neural input and the rat's paddle pressing control signal. An example of creating an NAV for N neurons with vector length of 10 and a negative latency is shown in Fig. 2.

D. SVM Implementation

Prediction algorithms are at the heart of all of the closed loop BMI studies. The two broad classes of prediction algorithms that are used are regression and classification. Regression algorithms attempt to map inputs to a continuous space of output variables. For example, monkey reaching task can map neural signals into a 2-D velocity space in a subset of $\Re^2$. Classification algorithms, on the other hand, map inputs onto a set of discrete classes usually with no implied ordering.

The prediction algorithm used here to map neural signals to a specific output class is the SVM. Intuitively, the SVM attempts to construct a separating line (or specifically a separating hyperplane) in a high-dimensional space to divide classes of data from one another. This separation is done to increase the "margin" between the two classes and is based on a subset of the training data called the support vectors. It is not always possible to absolutely separate two classes and, therefore, an alternative formulation of the problem utilizes risk minimization to optimally determine the linear separation. SVMs are popular not only because of their rigorous formulation, but also because they are widely applicable in real-world problems. The flexibility of the system is not hampered by high-bias problems that can sometime plague highly flexible systems (i.e., the overfitting problem of many approximation methods).

Training the SVM requires labeled sets of data. In this study, $+1$ was assigned to NAVs from a window associated with a right paddle press control signal, and -1 for a left paddle press control signal. We then seek to define a function on NAVs such that when evaluated at an input with a right NAV the output is positive, and vice versa. This is called the decision function. The solution for such a function is elegantly posed as a quadratic programming problem. Details of this problem and its solution appear in [16]. What is critical here is that the SVM allows us to solve for a function, based on a subset of the training examples called the support vectors, mapping NAVs into classes of behaviors corresponding to movement control signals.

SVMs have been developed extensively since they were introduced by Vapnik for solving classification and nonlinear function approximation problems. The training condition of SVMs can be reformulated as a convex quadratic programming (QP) problem hence a global and unique solution to the problem may be obtained by various numerical techniques. An upper bound on testing errors is theoretically available in terms of the Vapnik–Chervonenkis dimension.

Consider the binary classification problem. The training data consists of N pairs $\{(X_t, y_t)\}_{t=1}^N$ with input $X_t \in \Re^n$ and binary class labels $y_t \in \{-1, 1\}$. The classifier takes the form

$$y(X) = \text{sign}(W^T \phi(X) + b)$$

where ϕ maps the input space $\Re^n$ to a high-dimensional feature space $\Re^m$, and W is a weight matrix. The evaluation of the optimal separating hyperplane will lead to the following optimization problem:

$$\min_{W, \xi_1, \ldots, \xi_N} \quad \left\{ \frac{1}{2} W^T W + \gamma \sum_{t=1}^{N} \xi_t \right\}$$
$$\text{subject to} \quad y_t(W^T \phi(X_t) + b) \geq 1 - \xi_t$$

and

$$\xi_t \geq 0, \quad t = 0, \ldots, N.$$

The ξ_t's are slack variables which reflect the level of misclassifications for nonseparable samples and γ is a tuning parameter that expresses the relative sensitivity of the solution to misclassified examples. By constructing the Lagrangian, we deal with the dual optimization problem

$$\max_{\alpha_1,\ldots,\alpha_N} \left\{ \sum_{t=1}^{N} \alpha_t - \frac{1}{2} \sum_{t=1}^{N} \sum_{s=1}^{N} \alpha_t \alpha_s y_t y_s K(X_t, X_s) \right\}$$
$$\text{subject to} \quad 0 \le \alpha_t \le \gamma$$
$$\sum_{t=1}^{N} \alpha_t y_t = 0$$

where $K(X_t, X_s) = \phi(X_t)^T \phi(X_s)$ is a kernel function. Various types of kernel functions may be chosen so long as they satisfy the Mercer condition [16]. Popular choices include polynomials, radial basis functions (RBFs), and sigmoid functions. This study uses RBF kernels.

The formulation leads to the decision function with the form

$$f(X) = \sum_{t=1}^{N} \alpha_t y_t K(X, X_t) + b.$$

The observations which appear in the decision function, i.e., the data points with nonzero coefficients α_t, are called *support vectors*. Therefore, the complexity of the constructed learning machine depends on the number of support vectors rather than the dimension of the feature space.

E. Closed-Loop System

The closed-loop system is a real-time interface that seeks to use the predictions of directional control signals from the SVM algorithm to replace the actual pressing of paddles by the rat. So, when neural input indicates a control signal corresponding to the rat's desire to press the left/right paddle is detected, a relay on the left/right side of the chamber is actuated to functionally replace the paddle and send an audible reinforcement to the rat. Thus, the only difference in the task is the replacement of paddle pressing with the closed-loop system.

For the purposes of this study, only the inside left and inside right cues were given. This allowed both correct and incorrect trials to be given appropriate feedback: Correct trials moved the cue to the middle and resulted in a reward, incorrect trials moved to the corresponding outside light and result in a brief time-out. Refer to Fig. 3 for an illustration of the closed-loop system.

Fig. 4 is an illustration of how a traditional offline view of the task differs from the challenges faced in an online interface with respect to how NAVs are aligned. A major challenge for the closed-loop system is one of temporal alignment for obtaining NAVs. If the goal is only to record data and later make offline predictions, alignment is not a problem since the actual paddle press time is known and NAVs can be aligned to such events (with positive or negative latencies) as shown in the top panel of Fig. 4. In closed-loop applications, predicting paddle presses, or more precisely directional control signals, should occur with data available before any paddle is pressed. Waiting for a paddle press to occur is not appropriate since this is obviously too late to functionally replace said paddle press.

Instead of a fixed intertrial interval, which could sometimes catch the rat off guard grooming himself, this system allowed the rat to control the pace of the session. To accommodate this

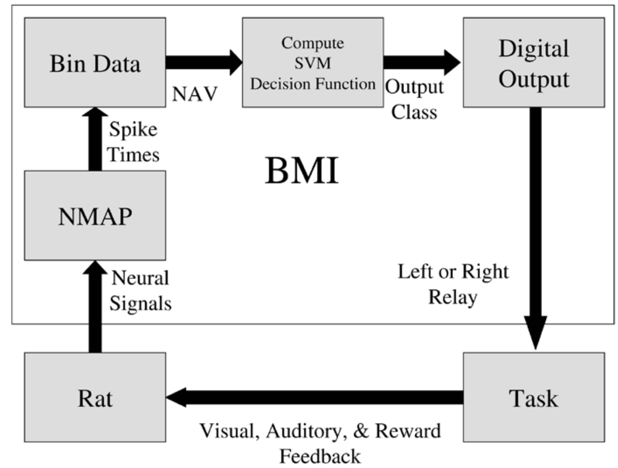

Fig. 3. Diagram of the closed-loop BMI system.

and ensure the rat was paying attention at the start of the trial, the ready paddle was added above the food trough (Fig. 1) and the animal was trained to press this paddle to start the task. At the start of the task, the cue light was immediately lit and 2 s later the paddles extended. This allowed alignment of NAVs to the paddle deployment time (or 2 s after the start of trial, refer to online calibration in Fig. 4). NAV parameters for animals in the closed-loop system were fixed at bin size of 100 ms, latency of -100 ms, and vector length of 10 bins after systematic optimization [17], thus the classification decision could be made before the paddles would normally be extended.

To derive the closed-loop SVM control decision function, an online calibration process was first conducted (Fig. 4). Calibration of the SVM came from the first 99–100 trials of the day. These trials were conducted with physical paddle pressing while collecting NAVs. The data from the correctly executed trials were then used to train the SVM model and to obtain the SVM parameters.

On all subsequent trials, the SVM model and parameters obtained from online calibration were applied, functionally replacing the paddles. Thus, after the rat started a trial by pressing the ready paddle, an NAV was extracted from the recorded data. The SVM decision function was evaluated at the NAV to determine if the neural signal corresponded to the left or right control signal class, and the corresponding relay was actuated eliminating the need for the paddles to be deployed (Fig. 3).

The total task duration (calibration and closed-loop system control) was about 45 min. Four rats were trained for this study and results from their first day of utilizing the interface with 8–10 neural signals are presented. Fig. 5 is an example of the perievent histograms of 10 neurons from R4 during a closed-loop experiment.

III. Results

A. Closed-Loop Study

Four rats were used to evaluate the performance of the closed-loop system. As discussed earlier, online calibration trials were conducted first to obtain the SVM model and its parameters. In the following, we make use of a few accuracy measures to illustrate how well the rats interfaced with the neuroprosthesis.

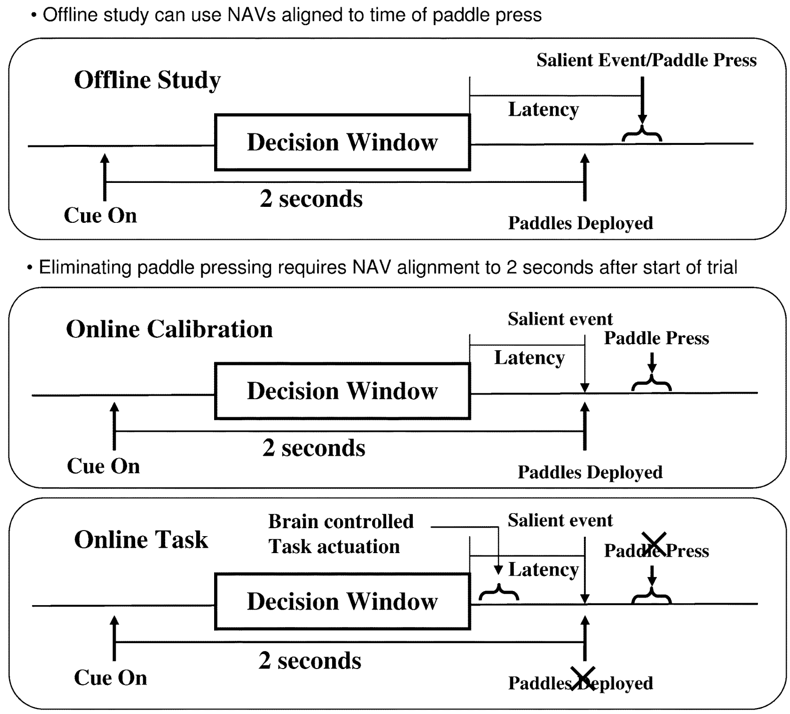

Fig. 4. Offline and online BMI system implementation and NAV alignment schemes.

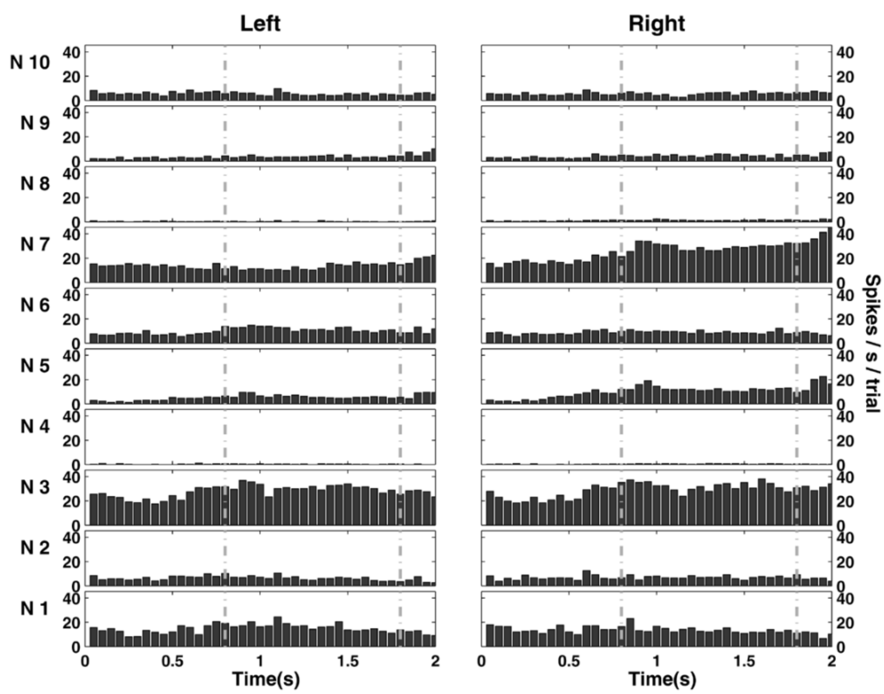

Fig. 5. Perievent histograms of firing activities of ten neurons of R4 in a closed-loop experiment. Each row shows the average firing rate (per second per trial) for one neuron during 0–2.0 s from cue light onset, broken down to left and right directions. the firing activity between the dashed lines (decision window) was used to form NAVs.

Table I is a summary of the results from those rats tested on the closed-loop system. The number of recorded neurons used in the study is given in the second column of the table. The third column shows the accuracy of the rat in the paddle pressing phase. That is, how many of the calibration trials were correctly executed by the rat using paddle pressing. This number should be thought of as how likely the rat is to plan a correct directional control decision in the algorithm decision window.

TABLE I
ONLINE STUDY RESULTS

Rat Name	Number of Single Unit Used	Accuracy of Calibration Paddle Press	Cross-Validation Accuracy	Online Control Accuracy
R1	10	87.88	85.06	77.03
R2	9	92.00	71.74	76.33
R3	8	33.33	78.79	71.70
R4	10	89.00	87.64	85.81

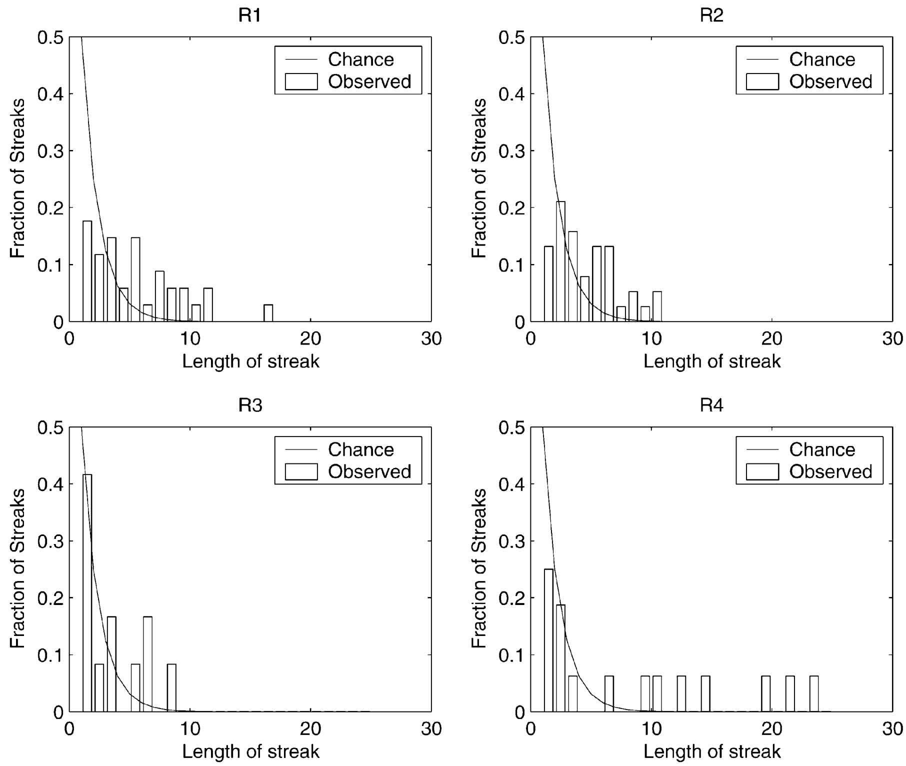

Fig. 6. Comparison of trends in closed-loop performance with trends expected by chance. using chi-square goodness-of-fit test, the null hypothesis that the distribution of the winning streak follows the distribution by chance was rejected with significance value $p = 0, 0, 0.02, 0$, respectively.

TABLE II
CONFUSION MATRICES FOR ONLINE CONTROL

	Trial Cues	Percentage Classified as *Left*	Percentage classified as *Right*	Overall Accuracy
R1	*Left*	58.18	41.82	77.03
	Right	4.46	95.54	
R2	*Left*	93.27	6.73	76.33
	Right	40.78	59.22	
R3	*Left*	62.96	37.04	71.70
	Right	19.23	80.77	
R4	*Left*	91.57	8.43	85.81
	Right	21.54	78.46	

TABLE III
ONLINE STUDY COMPARISON DATA

Rat Name	SVM Online Control Accuracy	Naïve Bayesian Accuracy
R1	77.03	65.32
R2	76.33	64.73
R3	71.70	58.49
R4	85.81	62.84

To obtain a quantitative evaluation of how the SVM model may perform for online application, a leave-one-out cross validation was performed utilizing the correct paddle pressing trials. This shows how often an NAV from a calibration trial would have been classified correctly if it were not one of the calibration trials. To some extent, these results, shown in the fourth column, suggest to us how "separable" the calibration data is. The final column shows the ability of each animal to use the closed-loop system. That is, of the trials, the rat completed using the interface, how many resulted in the correct paddle being actuated. The accuracy of the online closed-loop trials ranges from 71.70% to 85.81% (mean 77.72%) and are all well above 50% expected by chance.

Table II elucidates the nature of the errors in the online trials with confusion matrices. Here, we see that of the trials cued as *Left* or *Right*, what the accuracy is for the closed-loop system and what the type I and type II errors are, respectively. Note that the number of *Left* and *Right* trials is not always equal and thus the average of *Left* and *Right* accuracies is not necessarily the overall accuracy.

B. Naïve Bayesian Comparison

To determine the effectiveness of the SVM algorithm and thus the closed-loop system, the results obtained thus far were compared to analysis by standard methods using extensive offline data analysis. Specifically, we prepared a naïve Bayesian classifier [18] for each rat by utilizing the same calibration data with which the closed-loop SVM classifier was trained. The classifier was then tested using the neural data collected and acted upon during the online closed-loop study. That is, we compare the two approaches using the same training and testing data. The results follow in Table III. The results again demonstrated that the SVM is a robust and effective tool in implementing the closed-loop system.

C. Prolonged Use and Winning Streaks

One of the rats (Rat 4) used the interface for three consecutive days (with 100 calibration trials at the beginning of each day). The confusion matrices and overall accuracies follow in Table IV. The average accuracy over all three days was 90.51%.

In addition, to further examine usage trends from the closed-loop system and thus give us an idea of how well a given rat

TABLE IV
CONFUSION MATRICES OVER DAYS

	Trial Cues	Percentage Classified as *Left*	Percentage classified as *Right*	Overall Accuracy
Day1	*Left*	91.57	8.43	85.81
	Right	21.54	78.46	
Day2	*Left*	93.83	6.17	92.14
	Right	10.17	89.83	
Day3	*Left*	91.89	8.11	93.55
	Right	4.00	96.00	

could form a trajectory in a driving task, we extracted winning streak data from all four rats on the first day of online recording. A winning streak is measured as the number of trials that the rats were able to successfully use the interface before a mistake was made. Fig. 6 summarizes the results and compares the rats' performance with the case of making decisions simply by chance. It is obvious from the results that there is a level of control displayed by all four rats.

IV. CONCLUSION

This study introduces the first step along the path to a practical BMI for a driving task. First, we have shown that with a small number of nonspecific motor cortical neurons, nonstereotypical experimental conditions, and using behavioral and neural data in a real-time fashion, we could build a useful system allowing four rats to functionally replace paddle pressing movements with high degrees of accuracy. Second, we have shown that in this study we could improve accuracy of the task by over 10% without adding neurons, but by utilizing a sophisticated algorithm. Finally, we have shown that one animal was able to use the interface successfully over the course of three days with his overall accuracy improving each day.

Our success with determining directional control signal has inspired us to look further into the idea of a supervisory closed-loop system directing a vehicle. We have begun to expand the system into actual vehicle control and soon hope to allow for full velocity control using an asynchronous system interacting with a highly sophisticated vehicle capable of sensing its surrounding and interpreting the supervisory commands in light of such sensor readings.

REFERENCES

[1] E. Fetz, "Operant conditioning of cortical unit activity," *Science*, vol. 163, pp. 955–958, 1969.

[2] E. Schmidt, M. Bak, J. McIntosh, and J. Thomas, "Operant conditioning of firing patterns in monkey cortical neurons," *Exp. Neurol.*, vol. 54, pp. 467–477, 1977.

[3] A. Georgopoulos, J. Kalaska, R. Camintini, and J. 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.

[4] A. Georgopoulos, R. Kettner, and A. Schwartz, "Neuronal population coding of movement direction," *Science*, vol. 233, pp. 1416–1419, 1986.

[5] D. Serruya, N. Hatsopoulos, L. Paninski, M. Fellows, and J. Donoghue, "Instant neural control of a movement signal," *Nature*, vol. 416, pp. 141–142, 2002.

[6] D. M. Taylor, S. I. Tillery, and A. Schwartz, "Direct cortical control of 3-D neuroprosthetic devices," *Science*, vol. 296, pp. 1829–1832, 2002.

[7] M. Carmena, M. Lebedev, R. Crist, J. O'Doherty, D. Santucci, D. Dimitrov, P. Patil, C. Henriquez, and M. Nicolelis, "Learning to control a brain-machine interface for reaching and grasping by primates," *PloS Biology*, vol. 1, no. 2, pp. 1–13, 2003.

[8] J. Chapin, K. Moxon, R. Markowitz, and M. Nicolelis, "Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex," *Nature Neurosci.*, vol. 2, pp. 664–670, 1999.

[9] M. Nicolelis and J. Chapin, "Controlling robots with the mind," *Sci. Amer.*, vol. 287, no. 4, pp. 46–53, 2002.

[10] J. Wessberg, C. Stambaugh, J. Kralik, M. L. P. D. Beck, J. Chapin, J. Kim, S. Biggs, M. Srinivasan, and M. Nicolelis, "Real-time prediction of hand trajectory by ensembles of cortical neurons in primates," *Nature*, vol. 408, pp. 361–365, 2000.

[11] S. Musallam, B. D. Corneil, B. Greger, H. Scherberger, and R. A. Andersen, "Cognitive control signals for neural prosthetics," *Science*, vol. 305, no. 5681, pp. 258–262, 2004.

[12] B. Boser, I. Guyon, and V. Vapnik, "A training algorithm for optimal margin classifiers," in *Proc. 5th Annu. Workshop Computational Learning Theory*, Pittsburgh, PA, 1992, pp. 144–152.

[13] J. Williams, R. Rennaker, and D. Kipke, "Long-term neural recording characteristics of wire microelectrode arrays implanted in cerebral cortex," *Brain Res. Protocols*, vol. 4, pp. 303–313, 1999.

[14] B. Kolbe and R. Tees, *The Cerebral Cortex of the Rat*. Cambridge, MA: MIT Press, 1990.

[15] B. Hyland, "Neural activity related to reaching and grasping in rostral and caudal regions of rat motor cortex," *Beh. Brain Res.*, vol. 94, pp. 255–269, 1998.

[16] B. Schölkopf and A. Smola, *Learning with Kernels* . Cambridge, MA: MIT Press, 2002.

[17] B. Olson, J. Hu, J. Si, R. Clement, and J. He, "A support vector approach to online brain control," in *Proc. 25th Annu. Int. Conf. IEEE Engineering Medicine Biology Soc.*, 2003, pp. 2212–2215.

[18] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*, 2nd ed. New York: Wiley, 2001.

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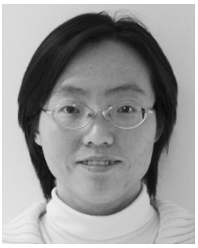

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