# Multi-state decoding of point-and-click control signals from motor cortical activity in a human with tetraplegia

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*Abstract*—**Basic neural prosthetic control of a computer cursor has been recently demonstrated by Hochberg *et al.* [1] using the BrainGate system (Cyberkinetics Neurotechnology Systems, Inc.). While these results demonstrate the feasibility of intracortically-driven prostheses for humans with paralysis, a practical cursor-based computer interface requires more precise cursor control and the ability to "click" on areas of interest. Here we present the first practical point and click device that decodes both continuous states (e.g. cursor kinematics) and discrete states (e.g. click states) from a single neural population in human motor cortex. We describe a probabilistic multi-state decoder and the necessary training paradigms that enable point and click cursor control by a human with tetraplegia using an implanted microelectrode array. We present results from multiple recording sessions and quantify the point and click performance.**

## I. Introduction

NEURAL interface systems (NISs) based upon an intracortical sensor aim to restore lost function to paralyzed humans by sensing movement-related activity of neurons, decoding this activity into control signals and using these signals to control external devices or the person's own limbs. Initial results from a human NIS [1] demonstrated that neural spiking activity could be detected from the motor cortex of humans with long-term paralysis, decoded, and used for voluntary control of prosthetic devices including robotic arms and computer cursors. Despite this initial success, the quality of neural cursor control in these initial demonstrations was below the level of cursor use typically achieved by able-bodied humans using standard pointing devices. This human NIS [1] used a linear regression method to directly decode cursor position from a history of neural firing rates. Studies in able-bodied monkeys, however, have demonstrated motor cortical neurons code for velocity [2] and that improved cursor control could be obtained by decoding velocity using a Kalman filter [3]. Recent work by our group, in collaboration with Cyberkinetics Neurotechnology Systems, Inc. (Foxborough, MA), has similarly improved the quality of human cursor control by decoding cursor velocity from motor cortical activity using a Kalman filter [4]. The results from multiple recording sessions showed more stable and accurate cursor control for reaching designated targets.

Beyond precise cursor positioning, practical applications of computer control typically assume the ability to click on targets of interest (e.g. select menu items on a computer screen). For an NIS, this point and click capability requires the simultaneous decoding of both continuous (cursor motion) and discrete (clicking) states in real time from a population of motor cortical neurons. Multiple recording devices might provide separate signals for continuous movement and click states but in our work a single recording array was used. Multi-state decoding then requires the extraction of both continuous and discrete states from a single neural population. Additionally this neural population is currently small (on the order of tens of cells) and hence much smaller than the number of neurons engaged in the actual performance of such a task.

Preliminary studies in non-human primates have shown that it was possible to decode both continuous and discrete states from the same population of motor cortical cells. Darmanjian *et al.* [5] decoded movement/rest states using hidden Markov models (HMMs) and hand position using multiple linear filters from multiple motor cortical areas of a monkey. Wood *et al.* [6] developed a Bayesian method to decode from MI firing activity both a discrete state, representing whether a monkey was performing a task or not, and the continuous kinematics of the monkey's arm movements. In this method, a discrete state was decoded using a linear discriminant analysis (LDA) classifier [7] and embedded into a particle filtering algorithm [8] for decoding

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continuous kinematics.

To decode discrete and continuous states from human motor cortical neural activity, we present a multi-state decoder based on the model of Wood *et al.* [6] but modified to use a Kalman filter decoder for real time performance. We also present the associated training paradigms sufficient for training the multi-state decoding algorithm. We report here results of using the multi-state decoder for point and click cursor control from one pilot clinical trial participant who is tetraplegic secondary to a brainstem stroke. We quantify the performance of the multi-state decoder during an eight direction radial-target acquisition task, using various metrics, including the target acquisition rate, movement time and the variability of movement.

## II. Filter Building and Evaluation

Effective use of an NIS requires training of the decoding algorithm. These training paradigms aim to extract useful signals from imagined motion and relate these to the control of a cursor. In a paralyzed human training of the decoding algorithm is complicated by the fact that there is no independent, observable measure of intended movement as in able-bodied monkeys. As a consequence, the design of training paradigms takes on increased importance. The training for multi-state decoding has two components: one for the continuous state and the other for click state.

Training of a Kalman filter for continuous state decoding was divided into "blocks" of open-loop (OL) and closed-loop (CL) phases. In OL blocks, the participant was shown a preprogrammed training cursor (TC) moving to targets on a computer monitor for 1.5 min. Although not controlling the TC, the participant was asked to imagine moving her arm or hand as if she was controlling it. The continuous state decoder was trained using a center-out paradigm in which one of four or eight visible peripheral targets was highlighted. The TC moved with a roughly bell-shaped velocity profile from the center circle to the target and stopped for 1 second. Then, the center circle was highlighted, and the TC retraced its trajectory back to the center circle. This sequence was repeated with different highlighted peripheral targets for 1.5 minutes. Neural spiking activity from multiple neurons was simultaneously recorded from the participant's motor cortex using the methods described in [1]. The synchronous TC velocity and recorded neural activity during imagined movement were used to train a Kalman filter decoding algorithm [9].

In CL blocks (1.5 min each), two cursors were displayed on the monitor: one was the TC and the other was a neural cursor (NC) that was driven by a control signal estimated from the neural activity using the Kalman filter. The participant was asked to imagine movements corresponding to TC movement as before while also being aware of the NC movement. Overall training typically involved 1 to 3 OL blocks which were used together to build an initial Kalman filter decoder, followed by a series of 4 to 6 CL blocks during which the Kalman filter decoder was retrained at the end of every other block using the data from previous 2 or 4 CL blocks.

We augmented the above paradigm to also train the discrete (click) state component of the multi-state decoder. To that end, we introduced new training blocks in which discrete state training was inserted in between short (e.g. ~20 sec) epochs of closed-loop continuous movement training with TC and NC. After three to five executions of target acquisition by TC (and tracking by NC), all cursors and targets were hidden and an instructive word such as "squeeze" appeared on the monitor for one and half seconds during which time the participant was to imagine squeezing her hand. This set of continuous and discrete state presentations repeated several times in each block.

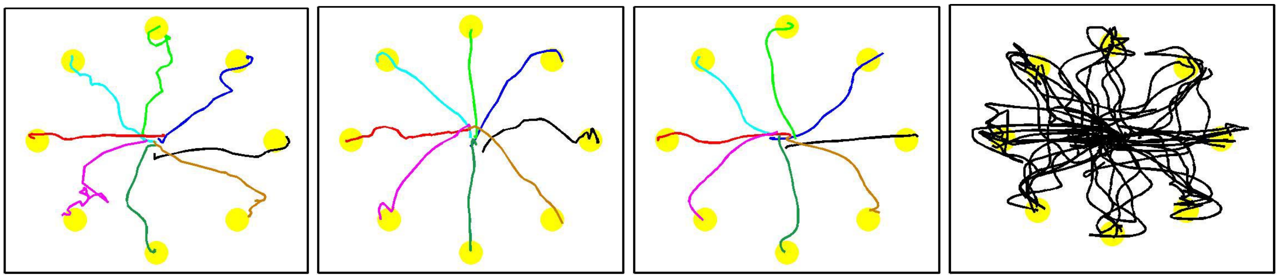
The neural activity recorded during imagined squeezing and continuous cursor movements was used to train a linear classifier to discriminate the two states squeeze/click versus movement. Note that during the discrete state training there was no visual feedback about classification performance (i.e. there was no discrete equivalent of the NC).

After training, the decoding algorithm was held fixed and an eight-direction radial-target acquisition task was used to evaluate point and click performance. At the beginning of the task, eight circle targets of an equal size were radially positioned with angles {0º, 45º, 90º, 135º, 180º, 225º, 270º, 315º} and the NC was placed at the center on the monitor. Then, one of eight targets was highlighted and the participant was instructed to move the NC to that target and click it. When the target was clicked, its color changed. A single trial of the task was completed when the (correct or incorrect) target was clicked or the timeout period (e.g. 9sec) expired. After a trial, the center target was highlighted and the participant had to move the NC back to touch the center circle to initiate the next trial (no click was required in the center target). The sequence of targets for each trial was pseudo-randomly ordered so that the number of trials per target was distributed as evenly as possible. The radial distance and the target size remained unchanged over recording sessions. We analyzed three recording sessions, across which a total of 160 trials were performed.

## III. Decoding Algorithms

In the decoding method of Wood *et al.* [6], a mixed discrete/continuous state space was employed. The Bayesian model for this mixed-state representation required a non-linear likelihood function and exploited a non-parametric particle filter for decoding. This particle filtering approach was computationally intensive and, therefore, not appropriate for real-time decoding in an NIS. To overcome this issue, we simplify this Bayesian approach by separating the inference of discrete and continuous state variables.

The variables used in our method are as follows: $\gamma_k$ is a discrete state variable at a time instance $k$, representing whether the cursor is in a click or a continuous movement state; $x_k$ is a continuous state (e.g. cursor velocity) vector; $z_k$ is a neural population firing rate vector estimated by spike counts within a non-overlapping time bin (100ms); $Z_k$ = [$z_k$,



(a) session 1: $n = 37$ (b) session 2: $n = 38$ (c) session 3: $n = 57$ (d) session 3

**Fig. 1. Human neural cursor control in an 8-direction point-and-click task.** (a)-(c) The mean paths of the neural cursor from the center to 8 radial targets (peripheral circles) for each of three recording sessions. $n$ is the number of recorded single/multi units. (d) The actual NC paths in session 3.

$z_{k-1}, \ldots, z_{k-L}]^T$ is a short-term (0.5 ~ 1 sec) history vector of neural firing rates, where $L$ is the history length.

For discrete states, we model the posterior of $\gamma_k$ given the neural firing activity $Z_k$ and $\gamma_{k-1}$:

$$p(\gamma_k \mid Z_k, \gamma_{k-1}) = p(\gamma_k \mid Z_k) \cdot p(\gamma_k \mid \gamma_{k-1}), \tag{1}$$

where we assume independence between the current neural activity and previous discrete states. $p(\gamma_k \mid Z_k)$ is modeled by an LDA classifier [7]:

$$p(\gamma_k \mid Z_k) = \frac{p(\gamma_k = \gamma^{(j)}) \cdot G(w^T Z_k; \mu_j, \sigma_j)}{\sum_j p(\gamma_k = \gamma^{(j)}) \cdot G(w^T Z_k; \mu_j, \sigma_j)}, \; j = 0, 1 \tag{2}$$

where $\gamma^{(0)}$ and $\gamma^{(1)}$ represent the click and the movement states, respectively. $G(\alpha;\beta,\sigma)$ denotes a Gaussian distribution of a random variable $\alpha$ with a mean $\beta$ and a standard deviation $\sigma$. $w$ is a projection vector computed as:

$$w = (C_0 + C_1)^{-1} \cdot (m_0 - m_1), \tag{3}$$

where $m_j$ and $C_j$ are the mean and a covariance of a set of $\{Z_k\}$ which belongs to state $\gamma^{(j)}$. Here we denote this set of $\{Z_k\}$ as $Z_j$. Once $w$ is obtained, $\mu_j$ and $\sigma_j$ are computed by taking the mean and the standard deviation of the projected firing rates, $w^T Z_j$. The state transition probability, $p(\gamma_k \mid \gamma_{k-1})$ is empirically estimated from the data. Finally, we assume the prior probability of either state is $p(\gamma_k = \gamma^{(j)}) = 0.5$.

Next, we build a Kalman filter to decode cursor movement during the continuous state. The Kalman filter is trained using the continuous movement data. From these data, we learn the parameters, $\{H, Q, A, W\}$ for modeling the likelihood and prior of the Kalman filter:

$$\begin{aligned} z_k &\sim G(Hx_k, Q) \\ x_k &\sim G(Ax_{k-1}, W) \end{aligned}, \tag{4}$$

using the least squares method. In our model, $x_k$ represents the x and y components of velocity. For details of training such a method on monkey data, where the kinematics $x_k$ are observable, see [9]. Since the intended kinematics are unobserved, we train the model using the velocity of the TC.

Once we train the classifier and the Kalman filter, motor signals can be decoded from novel neural firing activity. To begin, we initialize the velocity vector ($x_0 = [0,0]^T$), the discrete state ($\gamma_0 = \gamma^{(1)}$) and the history of firing rates ($Z_0 = [0\ldots0]^T$). Then, with a novel firing rate vector at each time instance $k$, the posterior of $\gamma_k$ is computed using equation (1). If the posterior probability of the movement state is higher than the click state, then $\gamma_k = \gamma^{(1)}$ and velocity is decoded using the Kalman filter to move the NC (see [3][9] for details of the Kalman filter decoding). Otherwise, $\gamma_k = \gamma^{(0)}$, and a click signal is generated with zero cursor velocity.

## IV. Results

The method was evaluated in one tetraplegic pilot trial participant whose paralysis resulted from a brainstem stroke that occurred nine years prior to trial enrollment. Neural population activity was recorded from her intact motor cortex using a Cyberkinetics microelectrode array. The training procedures from above were followed. The participant then moved the neural cursor using imagined movement to point and click on eight radial targets.

Fig 1 presents the mean paths of the NC towards each of eight targets for three sessions recorded on separate days (denoted as sessions 1, 2 and 3). To estimate the mean path, individual paths to each target were linearly interpolated to have the same number of time samples. Then, the mean vector was calculated for each sample point. The actual NC paths during the third session are also presented to illustrate the movement variability.

To quantify the point and click performance, we used the following metrics: First, the error rate (ER) was measured as the percentage of the trials in which the incorrect target was clicked or the timeout period expired before the target was clicked. The timeout period was set to 30 sec for sessions 1 and 2, and 9 sec for session 3. To evaluate discrete state decoding performance we count the number of times when the click signal was generated before the target was acquired per trial, termed as a false click rate (FCR). Second, we measured the movement time (MT) from the onset of the target to the time when the target was clicked. The MT was measured only for the trials when the correct target was clicked within the timeout period. Third, we measured the stability of the point-to-point NC movement using the movement variability (MV) [10]. For each trial, we defined a task axis connecting the starting NC point to the target. Then, the shortest Euclidean distance from each sample position of the NC to the task axis was calculated. The MV was defined as the standard deviation of these distances. Smaller MV indicates a straighter NC path.

These performance metrics were used to evaluate the cursor control performance for three recording sessions, as shown in Table 1. The ER results demonstrate that the participant was able to click 100% of the correct targets within 30 sec and 96.1% within 9 sec. Also, for all three sessions, the errors were registered only when timeout expired – there were no false target acquisition. The FCR results show that the average number of false clicks before reaching targets was 0.3 ~ 1 for each point-and-click trial. Note that the false click did not end the trial since clicking on the blank space was allowed in the task. The MV results were relatively small compared to the screen size (366mm x 305 mm (W x H)). We compare the MV measures to the results from other pointing device experiments [10] where subjects with Parkinson's disease (PD) and essential tremor (ET) performed point and click using the mouse, trackball and joystick. The mean MV results from that study for using the mouse, trackball and joystick were: 15.39, 18.08 and 19.98 mm, for the PD subjects; and 18.84, 21.95 and 26.23 mm for the ET subjects, respectively. These are roughly comparable to our NIS cursor control performance.

## V. Conclusion

We have demonstrated that continuous and discrete motor signals can be simultaneously decoded from a single population of motor cortical neurons in a human with tetraplegia. In particular, we decoded a continuous 2D velocity signal and a discrete click signal using a model that combined an LDA classifier for discrete decoding with a Kalman filter for continuous decoding. We also presented an on-line training method for paralyzed users that relied on imagined movement. We quantified the point-and-click performance of a single participant using this NIS over multiple recording sessions. To our knowledge, this is the first demonstration of point-and-click control in an NIS.

In our current work, we are conducting more extensive performance evaluation by varying target sizes and movement distances, which will more closely represent the type of standard graphical user interfaces typically adopted in modern computer software. We are also investigating the use of standard human computer interaction (HCI) metrics for pointing devices [11]. Using these standard metrics, it will be possible to directly compare the performance of our NIS with other devices controlled by able-bodied subjects.

We plan to replicate this study with additional participants, and to develop more advanced decoders which we anticipate will further improve the potential for NISs to provide rapid and precise control over a computer cursor and other assistive devices by people with tetraplegia.

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TABLE I
POINT-AND-CLICK PERFORMANCE MEASURES

| Metric | Session 1 ($n$ = 37)* | Session 2 ($n$ = 38) | Session 3 ($n$ = 57) | Average |
|---|---|---|---|---|
| *ER* (%) | 0 [30s] | 0 [30s] | 3.9 [9s] | |
| *FCR* | 0.81 | 1.03 | 0.31 | **0.72** |
| *MT* (sec) | 7.89 | 6.10 | 5.70 | **6.43** |
| *MV* (mm) | 16.79 ± 8.16 | 17.87 ± 12.74 | 15.17 ± 9.13 | **16.73 ± 10.61** |

* $n$ = the number of recorded neuronal single/multi units

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