Proceedings of the 26th Annual International Conference of the IEEE EMBS
San Francisco, CA, USA • September 1-5, 2004

Co-Adaptive Kalman Filtering in a Naïve Rat Cortical Control Task

G. J. Gage[1], K. J. Otto[1], K. A. Ludwig[1], D. R. Kipke[1,2]
[1]Department of Biomedical Engineering, University of Michigan, Ann Arbor, MI USA
[2]Department of Electrical Engineering, University of Michigan, Ann Arbor, MI USA

Abstract— **Control of prosthetic devices is possible via extra-cellular recordings from cortical neurons. Many of the current cortical control paradigms consist of analyzing the relationship between cortical activity and measured arm movements, and then using this known relationship to map cortical activity to similar prosthetic arm movements. However, measured arm movements are not feasible for amputees or patients with mobility limitations hindering their ability to perform such movements. Here we explore an alternative approach using a rat model in which subjects learn prosthesis control via an adaptive decoding filter that adjusts to the modulation patterns recorded from neurons in the motor cortex. Our methodology takes into account the ability of a subject to learn an effective response strategy in conjunction with online filter adaptation. A modified Kalman filter is demonstrated to "co-adapt" by training on past periods of significant modulation during expected prosthetic device movement. Feedback pertinent to completing the cortical task is given to aid the animal in adopting a response strategy maximizing reward. One subject was able to perform the task consistently above chance after 2 days (4 sessions) of training.**

Keywords— **extracellular recording; neuroprostheses; silicon microelectrodes; brain-machine interface; motor cortex; operant conditioning; BCI; Kalman filter**

I. INTRODUCTION

The use of the motor cortex in a neuroprosthetic system has received much attention recently, as evidenced by many high profile publications[1-3]. Many of these studies involved subjects that initially learned a motor task, and then switched to a cortical control task in which the neural prosthetic device replaced the natural motor activity. However, there are many situations where there is not a physical human movement that natively correlates with prosthetic control. Examples where an immobile patient would use such devices are: powered wheelchairs, trolleys, calipers, 2-D microcomputer cursors, communication boards, and various adapted vocational tools. If used as neuroprosthetic devices, control of these practical "foreign" devices must be learned completely from a naïve state.

In this study, we investigate this naïve scenario in a rat animal model to understand if cortical control can be obtained without *a priori* movement measurements. We argue that rats are an ideal testbed for investigating novel naïve decoding techniques because they (1) have a rich history in neurological literature, (2) are the most often used animal model for SCI patients[4], (3) are intelligent, (4) are able to use brain machine interfaces[5], (5) are easy to handle, (6) are relatively inexpensive, and (7) are easily obtainable. Based on these arguments, a rat animal model was developed to study the learning of a cortical control task in a naïve subject.

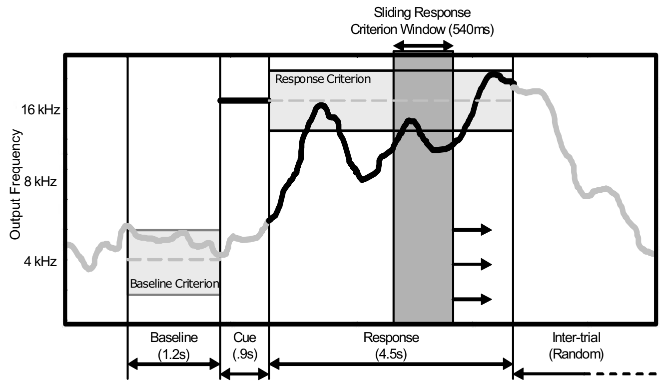

Fig. 1. Tone Matching Behavioral Paradigm: Dark line indicates auditory tone frequency fed back to the subjects (initial cue followed by 90 ms feedback pips). Responses were determined correct and were rewarded if the feedback frequency was maintained within the response criterion of the set point frequency, for the duration of a 540 ms sliding window, incrementing in 90 ms steps.

II. METHODOLOGY

A. Device and Surgical Implantation

16-channel chronic silicon-substrate microelectrode arrays were implanted into 2 rats[6, 7]. These microelectrode assemblies, commonly referred to as "Michigan" electrodes, were provided by the Center for Neural Communication Technology funded by the NIH National Institute for Biomedical Imaging and Bioengineering (catalog # 4x4_4mm200 chronic). Each electrode has four separate shanks (200 µm inter-shank spacing) with four recording sites spaced evenly along each shank (200 µm inter-site spacing). The electrode was implanted into the forelimb area of primary motor cortex in the left hemisphere (stereotaxic coordinates of AP: +3.0um, ML: 2.5 µm). This electrode geometry provided simultaneous sampling from a region below the surface of the cortex spanning 600 µm. An areflexive state was maintained using intra-peritoneal injections of an anesthetic cocktail (ketamine, xylazine, and acepromazine). The craniotomy was rectangular in shape spanning approximately 3 mm in the anterior-posterior direction, and 2 mm in the medial-lateral direction. After the electrodes were manually inserted, ALGEL® was applied[8], followed by a silicone polymer (Kwik-Sil™ World Precision Instruments), and dental acrylic (Co-Oral-Ite, Dental Mfg.

Co.). The animals were allowed 48 hours to recover from surgery.

During each experimental session neural electrophysiological data from the 16 electrode channels was sampled at 40 kHz. This signal was simultaneously amplified and bandpass filtered (450 – 5000 Hz) on a Multichannel Neuronal Acquisition Processor (MNAP; Plexon Inc, Dallas, TX). Operator-controlled unit discrimination criteria was established at the beginning of each recording session prior to behavioral training. Multichannel spike times were transmitted via a local TCP/IP connection to a second computer running custom Matlab-based neural decoding software and the environmental control hardware (Tucker-Davis Technologies, Gainesville, FL).

B. Behavioral Paradigm

A naïve Long-Evans rat was trained to perform a tone matching task using a co-adaptive algorithm. Each experimental session consisted of 100 trials. Trials consisted of an inter-trial period (pseudo random 10-20 s), a baseline period (1.2 s), a cue (900 ms), and a response window (4.5 s) (see Figure 1).

The awake, behaving subject was placed into a behavioral box (Coulbourn Instruments, Allentown, PA), and cortical firing rates were acquired and processed in real-time. Trials were initiated when the predicted feedback fell within a criterion window about the baseline frequency (4 kHz) for 540 ms. An auditory cue (0.9 s, 16 kHz) was presented signifying the initiation of the response window. The rat was then given neural control over an auditory feedback frequency, and was required to match the feedback frequency to the initial target tone frequency. If the feedback frequency was maintained within a criterion window for 540 ms in a 4.5 s response window, the animal was rewarded with a food pellet. The feedback signal was updated in 90 ms increments.

C. Co-adaptive Decoding

At each 90 ms time interval, a prediction of the current controlled feedback frequency was inferred from the neural recording data via a modified Kalman filter[9]. The Kalman filter is a set of mathematical equations that provides an efficient computational means to estimate the state of a process, even when the precise nature of the modeled system is unknown (Figure 2). Here, the controlled feedback frequency was modeled as a system state variable $\mathbf{x}_k$, and was assumed to propagate in time according to the unobserved difference equation:

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{w}_k; \tag{1}$$

where k = 1, 2, ···, M; where M is the number of time steps in the session. A is the coefficient matrix and $\mathbf{w}_k$ is a white noise term that is assumed to have a normal probability distribution, $\mathbf{w}_k = \mathrm{N}(0,\mathbf{W}_T)$. Equation (1) states that the

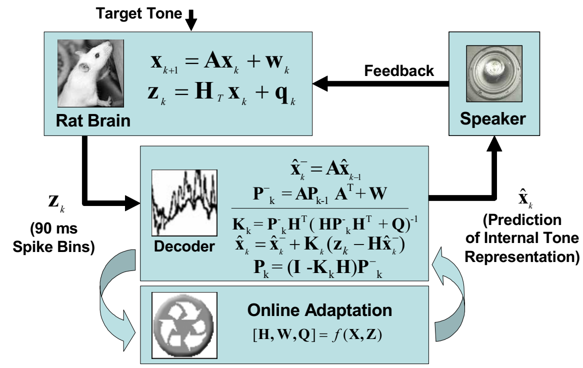

Fig 2. Flow diagram of a closed-loop Naïve Co-Adaptive Model

feedback tone frequency at time *k+1* is linearly related to the state at time *k*.

The recorded firing rates were modeled as an observed noisy response to the unobserved state process. We define the measurement model that describes the relationship between the controlled frequency ($\mathbf{x}_k$) and the recorded spike bins ($\mathbf{z}_k$) as:

$$\mathbf{z}_k = \mathbf{H}_T\mathbf{x}_k + \mathbf{q}_k; \tag{2}$$

where $\mathbf{H}$ is a matrix that linearly relates the frequency state to the neural firing, and T = 1, 2, ···, N; where N is the total number of trials in a session. Again, we assume that the noise in the observations has zero mean and is normally distributed, i.e. $\mathbf{q}_k = \mathrm{N}(0,\mathbf{Q}_T)$.

At the beginning of the training sessions, the required task is unknown to the rat, and the relationship between unit recording and feedback tone is unknown to the decoding filter. A non-linear algorithm for decoding the neural signal begins to adapt to the capabilities of firing rate control based on correlations of natural patterns observed in unit firing with the expected outcome of the feedback frequency movement. This novel adaptation method is accomplished by selecting the time in the response window with the largest correlation to the expected tone. The time at which this occurred was determine by calculating the correlation coefficient of a sliding window of the recorded unit response with a window of the correct frequency for the given trial. For an *n*-length window, the time chosen for training (*l*) was calculated across *C* cells using:

$$l = \arg\max_j [\max_{k\in[1\ldots C]} [corr(\left[\mathbf{X}_{base(1:n)}\ \mathbf{X}_{resp(j:j+n)}\right], \left[\mathbf{Z}_{base(1:n),k}\ \mathbf{Z}_{resp(j:j+n),k}\right])]]; \tag{3}$$

where $j \in [1, 2, \cdots, R-n]$, where R is the total number of response bins, $\mathbf{X}_{base}$ is the baseline frequency, $\mathbf{X}_{resp}$ is the response (target) frequency, $\mathbf{Z}_{base(1:n),k}$ are the first n baseline firing bins for unit k, and $\mathbf{Z}_{resp(j:j+n),k}$ is the j^{th} windowed response firing rate for unit k. $\mathbf{X}_{base}$, $\mathbf{X}_{resp}$, $\mathbf{Z}_{base}$, and $\mathbf{Z}_{resp}$ are all row vectors of length n. The function *corr* is defined as:

$$corr(\mathbf{X},\mathbf{Z}) = \frac{\sum_i (\mathbf{X}_i - \overline{\mathbf{X}})(\mathbf{Z}_i - \overline{\mathbf{Z}})}{\sqrt{\sum_i (\mathbf{X}_i - \overline{\mathbf{X}})^2 \sum_i (\mathbf{Z}_i - \overline{\mathbf{Z}})^2}}, \overline{\mathbf{X}} = \frac{1}{n}\sum_{i=1}^{n} \mathbf{X}_i \ . \quad (4)$$

The co-adaptive algorithm then trained the filter to use the relationship that maximized the above correlation by calculating the **H** matrix:

$$\mathbf{H} = (\mathbf{Z}\mathbf{X}^T)(\mathbf{X}\mathbf{X}^T)^{-1}, \quad (5)$$

where the vector:

$$\mathbf{X} = \left[\mathbf{X}_{base(1:n)} \ \mathbf{X}_{resp(l:l+n)} \right], \quad (6)$$

and the matrix:

$$\mathbf{Z} = \left[\mathbf{Z}_{base(1:n)} \ \mathbf{Z}_{resp(l:l+n)} \right]. \quad (7)$$

The noise matrices **Q** and **W** were then calculated using the result from equations (1) and (5) as described in [10].

Since the relationship in equation (2) is unknown at the beginning of the session **H**, **Q**, and **W** are initially randomized. These matrices were adapted over a 10 trial moving window; as a result the Kalman filter adjusted the decoding weights to account for modulation patterns that could be produced by the recorded units. Auditory feedback was supplied to the subject which allowed the subject to co-

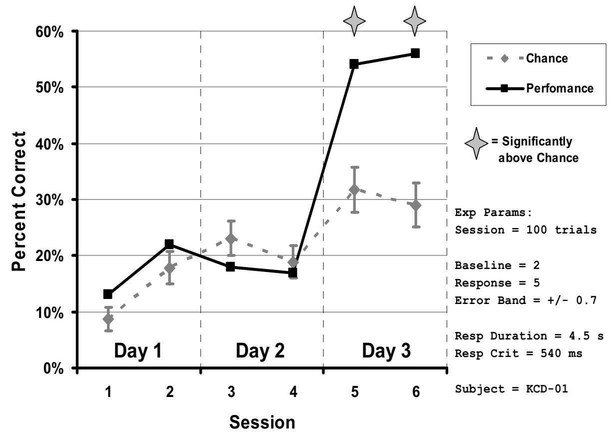

Fig 3: Behavioral Performance of subject KCD-01 over the first 3 days. Error bars indicate one standard deviation of chance.

adapt with the decoding filter. Correct responses were operantly conditioned using a food pellet reward.

RESULTS

A. Behavioral Data

The co-adaptive process allowed both the subject and filter to converge on a particular response strategy that optimized the subject's reward. One subject was run for 2-3 experimental sessions a day for 8 weeks. Within 6 sessions over 3 days, the subject was able to generate the correct response significantly above chance ($p<0.01$) (Figure 3). Chance for a given behavioral session is based on a number

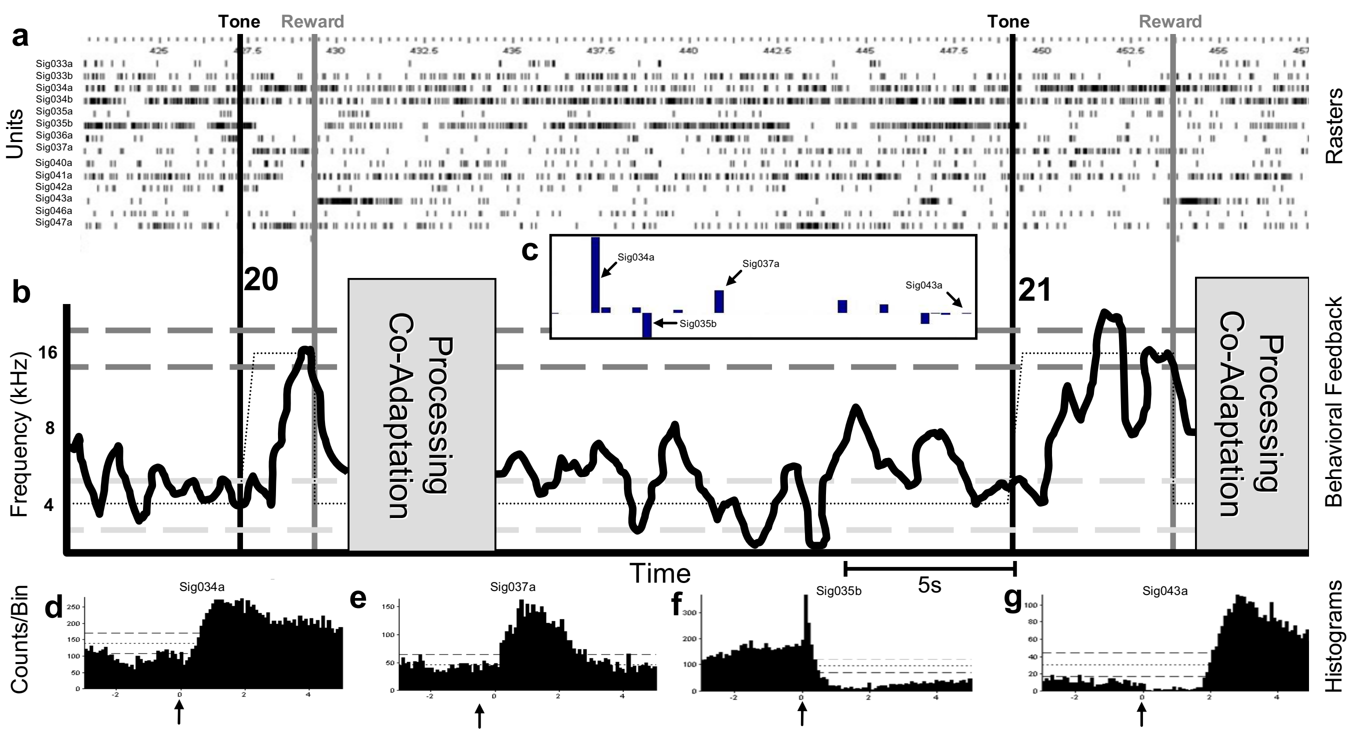

Fig 4: Example of trial output aligned with neural ensemble response. a) Spike train output from 14 units. b) Behavioral paradigm output c) weighted translation decoding "**H**" matrix d-g) Peri-Event Time Histograms over 100 trials, centered at cue (indicated by arrow).

of confounding factors: the number of units available, the motivation of the subjects, the signal to noise ratio, the inherent firing rates of the given neurons, and other factors. We determined chance for each session individually to account for these factors. By using the randomization method, the mean and variance of chance was calculated by randomizing the time in which stimuli were presented and calculating the percent correct that the algorithm would have counted with the actual feedback from the session. This analysis is recalculated 50 times to determine the chance distribution for a given session.

B. Neural Recordings

Figure 4 shows a typical output of this experimental paradigm. Two trials (20-21) are shown of a session run 25 days post surgery. A raster of the spike train outputs from the 14 sorted single and multi-unit clusters are shown in (a). The behavioral data (b) shows the decoded predicted frequency as a thick solid line, while the ideal intended frequency (target cue) is shown as a dotted line. Error bars for this target frequency are shown as dashed lines. The beginning of each trial is marked with a black vertical line indicated by "Tone" and the trial number. Gray vertical lines indicate when the subject produced a correct response and was positively reinforced. After each trial, the co-adaptive algorithm updated the weights (c) of the decoding filter to minimize the output frequency error based on the neural ensemble responses from the past 10 trials. The processing time for this updating algorithm to run is indicated in the figure (typically between 2-8 s). Peri-Event Time Histograms (PETHs) averaged across all 100 trials are shown in (d-g). The PETH is centered at the time that the 16 kHz tone was presented (indicated by arrows). Excitatory and inhibitory responses can be observed in reference to the tone in both the raster plot (a) and the averaged PETH (d-g), which allowed for control of the feedback tone along a one-dimensional axis.

III. Discussion

The results shown in Figure 4 demonstrate the ability of the subject to use the ensemble of neurons to adopt a one-dimensional control strategy to maximize reward. For example, two units (sig34a, sig37a) were tuned to move the output to a higher frequency as evident in PETHs (d-e), rasters, and behavioral feedback; while one unit (sig35b), fired to lower the frequency. Through the interplay of these responses, the subject was able to control the feedback to match the cue tone on 75% of the trials (chance: 21% ± 4%) from a session which began with random decoding filter weights.

IV. Conclusion

With the use of a co-adaptive Kalman filter, it is possible to train a "foreign" cortical control task in situations where both (1) the subject is naïve to the neuroprosthetic system, and (2) the *a priori* cortical activity to device movement mapping is unavailable.

Acknowledgment

The authors would like to thank Ed Ionides, Rio Vetter and Timothy Marzullo for their assistance. Probes were provided by the Center for Neural Communication Technology sponsored by NIH NIBIB grant P41-EB002030-11.

References

[1] J. M. Carmena, M. A. Lebedev, R. E. Crist, J. E. O'Doherty, D. M. Santucci, D. F. Dimitrov, P. G. Patil, C. S. Henriquez, and M. A. L. Nicolelis, "Learning to Control a Brain-Machine Interface for Reaching and Grasping by Primates," *PLoS Biology*, vol. 1, pp. e42, 2003.

[2] P. R. Kennedy, R. A. Bakay, M. M. Moore, K. Adams, and J. Goldwaithe, "Direct control of a computer from the human central nervous system," *IEEE Trans Rehabil Eng*, vol. 8, pp. 198-202, 2000.

[3] D. M. Taylor, S. I. Tillery, and A. B. Schwartz, "Direct cortical control of 3D neuroprosthetic devices," *Science*, vol. 296, pp. 1829-32, 2002.

[4] M. L. Sipski, "From the bench to the body: Key issues associated with research aimed at a cure for SCI," *Journal of Rehabilitation Reserach and Development*, vol. 40, pp. 1-8, 2003.

[5] 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, pp. 664-70, 1999.

[6] R. J. Vetter, J. C. Williams, J. F. Hetke, E. A. Nunamaker, and D. R. Kipke, "Chronic neural recording using silicon-substrate microelectrode arrays implanted in cerebral cortex.," *IEEE Transactions On Bio-Medical Engineering*, In Press.

[7] D. R. Kipke, R. J. Vetter, J. C. Williams, and J. F. Hetke, "Silicon-substrate intracortical microelectrode arrays for long-term recording of neuronal spike activity in cerebral cortex," *IEEE Trans Neural Syst Rehabil Eng*, vol. 11, pp. 151-5, 2003.

[8] R. J. Vetter, T. A. Becker, and D. R. Kipke, "The use of ALGEL® as an artificial dura for chronic cortical implant neuroprosthetics," presented at 1st International IEEE EMBS Conference on Neural Engineering, Capri, Italy, 2003.

[9] G. Welch and G. Bishop, "An Introduction to the Kalman Filter," University of North Carolina at Chapel Hill, Chapel Hill, NC 27599-3175 TR 95-041, 2004.

[10] W. Wu, Black, M. J., Gao, Y., Bienenstock, E., Serruya, M., Shaikhouni, A., Donoghue, J. P., "Neural decoding of cursor motion using a Kalman filter," *Neural Information Processing Systems, NIPS Vancouver, BC*, 2002.