33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Variable-arrival-time reaching with the brain-machine interface: performance comparison on empirically-derived movements

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Abstract—**Patients with paralysis will one day rely on clinically-available brain-machine interfaces (BMI) to facilitate activities of daily living. As such, the ability to generate dexterous reaching movements remains a prime target of BMI algorithms research. The Bayesian approach to BMI algorithms requires a statistical model to describe reaching movements. To date, available models have either required fixed targets or fixed arrival times, neither of which can be assumed under natural operating conditions. Recently, we described a generative reach model, GPFD-RSE, that simultaneously breaks both restrictions. This method combines the reach state equation (RSE) with General Purpose Filter Design (GPFD). In the following paper, we further compare GPFD-RSE against standard methods in simulated open-loop decoding using empirically-derived movements, as an adjunct to the idealized movements tested previously. Our results indicate that GPFD-RSE continues to outperform standard methods when reconstructing more realistic arm movements in simulation.**

I. Introduction

While reaching movements in daily living may be fast or slow, algorithms for the control of reaching movements in brain-machine interfaces (BMI) are not specifically designed for this capability. In a recent paper, we studied this problem, developing a specific BMI method to convert neural activity into reaching movements with variable intended arrival time and arbitrary intended target locations [1]. Our strategy was to extend the reach state equation (RSE), a previous method for decoding reaching movements when the intended arrival time was known and fixed [2]. Because the RSE uses a simple generative model of reaching behavior, it provides a convenient formulation to describe arbitrary arrival times and targets. To extend the RSE, we allowed the user's intention to span a range of discretized arrival times rather than a single fixed arrival time. This design choice allowed us to apply General Purpose Filter Design (GPFD), a Bayesian prescription for generating real-time, recursive BMI algorithms from a set of discrete and continuous intentions for the target application [3]. This extension of RSE to variable-arrival-times was called GPFD-RSE.

Previously, we compared the performance of GPFD-RSE against two existing methods, the Unconstrained Model (UM), and the Standard Model (SM). All three methods used identical models of neural activity (called observation models in the Bayesian approach), but differed in the way that reaching movements were modeled (called state evolution models in the Bayesian approach). The UM uses a random walk model of movement, commonly seen in the Kalman filter implementation of BMI, which is one type of Bayesian approach. The SM uses a linear Gaussian state equation that is empirically fit to a database of sample movements. In contrast to the UM and SM, our GPFD-RSE uses the RSE to model reaching behavior, which provides the added convenience of bypassing database training or on-the-fly parameter adjustments.

In the present work, we further evaluated the GPFD-RSE against SM and UM using empirically-derived reaching movements. Specifically, we employed arm movements recorded from primates during a variable-arrival-time reaching task, reported in prior experimental literature [4]. In contrast, our recent paper used purely simulated reaching movements without empirical basis. The goal of our present analysis was to determine whether GPFD-RSE continued to outperform SM and UM under more realistic conditions. Below, we describe our process for generating this empirically-derived movement data. We then present a performance comparison between the various methods on this more realistic simulated data, using metrics that parallel our recent paper [1] and related literature [5, 6].

II. Methods

We employ a three-step simulation process to compare the relative performance of these methods. First, variable-arrival-time arm movements are simulated with a reaching model. Second, ensemble spiking neural activity from primary motor cortex (MI) is simulated using an empirically-derived point process model of MI spiking activity. Third, the GPFD-RSE, SM, and UM methods are used to translate this neural activity into arm movements. The error between intended and resulting arm movements provides a comparative measure of each BMI algorithm.

The reader is directed to our recent paper for methodology related to point-process simulation of primary motor cortical activity, as well as implementation of GPFD-RSE, UM, and SM [1]. Below, we describe changes to this methodology that were implemented to accommodate empirically-derived reaching.

Manuscript received March 30, 2011. This work was supported in part by the American Heart Association and UCLA Radiology.

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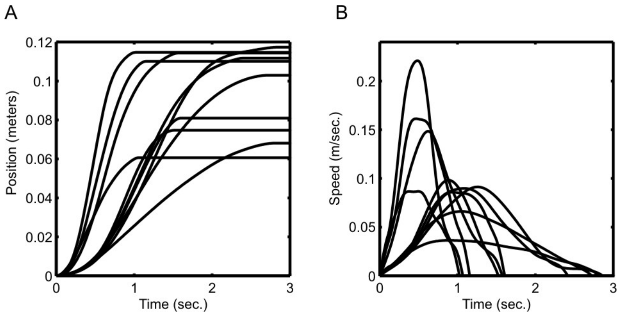

Figure 1. Sample trajectories of scaled primate movements (SPM). These trajectories are samples of temporally scaled versions of 20 unique primate reaching arm movements published previously (Fig. 2A, Churchland et al. 2006). Arrival times are drawn from a uniform distribution between 1 and 3 seconds. Observe the bimodal distribution of arrival locations induced by the experimental data. SPM trajectories were collapsed onto one dimension, where trials with overshoot relative to the final position were eliminated as error trials.

A. Generating Empirically-Derived Reaching Movements

To generate empirically-derived reaching movements, we traced the values of speed profiles reported in Figure 2A of [4]. The velocity profiles in this figure were originally generated by non-human primates trained to make reaching movements of variable arrival time and variable distance within a two dimensional workspace. Each velocity profile represented velocity in the direction of the corresponding target. Profiles where the animal overshot the target were eliminated as error trials. The rationale for eliminating these trials was that for a task where the intention is to reach to an endpoint, overshooting the endpoint is undesirable. The traced set included 20 reaching movements with a bimodal distribution of target positions.

Once traced, velocity profiles were collapsed into one is vector direction along the positive x-axis. These profiles were then rescaled in time to produce one-dimensional reaching movements with arbitrary arrival times drawn from a uniform distribution between 1 and 3 seconds (Fig. 1). In our previous work [1], simulated movements arrived at only two unique endpoints locations. In contrast, the scaled primate movements (SPM) generated in the present work tested 20 unique endpoints clustered around two modes.

B. Generating Sample Neural Data

We also increased the neural ensemble size from 9 (used in [1]) to 25. This was to illustrate that performance improvement was not restricted to a specific ensemble size. The remainder of the validation process was identical to that of the main text. Simulation of MI neural ensemble activity and prosthetic control with GPFD-RSE, SM, and UM neural prosthetic algorithms were unchanged. Specifically, spiking rates were modulated as velocity-dependent inhomogeneous Poisson processes:

$$\lambda(k \mid v_x, v_y) = \exp(\beta_0 + \beta_1 (v_x^2 + v_y^2)^{1/2} \cos(\theta - \theta_p)) \qquad (1)$$

Here, v_x and v_y are velocities at time step k in orthogonal directions. The model parameters are drawn to approximate primate recordings of primary motor cortex [7]: β_0 = 2.28 (unitless), β_0 = 4.67 s/m, and $\theta_p \sim$ uniform($-\pi$,π) (angle in radians).

C. Implementing GPFD RSE and SM with This Data Set

In order to match the new SPM-generated bimodal distribution of target positions, GPFD-RSE was run using a non-zero target position variance (Π_T). While this target position variance could be estimated from the sample variance of the target positions from each mode, we simply chose 10^{-5} m^2 from a constrained optimization on decoding error. The discrete target locations of the GPFD-RSE were assigned to the means of the two endpoint clusters at 0.067647 m and 0.113023 m from the origin in the one-dimensional workspace. The arrival times modeled by the GPFD-RSE were unchanged from the main text at 1.0, 1.7, 2.3, and 3.0 seconds.

The SM was formed with one state equation for each of the two target clusters. Maximum likelihood parameter fitting was performed on a database of 1000 rescaled simulated movements to each target cluster. Simulated arrival times were drawn from the same distribution as the test set of trajectories. The general form of the SM was unchanged.

III. Results

Figure 2 presents results using the SPM data analogous to Figure 5 in [1] that used reach-model-based movements. Again, the GPFD-RSE distinguishes itself in comparison to SM and UM algorithms. In particular, only the GPFD-RSE produces fully damped movements in the post-arrival period (Fig. 2D). Note that with SP movements, endpoint position errors of the GPFD-RSE (Fig. 2C) are non-zero in contrast to [1] (Fig. 5C). This is because the scaled primate movements produce one of 20 distinct endpoints. Although the GPFD-RSE algorithm is capable of incorporating endpoint-related planning information for arbitrary target locations, no such information was provided to the algorithms in this test. With priors on the endpoints loosely constrained, GPFD-RSE on SP movements converged to an endpoint that was less accurate (Fig. 2C) than with the simulated reaches reported in [1] (Fig. 5C). Nevertheless, GPFD-RSE consistently outperformed SM and UM algorithms in reproducing variable-arrival-time reaches across both comparisons.

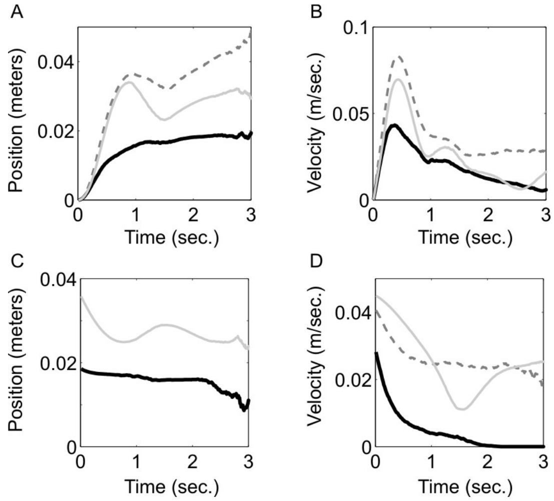

Figure 2. Performance errors in tracking scaled primate movements (SPM). GPFD-RSE (solid black), SM (solid gray), and UM (dotted gray) errors are averaged across reaches of various duration. (A, B) RMSE in (A) position and (B) velocity as a function of time post movement onset. (C, D) RMSE in (C) position and (D) velocity as a function of time post-intended-stop-time.

IV. Discussion

In this paper, we applied empirically-derived arm movements to further compare three BMI algorithms in their ability to reconstruct reaching movements with variable arrival times and target locations. Previously, we had introduced GPFD-RSE to break the fixed-target or fixed-arrival-time restrictions faced by existing BMI methods designed for reaching movements (SM, RSE) [1]. In this present work, simulation with empirically-derived models of neural activity has allowed us to derive, prototype, systematically evaluate, and refine candidate BMI methods prior to more costly experimental testing. Future work will need to examine the effect of experimentally-recorded neural signals and closed-loop control.

Acknowledgment

LS thanks Rengaswamy, Uma, and Shyam Srinivasan for scientific discussions. This work was supported in part by the American Heart Association Scientist Development Grant and UCLA Radiology.

References

[1] L. Srinivasan and M. J. da Silva, "Breaking the fixed-arrival-time restriction in reaching movements of neural prosthetic devices," *IEEE Transactions on Biomedical Engineering, Epub ahead of print, DOI 10.1109/TBME.2010.2101599*, 2010.

[2] L. Srinivasan, U. T. Eden, A. S. Willsky, and E. N. Brown, "A State-Space Analysis for Reconstruction of Goal-Directed Movements using Neural Signals," *Neural Computation*, vol. 18 (10), 2006.

[3] L. Srinivasan, U. T. Eden, S. K. Mitter, and E. N. Brown, "General Purpose Filter Design for Neural Prosthetic Devices," *J Neurophysiol*, vol. 98, pp. 2456-2475, 2007.

[4] M. M. Churchland, G. Santhanam, and K. V. Shenoy, "Preparatory activity in premotor and motor cortex reflects the speed of the upcoming reach," *J Neurophysiol*, vol. 96, pp. 3130-46, 2006.

[5] G. H. Mulliken, S. Musallam, and R. A. Andersen, "Decoding trajectories from posterior parietal cortex ensembles," *J Neurosci*, vol. 28, pp. 12913-26, 2008.

[6] B. M. Yu, C. Kemere, G. Santhanam, A. Afshar, S. I. Ryu, T. H. Meng, M. Sahani, and K. V. Shenoy, "Mixture of Trajectory Models for Neural Decoding of Goal-Directed Movements," *J Neurophysiol*, 2007.

[7] W. Truccolo, U. T. Eden, M. R. Fellows, J. P. Donoghue, and E. N. Brown, "A point process framework for relating neural spiking activity to spiking history, neural ensemble, and extrinsic covariate effects," *J Neurophysiol*, vol. 93, pp. 1074-89, 2005.