Proficient BMI Control Enabled by Closed-Loop Adaptation of an Optimal Feedback-Controlled Point Process Decoder

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Much progress has been made in brain-machine interface (BMI) development using closed-loop decoder adaptation (CLDA) methods. CLDA fits the decoder parameters during closed-loop BMI operation based on the neural activity and inferred user velocity intention. This progress has resulted in the recent high-performance ReFIT Kalman filter (ReFIT KF) [1]. Here we develop an adaptive optimal feedback-controlled point process filter (PPF) that allows users to issue neural commands and receive feedback of the consequence of such commands at a faster rate (every 5ms) than the KF (typically every 50-100ms). We explore how the increased rate of control and feedback provided by the PPF influence subject's BMI performance. We also examine the effect of increasing the rate of decoder parameter adaptation on subject's performance. Moreover, we develop an infinite-horizon optimal feedback control (I-OFC) model of BMI control to infer the velocity intention during decoder adaptation. We investigate whether this model better approximates the user's strategy, which would result in improved performance. Such model-based CLDA approaches could in turn provide a framework for evaluating models of closed-loop BMI control. We refer to the overall BMI architecture as adaptive I-OFC PPF (Fig. 1). Variability in recordings and task designs make across-study comparisons difficult, so here we compare performance across different decoders within the same subject. Our preliminary data collected from one rhesus macaque suggests that increasing the control and feedback rate in a BMI by using the adaptive I-OFC PPF improves BMI control. Also, the I-OFC model arrives at a BMI decoder with higher performance compared with current intention estimation methods. In online experiments performed over tens of days in this monkey, adaptive I-OFC PPF resulted in a 30% performance improvement over ReFIT KF in a self-paced center-out movement task with 8 targets (Fig. 2, 3). Performance improvements also extended to more challenging tasks beyond those used for CLDA training, including a target jump and a multi-curvature obstacle avoidance task (Fig. 4).

To infer velocity intention, inspired by the optimal feedback control theory of the sensorimotor system, we model the brain in BMI operation as an infinite-horizon optimal feedback controller. In this model, the BMI subject decides on the control command based on the intended target position and sensory feedback of the current decoded kinematics (Fig. 1). Using this model, we solve for the optimal intended velocity and use this intention and the recorded neural activity to adapt the decoder. In contrast, current ReFIT methods infer the velocity intention at each time by rotating the decoded velocity vector towards the target while keeping the speed intention the same as the decoded speed (CursorGoal method [1]). We also use the I-OFC model to develop an assisted training technique by designing a target-directed optimal feedback-controlled PPF in which the target direction is reflected in the decoder's state-space model [2].

To investigate the effect of neural control rate and feedback rate on control quality, we use a point process neural encoding model in which the instantaneous firing rate is a log-linear function of velocity. PPF allows the subject to control the movement with quasi-single spike resolution (bin size 5ms) instead of every 50-100 ms used in the KF. Similarly, unlike other CLDA algorithms that update the parameters on the time-scale of minutes [1, 3]), adaptive PPF can update the decoder parameters on a spike-by-spike basis. We use the number of successful trials per minute (TPM) as the measure of performance. We also calculate the movement error and the reach time.

We recorded from 17-20 multiunits in the primary motor cortex of one rhesus macaque over tens of online BMI sessions. In this monkey, adaptive I-OFC PPF performed better than ReFIT KF across all measures (Fig. 2), improving TPM by 30%, movement error by 15%, and reach time by 14%. This improvement was due to both the faster control and feedback rate in the PPF and to the I-OFC intention estimation model. In particular, TPM in I-OFC PPF was 30% higher than a ReFIT KF that used the I-OFC intention estimation method, demonstrating that PPF's faster control and feedback rate was essential for control improvement. Moreover, I-OFC PPF improved the TPM 27% compared to a PPF trained with CursorGoal, demonstrating the advantage of the I-OFC intention estimation. We also found that continuous spike-by-spike adaptation of decoder parameters allowed the subject to achieve proficient control faster than SmoothBatch adaptation [3] in which the parameters were adapted smoothly once every 90 sec (Fig. 3). Finally I-OFC PPF outperformed ReFIT KF in a target jump task (Fig. 2) and in an obstacle avoidance task that required the subject to perform reaches of differing curvatures (Fig. 4). I-OFC PPF success rate in the obstacle task could reach 87% compared to 72% for ReFIT KF.

These preliminary data from decoder comparisons in one monkey suggest that increasing the control and feedback rate using a PPF and spike-by-spike continuous closed-loop adaptation, and employing an I-OFC model of BMI in the adaptive decoder result in higher BMI performance.

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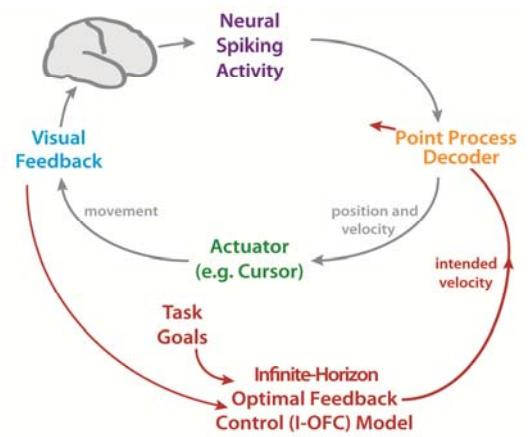

Figure 1 BMI architecture Adaptive I-OFC PPF is used to control the movement and adapt the point process decoder parameters on a fast spike-by-spike time scale. I-OFC model finds the optimal intended velocity based on the task goals and the visual feedback of the current decoded kinematics. This velocity intention is then used in the point process decoder to adapt its parameters.

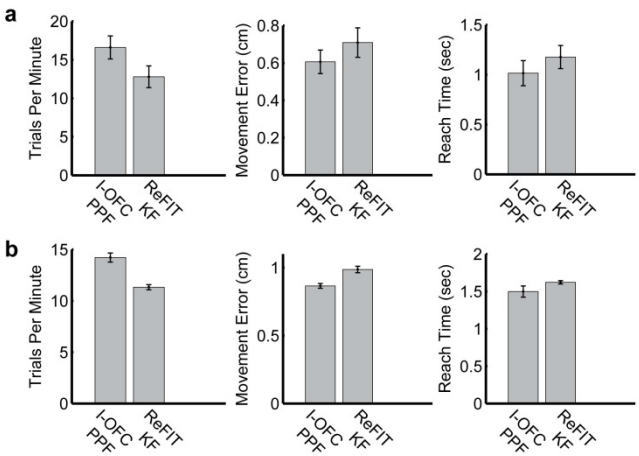

Figure 2 Performance comparisons in self-paced center-out and target-jump tasks Performance comparison between the adaptive I-OFC PPF and ReFIT KF in one monkey in a self-paced center-out task with 8 targets (a) and in a target jump task in which the target changes randomly to one of the other 7 targets 500 ms after the cursor leaves the center (b). Bars reflect mean and error bars reflect standard deviation across multiple sessions.

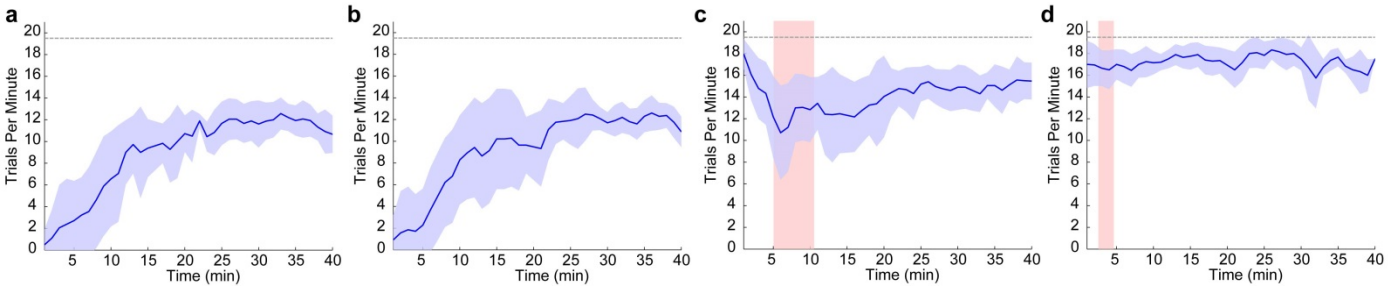

Figure 3 Closed-loop decoder adaptation and convergence Performance convergence from a visually trained decoder seed in the self-paced center-out task using (a) ReFIT KF with SmoothBatch adaptation (b) PPF trained using CursorGoal and SmoothBatch adaptation (c) I-OFC PPF with SmoothBatch adaptation (d) I-OFC PPF with spike-by-spike continuous adaptation. The horizontal dashed line shows the mean task performance with the arm. In (c) and (d) we also applied our I-OFC based assisted training algorithm. The BMI architecture automatically stopped the assistance once the subject exceeded a TPM of 5 trials per minute. Blue curves show the mean TPM over multiple days of experiments and shading reflects the standard deviation. The red bar shows the time range in which the BMI architecture stopped the assistance across the multiple sessions. Our assisted training paradigm helped with subject's motivation level and the decoder's exploration of space, and hence increased the speed of convergence. Moreover, continuous spike-by-spike adaptations resulted in faster convergence and less variability compared with SmoothBatch adaptation that updated the decoder parameters every 90 seconds.

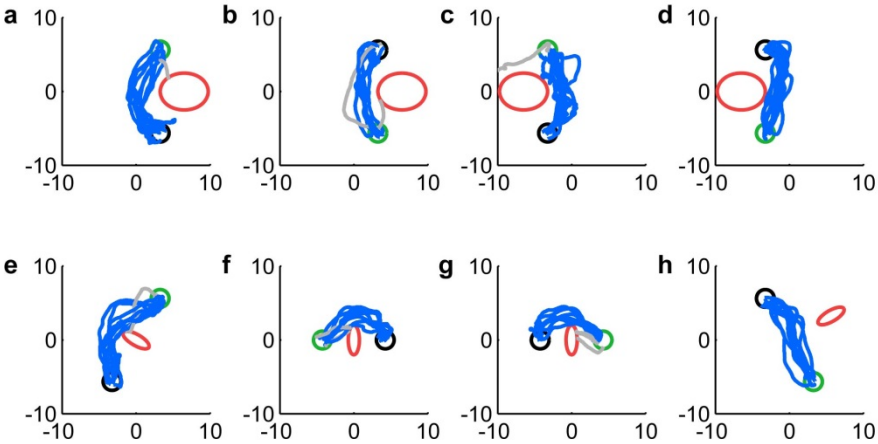

Figure 4 Multi-curvature obstacle task The obstacle task required the subject to move a cursor from a start target (green) to an end target (black) without hitting the obstacle (red). To require the subject to take curved trajectories of varying curvatures and in all parts of the workspace, we designed 4 types of trials: medium curvature (a, b, c, d), long distance high curvature (e), short distance high curvature (f, g), and unobstructed (h). Each subfigure shows 10 random trials performed with I-OFC PPF. Successful trials are shown in blue and unsuccessful trials are shown in grey. Using the I-OFC PPF improved the success rate compared to ReFIT KF.

References:

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