

Abstract with Supplementary Figures

To be clinically useful, neural prosthetic systems and their decode algorithms must interact in closed-loop with a human user. Decode algorithms are typically studied offline with previously-gathered neural activity, and there has been little closed-loop testing of algorithms. Here we propose an online human prosthetic simulator (OHPS) that allows subjects, interacting with a prosthesis driven by synthetic neural activity, to inform the design of prostheses and decode algorithms.

As a first demonstration of the utility of the OHPS, we optimize the integration bin width of the Kalman Filter, a key parameter previously discussed in literature. Five human subjects make arm reaches to eight targets in a 3D reaching environment. Synthetic neural activity is generated from recorded kinematics via a Poisson process with velocity-tuned rate. Preferred directions and average rates are randomly chosen with statistics to produce decode quality quite similar to our non-human primate experiments. Control reaching trials provide synthetic neural activity for standard offline analysis. In online mode, subjects use feedback and other behavioral strategies to drive a closed-loop prosthetic reach. Decoded kinematics within each randomized block are generated by a Kalman filter integrating neural activity at bin widths selected from {50,100,150,200,250,300}ms.

We analyze our data with several performance metrics, all of which produce statistically significant differences suggesting similar optimal bin widths. In online data, we tested failure rate (target not acquired and held) and time required to reach the target. Both show statistically significant reductions ($p < 0.05$) for bin widths of 100 and 150ms (failure rate also shows reduction for 200ms) (Figure 1). These metrics can not be calculated for offline data, so we also tested integrated distance to target. Again, we find a statistically significant optimum in the 100-150ms range ($p < 0.05$, Figure 2A). This first result indicates that the OHPS can be used to sweep and evaluate parameter settings in an online prosthesis.

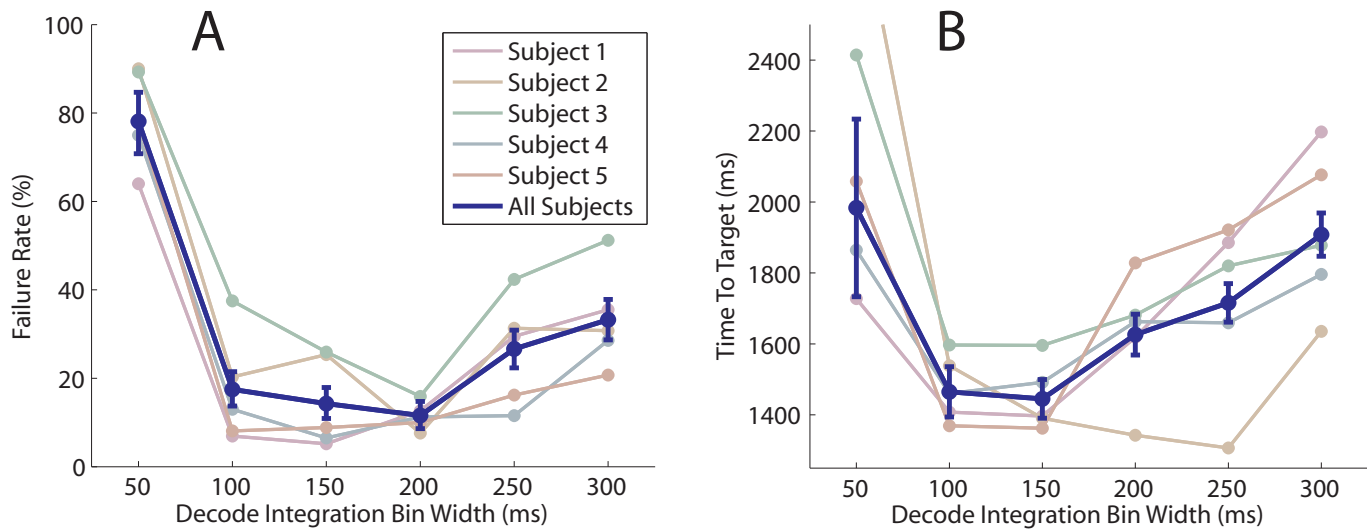


Figure 1: Performance metrics for online human prosthetic simulator (OHPS) decode trials. **(A)** Failure Rate: the percentage of trials where the subject did not successfully acquire and hold the reach target. **(B)** Time to Target: the time required to reach the target. In both panels, data from five subjects are shown in light colors. The average of all trials is shown in dark blue. This average shows in both cases the characteristic “U-shape” indicating performance optima around 100-200ms. 95% confidence intervals (panel A: binomial distribution, panel B: Gaussian) are shown flanking the blue trace.

The second result shows that online analysis suggests different parameter optima than offline analysis. Using control trials, we decode offline data across the same bin widths. We estimate offline and online optima (bootstrap, minimum of a quadratic fit). For OHPS trials, we find an optimum of 156ms (s.d. of 4ms, Figure 2B). Offline, this optimum is at 209ms (s.d. of 1ms, Figure 2B), a number that better matches previous offline studies in non-human primates (Wu et al (2006) Neural Comp). These data demonstrate that there is a highly significant ($p < 0.0001$) difference between optimizations done in offline and online analyses.

The OHPS enables careful design of a closed-loop system without the high cost and risk of neural implants. We use this system to inform our own closed-loop experiments (Gilja et al (2010) COSYNE), so these results directly feed (and

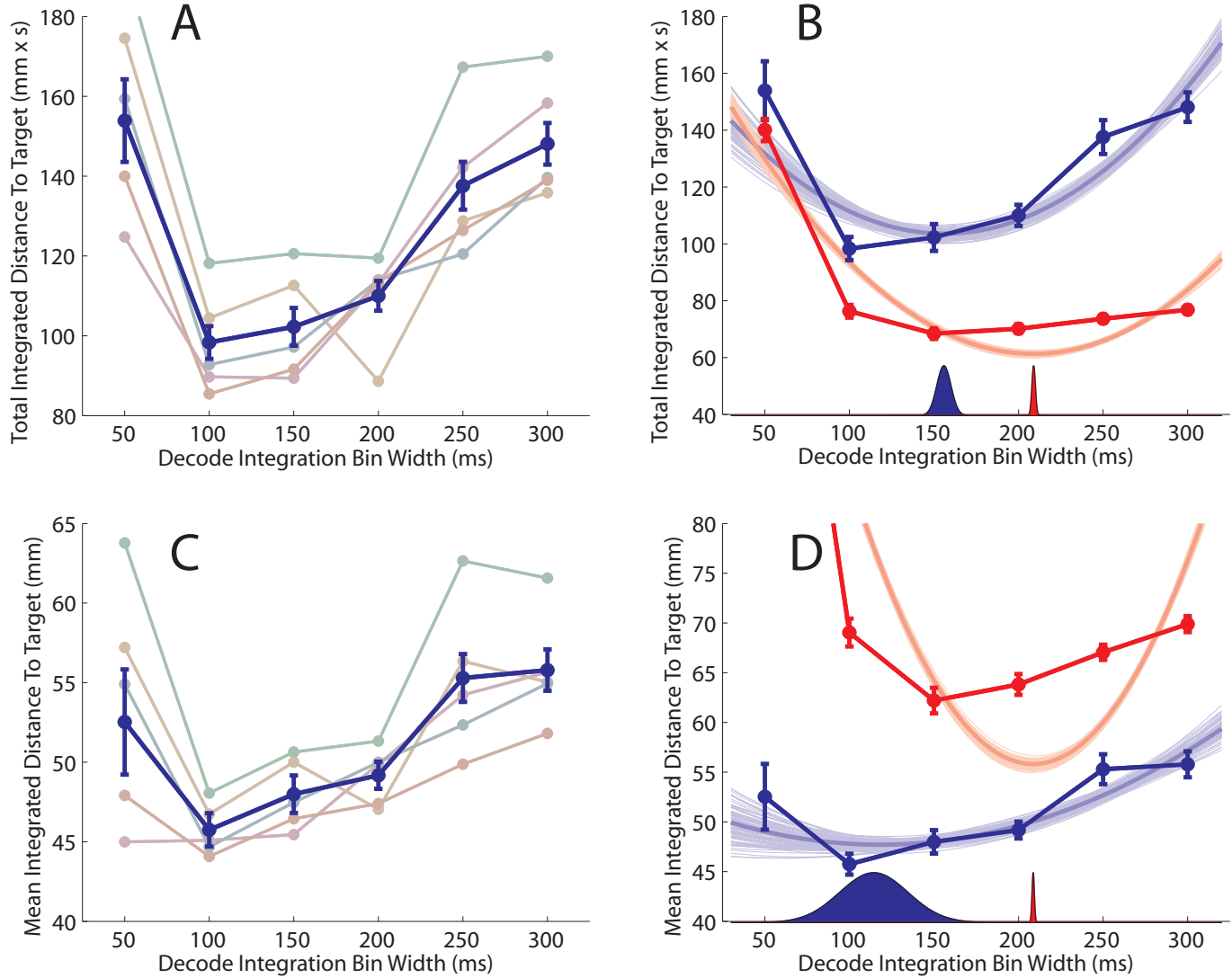


Figure 2: To compare offline and online data, we use integrated distance to target (the metrics of Figure 1 can not be calculated for offline data). **(A)** The characteristic “U-shape” from Figure 1 is preserved and again indicates significant reductions in error between 100-150ms in the online OHPS data. **(B)** A bootstrap procedure is done (10,000 times), and a quadratic fit to each sample set produces a distribution of estimated minima. The light blue sample quadratics (with mean in slightly darker blue) imply a distribution of minima shown on the x-axis as a blue Gaussian with mean 156ms and s.d. 4ms. The same procedure is done for the offline data (in red), implying a minima of 209ms (s.d. 1ms). Thus, online data analysis suggests a significantly different optimum than offline analysis. **(C)** Because prosthetic reach trials are generally longer than control trials, total integrated distance of panels A and B is larger for online data. As a control, we also test the mean integrated distance to target, and we see the same “U-shape” is preserved. **(D)** As in panel B, there is a highly significant difference between the optima implied by online and offline analysis. The optima implied by online analysis is 114ms (s.d. 20ms), which again is significantly different than offline (209ms; s.d. 1ms, only slightly different than in panel B due to the consistent reach time in control trials). This figure also shows that feedback unsurprisingly improves absolute error (blue lies significantly below the red).

will be tested by) that experimental program. Here we have taken one example, the Kalman filter bin width, and we have shown: (1) that significant online performance differences suggest an optimum of roughly 150ms, and (2) that online testing suggests different parameter choices than offline analysis, indicating the importance of closed-loop validations of algorithms and algorithmic parameters.