

In their influential paper, “Bayesian integration in sensorimotor learning,” Körding and Wolpert (2004) showed that subjects utilize sensory information in a manner consistent with Bayesian statistical theory. While powerful, their method did not consider the temporal integration of sensory information and the impact of recent experience on future movements. Using the same dataset, we employed three techniques to consider the temporal dynamics of reaching strategies and found that subjects employ suboptimal strategies that are strongly influenced by recent experience.

The Körding and Wolpert task consisted of reaching movements to a target while different types of visual information about the movement were displayed via a cursor. The cursor was displaced by a random lateral shift drawn from a Gaussian distribution. At the trajectory midpoint, the cursor was either displayed veridically, displayed with a medium or large blur, or not displayed at all. We used a linear model to describe the displacement of hand position from the midpoint to the endpoint as a function of four input parameters: the hand and cursor position at midpoint in the same trial, the cumulative mean of hand end positions, and a running mean of the last five hand end positions. We calculated the coefficients of the regressor parameters on the first 1000 trials, and used these values to predict the mid-to-end point displacement on the last 1000 trials (Figure 1a). In our model, the most powerful predictors of corrective movements were the midpoint cursor position and the local mean of end point hand positions (Figure 1b). It is surprising that a local mean is a significant predictor because it is more optimal to rely on the mean of total shifts experienced thus far. Separate linear regressions for each of the different degrees of feedback clarity with the same input parameters shows that the influence of midpoint cursor position increases as a function of feedback reliability (Figure 1c).

Using Bayesian theory, we were able to determine subjects’ mean prior estimate over the course of the experiment. To solve for subjects’ estimate of the true lateral shift (μ_{prior}), we performed a linear least squares regression on: $\mu_{posterior} = r \mu_{likelihood} + (1-r) \mu_{prior}$ in 100-trial bins (Berniker, Voss, & Körding, 2009). For this analysis, $\mu_{posterior}$ and $\mu_{likelihood}$ were the negative of the end hand position on each trial and the lateral shift on each trial, respectively. We found that subjects’ estimate of μ_{prior} rapidly increased to 1 cm (the true mean), and remained stable throughout the course of the experiment (Figure 2a).

We also used a Kalman filter to estimate subjects’ belief about the lateral shift. The model’s state includes both the lateral shift in the current trial and the cumulative mean of estimated lateral shifts over all former trials. The state dynamics were modelled such that the cumulative mean was accurately updated by including the estimate of the current lateral shift, while the next estimate of the lateral shift was composed of a combination of the current estimated lateral shift and the cumulative mean. The ratio in which these estimates were combined was optimized for each subject using the first half of their trials. The Kalman filter was able to capture local trends in the data, as shown in Figure 2b. Importantly, when predicting the current lateral shift, subjects weighed their previous estimate of lateral shift with coefficient 0.35 ± 0.21 . The fact that subjects partially used their previously estimated lateral shift rather than using only the cumulative mean of lateral shifts shows that recent experiences are trusted disproportionately, confirming the results obtained using the regression analysis.

Despite the fact that subjects learned the prior in the first hundred trials, subjects heavily weighed their recent experience when executing reaching movements. This dependence on recent experience was confirmed independently using a Kalman filter and a regression analysis. Since lateral shifts were chosen independently, these results suggest that subjects use a suboptimal strategy to

estimate the lateral shift on a trial-by-trial basis.

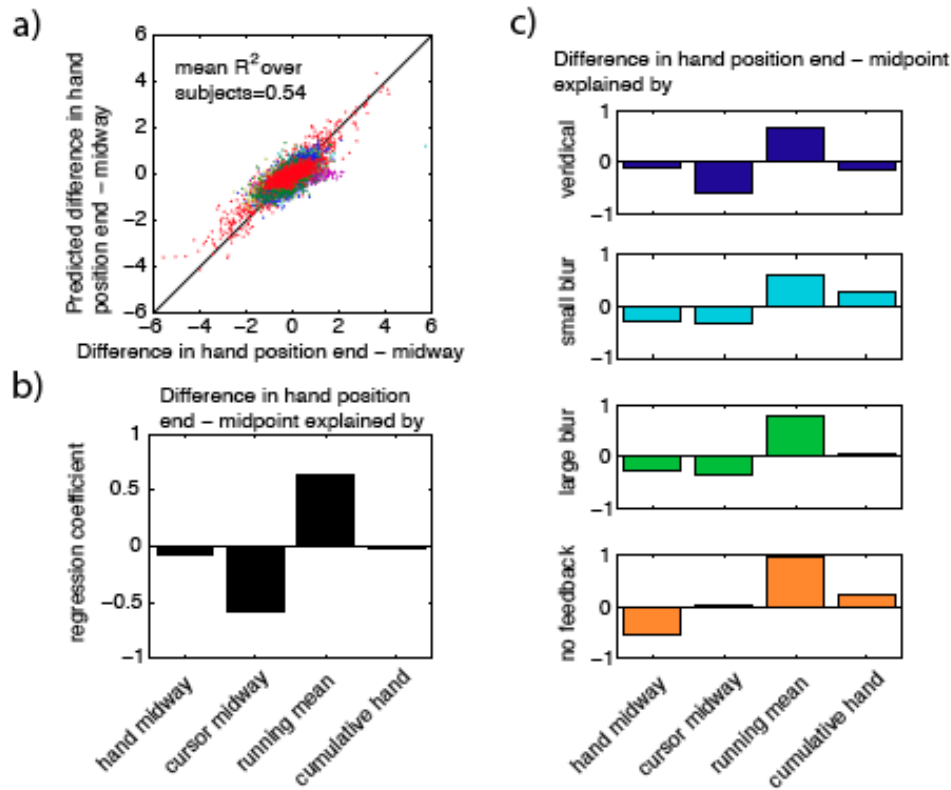


Figure 1. Linear regressions. (a) End positions of the hand against predicted hand positions with the linear regression for all subjects. (b) Regression coefficients for one typical subject. (c) Regression coefficients for the different degrees of clarity of the feedback for the same typical subject.

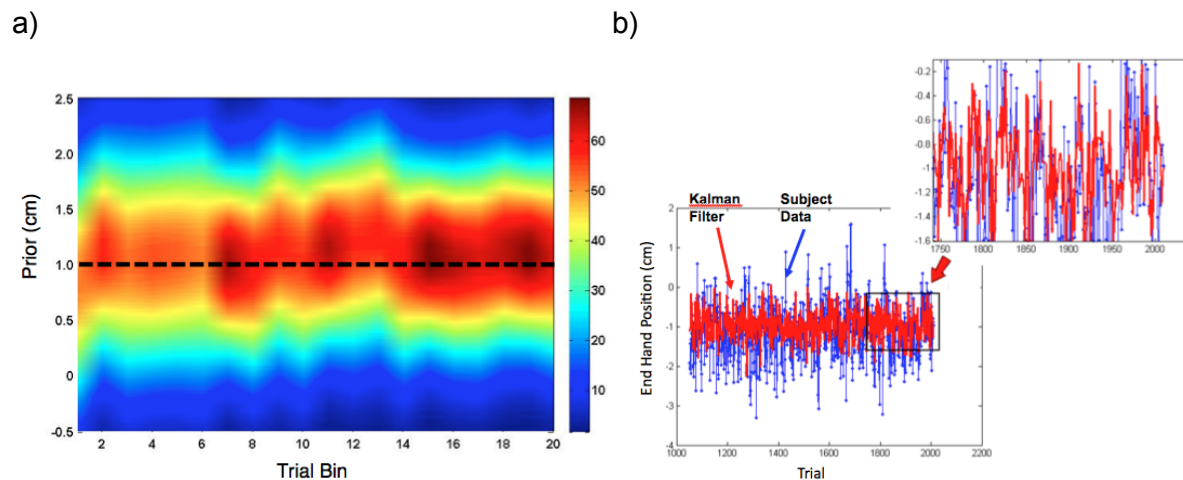


Figure 2. Modeling Results. (a) Evolution of the prior mean over the 2010 experiment trials. Each 100-trial bin was fitted to a Gaussian distribution. The dashed line shows the true prior. (b) Hand positions at the end point trial by trial (blue) and Kalman filter estimation (red) for a typical subject.