

The Effect of Visual Uncertainty on Implicit Sensorimotor Adaptation

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The sensorimotor system successfully learns to perform a wide array of goal-directed actions in the face of environmental and physiological changes. An integral part of this process takes place in an implicit manner, driven by sensory prediction error, the difference between the predicted and actual sensory feedback. According to optimal integration models (Burge, 2008), the predicted sensory consequence and actual sensory signal are weighted by their precision (inverse of variance) to form the error signal. Thus, when there is uncertainty in either variable, the error signal is weakened, resulting in attenuated learning, an effect that would be evident for all sizes of error. A variant of the basic optimal integration model that incorporates causal inference, holds that large errors are discounted (Wei, 2009), and thus the impact of the visual uncertainty will be reduced for large errors (relevance estimation model). Indeed, if we assume that uncertainty impacts the perceived location of the error, then there will be a limited window in which the situation reverses such that uncertain feedback induces greater learning (cross-over, see below). We have proposed an alternative, motor correction model in which the size of the error modulates the size of change in the motor output (Kim, 2018). This model was inspired by the observation that variation in the early adaptation rate is only observed over small error sizes; for errors larger than approximately 5° , the rate is essentially invariant. In its basic form, the motor correction model is agnostic on the issue of uncertainty. As with optimal integration models, the system may be less confident in producing a change in motor output in the face of uncertainty. Alternatively, the perceived location of the feedback will be more variable with uncertainty and this will influence the size of change in the motor output (Fig 1); in the extreme, the sign of the error and thus update might be reversed due to mis-localization, an effect that would be pronounced for small errors. Large errors should be immune to uncertainty given that the perceived location always results in an error where the update is invariant.

Here we explore this issue by varying the uncertainty of the sensory feedback. To isolate learning to implicit adaptation, we used clamped visual feedback. Unlike standard visuomotor rotation tasks in which the angular position of perturbed feedback is contingent on hand position, clamped feedback is invariant on all trials, with the cursor following a trajectory that is offset by a fixed angle relative to the target (Fig. 2a). We fully informed participants of the manipulation and instructed them to ignore the feedback. Despite these instructions, the participant's movements deviate in the opposite direction of the clamp. To examine the impact of visual uncertainty on implicit adaptation, we varied the uncertainty of the visual feedback (Fig. 2b). For low uncertainty, feedback was given by a single white 3 mm cursor; for high uncertainty, the feedback signal was composed of a cloud of dots (25 grey 3 mm cursors drawn from a 10° 2D isotropic Gaussian distribution, with center of mass at the desired clamp angle).

Experiment 1 used a between-participant 2×2 factorial design ($n = 96$, 4 groups, 24/group) in which we manipulated the uncertainty (cursor/cloud) and size ($3.5^\circ/30^\circ$) of the visual feedback. We analyzed two dependent variables, the rate of early learning (change in hand angle over cycles 2-7) and asymptotic learning (average of the last 10 clamp feedback cycles). For both measures, uncertainty had a profound impact in the 3.5° condition and no effect in the 30° condition (Fig. 2d - e, interaction terms: Early: $F(1, 92) = 7.28$, $p = 0.008$, Late: $F(1, 92) = 7.60$, $p = 0.007$). This dissociation is consistent with the two models that assume perceptual mis-localization of the error, the relevance estimation model and one variant of the motor correction model. A critical difference in these two models is that the relevance estimation model predicts a cross-over in terms of the response to certain and uncertain error signals. The results of Exp. 1 hint at this cross-over, but the effect is far from significant. To provide a stronger test, we conducted a second experiment ($n = 24$) to characterize the effect of uncertainty across a large range of error sizes. We used a random perturbation schedule in which the size of the error could take on one of 10 values ranging from 0° to $\pm 90^\circ$. Our dependent variable was the trial-to-trial change in hand angle. As shown in Fig. 3, learning was attenuated in the cloud condition for the clamp sizes of 3.5° , 10° , and 18° . There was no indication of a cross-over effect, arguing against the relevance estimation model.

Fig. 4 provides fits for the optimal integration, relevance estimation and motor correction models, with the latter two based on the assumption that uncertainty increases variability in the perceived location of the error. The top two rows are best fits for Exp. 1 and 2, respectively, with uncertainty modeled as a free parameter. This parameter is constrained in the fits (bottom row), set to values determined in a perceptual location discrimination task with the cursor or cloud. The relevance estimation and motor correction models provide similar quality fits when the uncertainty parameter is unconstrained. Qualitatively, the shape of the fitted functions for the motor correction model provides a better match to the data. When the uncertainty parameter is constrained by empirical values from the perceptual task, the motor correction model provides a much better fit, although the degree of separation between the two functions is markedly less in the fits compared to the data.

Taken together, the results and modeling work presented here provide a novel perspective on the effect of uncertainty on sensorimotor adaptation. Rather than view uncertainty as impacting the salience of the error signal, the change in performance may be a consequence of mis-localization of the feedback, with the perceived location dictating the size of change in the motor output.

Motor Correction Model

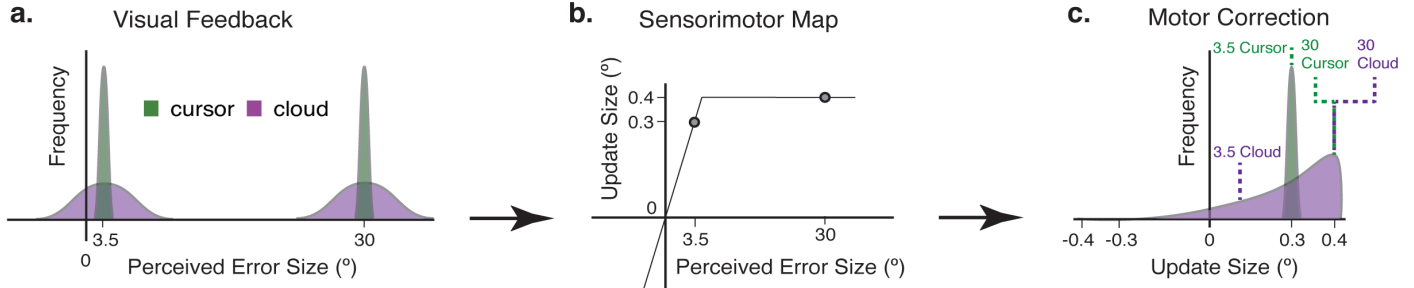


Fig. 1 (a) Histogram of perceived location of the feedback for a cursor (low uncertainty) or cloud of dots (high uncertainty), when the actual means are centered at 3.5° or 30° error. (b) Mapping between the size of error and change in motor output. (c) Histogram of motor corrections for different combinations of error size and visual uncertainty. Note that the “correction” will be in the wrong direction for some trials when the error is small but uncertainty is high.

Method and Exp. 1 Results

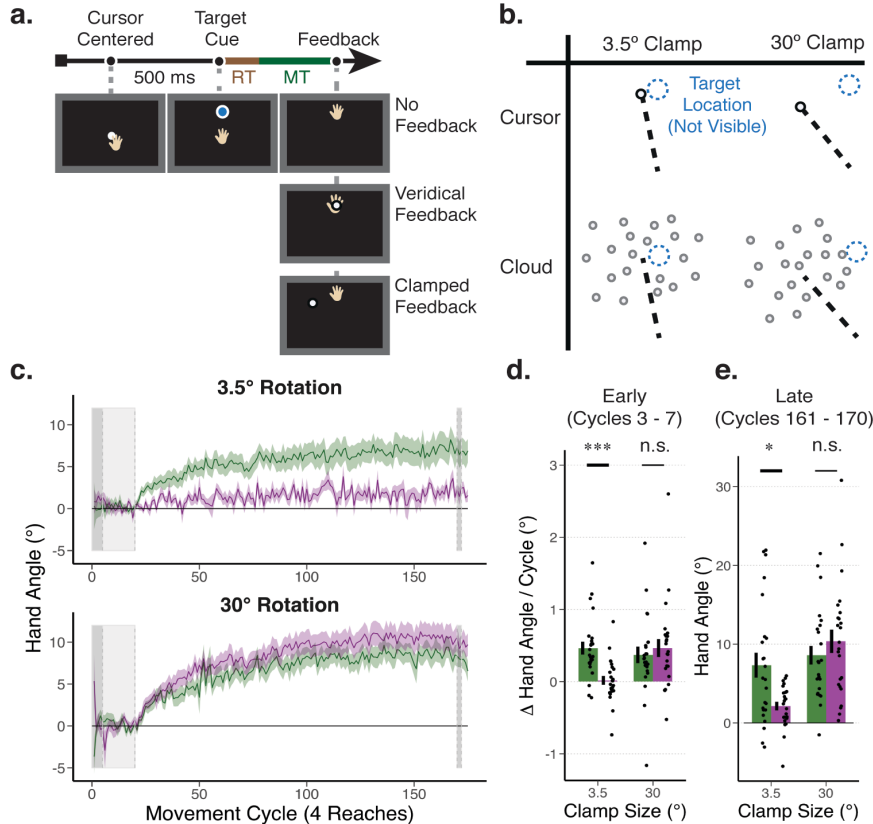


Fig. 2 (a) Time course of the Error Clamp Method. (b) 2 (cursor/ cloud) \times 2 (3.5°/ 30°) between group design. The cursor (white dot) or the centroid of the cloud (grey dots) corresponded to the clamp size. (c) Mean time course of hand angles. Early (d) and late (e) adaptation were attenuated by visual uncertainty for 3.5° but not 30° (unpaired t-test: *** $p < 0.001$, * $p < 0.05$).

Exp. 2 Results

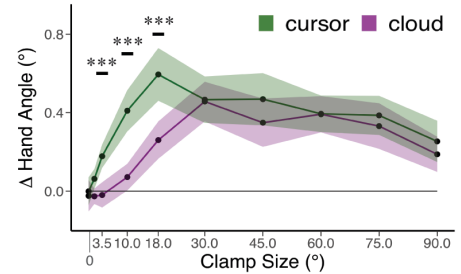


Fig. 3 Change in hand angle on trial $n + 1$ as a function of the clamped feedback on trial n . Within subject design, 2 (cursor/ cloud) \times 10 (error size). Data represent mean corrections across participants. Shaded region represents SEM (paired t-test: *** $p < 0.001$).

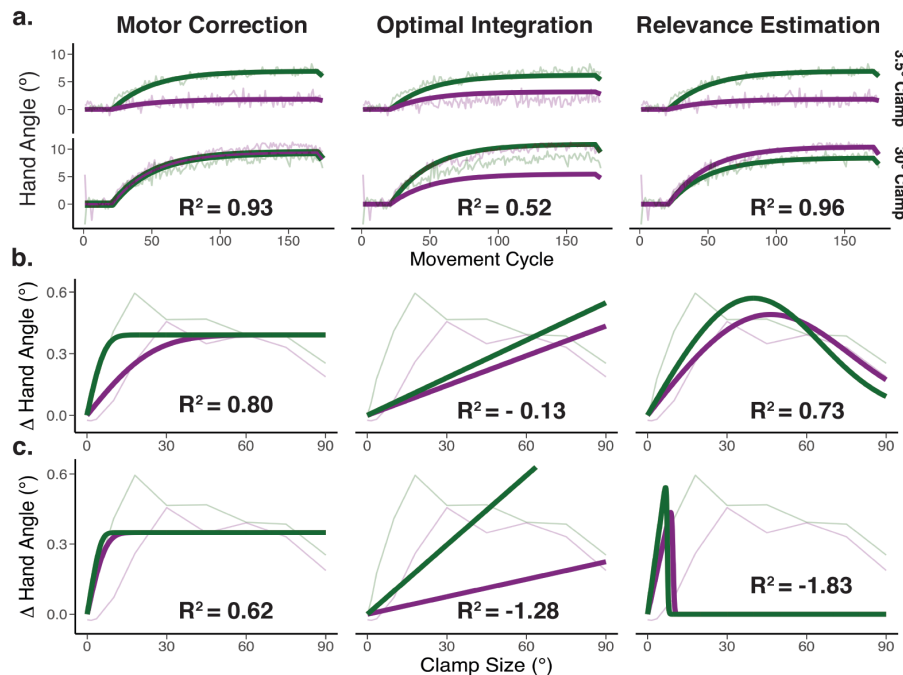


Fig. 4 (a) Fits for three models of the learning functions from experiment 1. The thin lines correspond to experiment 1 data. All three models capture the attenuating effect of visual uncertainty for the 3.5° conditions. However, the quality of the fits diverged for the 30° conditions, where OIM cannot recapitulate the dissociation. (b) Model fits of the trial-by-trial effects in experiment 2 with free parameters for cursor and cloud variability and (c) where these terms were fixed based on the difference thresholds obtained in a perceptual location discrimination task (cursor $\sigma_v = 1.95^{\circ}$; cloud $\sigma_v = 4.41^{\circ}$). The behavioral pattern observed in both experiments, complemented by the modeling results, are problematic for the hypothesis that the effect of visual uncertainty on adaptation arises from a weaker error signal (OIM). Rather, the results suggest that the effect of visual uncertainty is due mis-perception in the location of the feedback and the consequences of this on learning (MCM).