# Supplementary Materials

## Estimation of trial-to-trial generalization under noise influence

Here we provide supplementary simulation results for evaluating the performance of the parameter estimation method (the prediction-error method) in the presence of process and observation noises. Because human adaptation processes are inherently noisy, it is necessary to assess how robust the estimation method is. Noise terms are included to the single-state state-space model as

$$\begin{cases} \Phi_{k+1} = \Phi_k + BH_k^T \Delta\phi_k + w_k \\ \phi_k = H_k \Phi_k + v_k \end{cases} \qquad \text{(S1)}$$

where *w* and *v* are process and observation noises with zero means and covariances $\sigma_{proc}^2 \cdot I$ and $\sigma_{obs}^2$, respectively. Using various representative values of $\sigma_{proc}$ and $\sigma_{obs}$, the state-space model generated 200 independent realizations of artificial error data for randomized target orders. In the simulations shown below three values of generalization widths ($1^\circ$, $30^\circ$ and $60^\circ$) were used to define the matrix *B* as in Fig.1 of the main text. The prediction-error method was then applied to the artificial error data to estimate the eight parameters of *B* matrix.

First, we examined the individual effect of process and observation noises separately (($\sigma_{proc}$, $\sigma_{obs}$)=(0.4, 0.0) in Fig.S1 and ($\sigma_{proc}$, $\sigma_{obs}$)=(0.0, 3.0) in Fig.S2). The simulation results demonstrate that the prediction-error method essentially reproduced the shape of generalization functions. Note that we needed to use a smaller value of $\sigma_{proc}$ than that of $\sigma_{obs}$ because the process noise has an accumulative influence over error time courses. Next, we investigated the combined effects of process and observation noises (($\sigma_{proc}$, $\sigma_{obs}$)=(0.2, 2.) in Fig.S3, ($\sigma_{proc}$, $\sigma_{obs}$)=(0.4, 2.) in Fig.S4, and ($\sigma_{proc}$, $\sigma_{obs}$)=(0.2, 4.) in Fig.S1). Again, the prediction-error method could recover the generalization functions reasonably well.

Besides the simulation results demonstrated above, various combinations of noise levels and generalization function width were tested and confirmed that the prediction-error method was reasonably robust for a wide range of noise values. To conclude, the above numerical results guarantee that the prediction-error method is able to reliably reproduce the generalization width for a variety of process and observation noise strengths and may safely be applied to human psychophysical error data.

**Fitting of the state-space model to individual data**

Fig S6 shows three individual error data together with the state-space model fitting (left column) and the derived individual trial-to-trial generalization functions (right column), using the same format of Fig. 6A and 6B. Each $R^2$ value of fitness is included below the trial-to-trial error data. Each generalization function, though noisy, exhibits essentially a narrow single-peaked shape that was found in the group average (Fig. 6B).

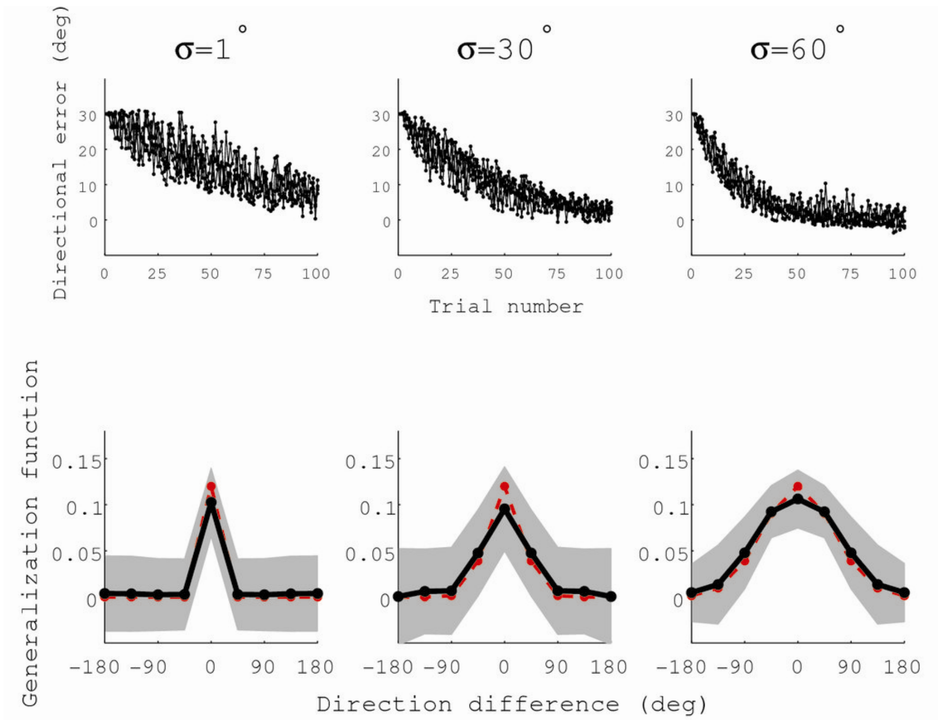


Figure S1: Estimation of generalization functions using the least-squares method. Left, middle, right columns are for generalization widths $\sigma = 1^{\circ}, 30^{\circ}, 60^{\circ}$. Panels in top rows are five typical error time courses, and panels in bottom are estimated generalization functions. Red dash lines represent true values. $\sigma_{proc} = 0.4$ and $\sigma_{obs} = 0$.

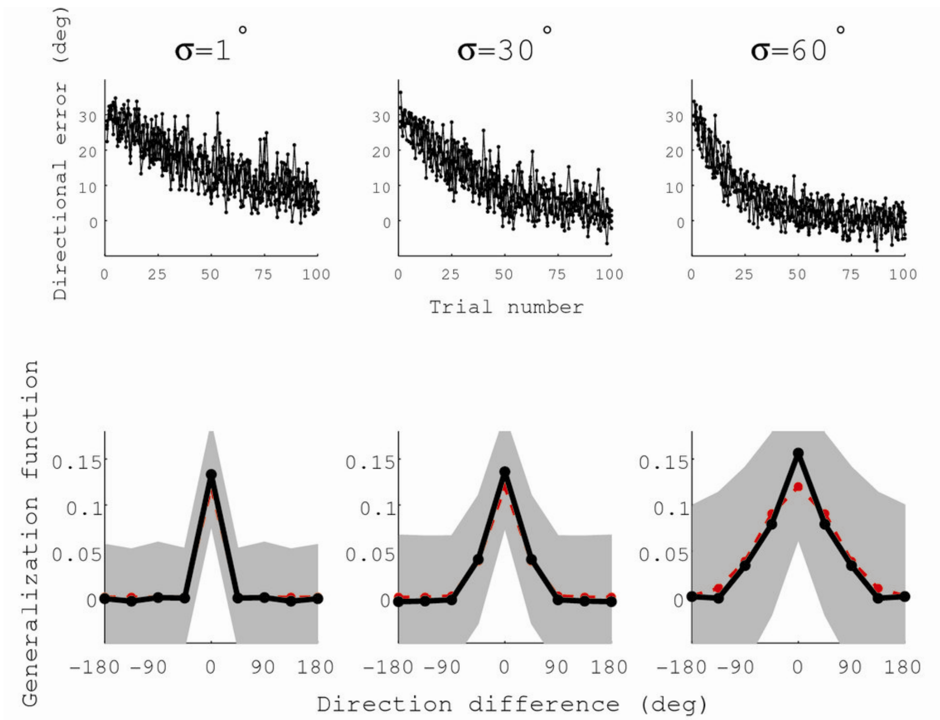


Figure S2: $\sigma_{proc} = 0.0$ and $\sigma_{obs} = 3.0$.

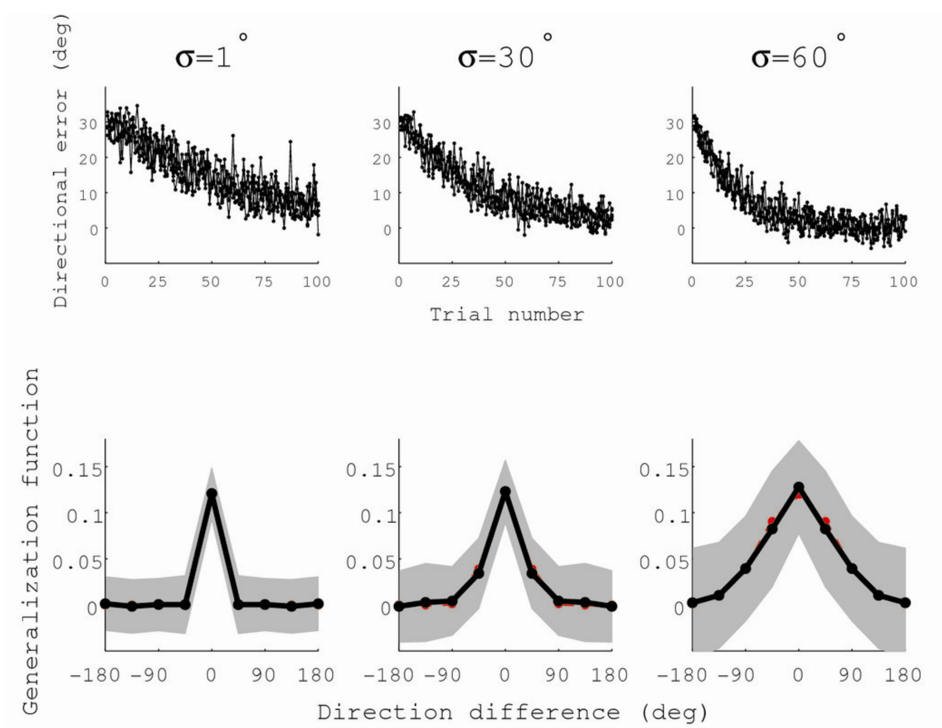


Figure S3: $\sigma_{proc} = 0.2$ and $\sigma_{obs} = 2.0$.

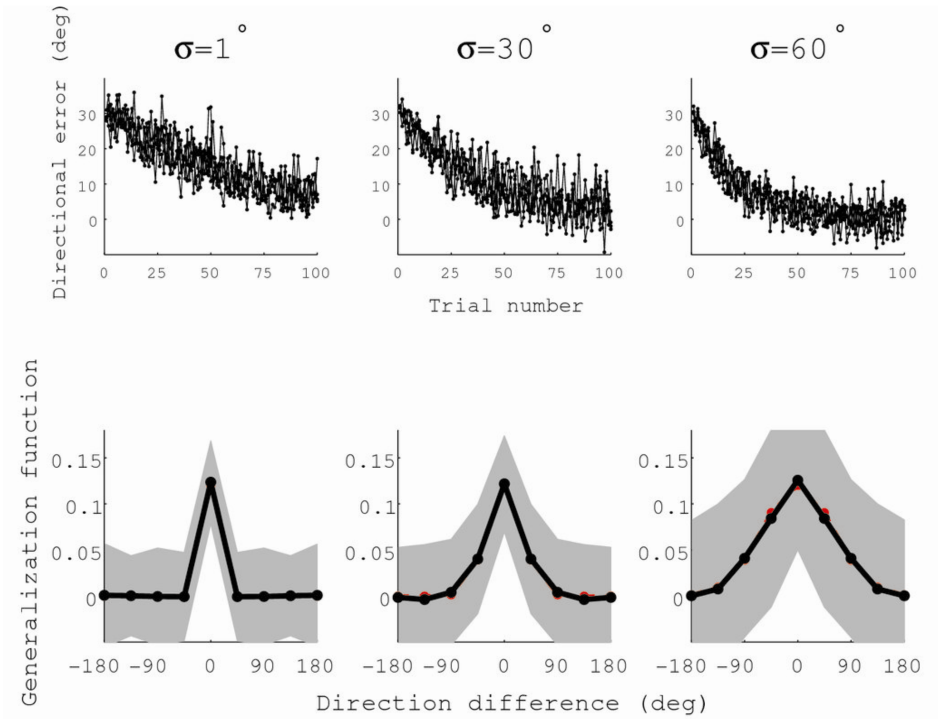


Figure S4: $\sigma_{proc} = 0.4$ and $\sigma_{obs} = 2.0$.

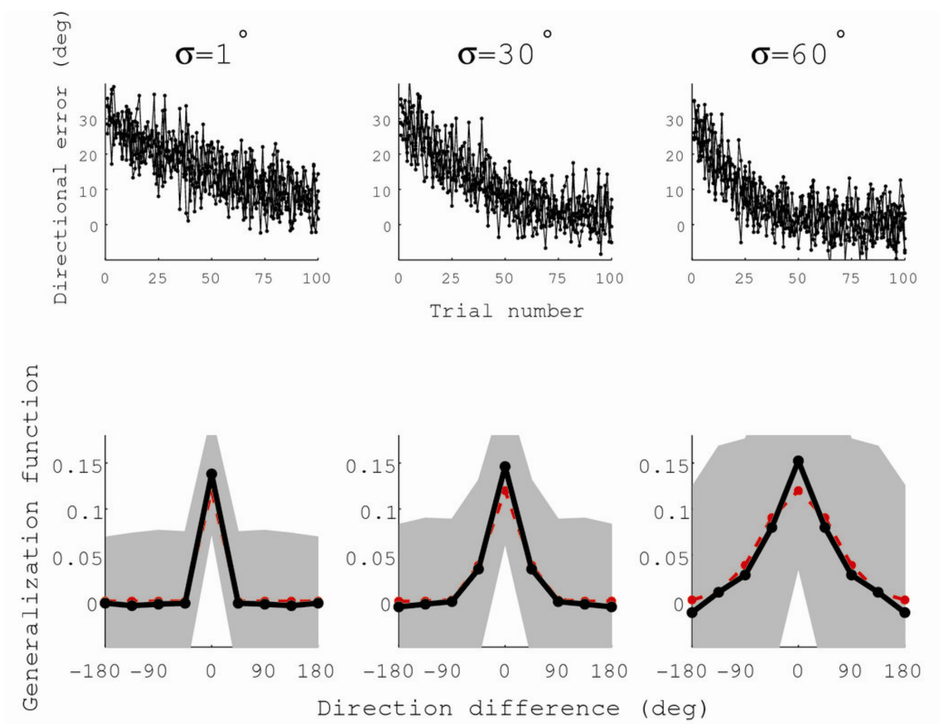


Figure S5: $\sigma_{proc} = 0.2$ and $\sigma_{obs} = 4.0$.

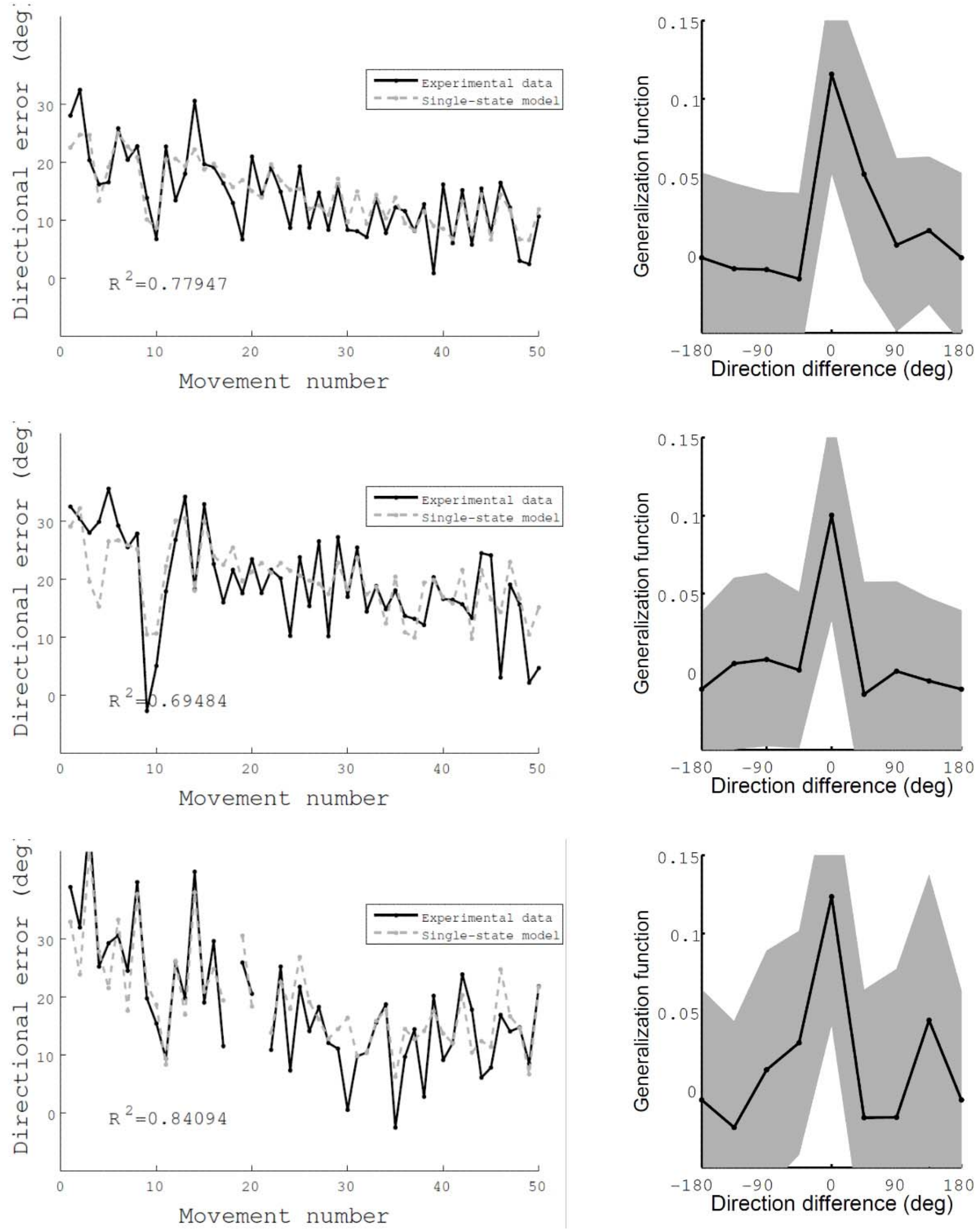


Figure S6: Experimental error data and the state-space model fitting (left column) and corresponding trial-to-trial generalization functions (right column) from three typical participants.