

Acquisition, representation, and transfer of models of visuo-motor error

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We examined how human subjects acquire and represent models of visuo-motor error and how they transfer information about visuo-motor error from one task to a closely related one. The experiment consisted of three phases. In the *training phase*, subjects threw beanbags underhand towards targets displayed on a wall-mounted touch screen. The distribution of their endpoints was a vertically elongated bivariate Gaussian. In the subsequent *choice phase*, subjects repeatedly chose which of two targets varying in shape and size they would prefer to attempt to hit. Their choices allowed us to investigate their internal models of visuo-motor error distribution, including the coordinate system in which they represented visuo-motor error. In the *transfer phase*, subjects repeated the choice phase from a different vantage point, the same distance from the screen but with the throwing direction shifted 45°. From the new vantage point, visuo-motor error was effectively expanded horizontally by $\sqrt{2}$. We found that subjects incorrectly assumed an isotropic distribution in the choice phase but that the anisotropy they assumed in the transfer phase agreed with an objectively correct transfer. We also found that the coordinate system used in coding two-

dimensional visuo-motor error in the choice phase was effectively one-dimensional.

Introduction

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Possibility two

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Goals

1. Testin isotropy bi s

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Isotropy bias

isotrop bias.

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Possibility one

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3. Coordinate systems

$\phi(x, y)$.

(r, θ)

r

Estimating internal models

Σ

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Subjects

1 36 (22)

\$12

incorrect,

Apparatus and stimuli

22- (47.6 × 30.2)

1.3

Methods

Ethics statement

130 .

, (0.5 × 0.5).

1 7 , 1 7)

2. , 3. , 5.3, 7.1 , 4

Procedure and design

60 × 60 =

2.5 .

4 0

Transfer phase

0° , (1).

Transfer phase

new position,

(2) ()

45° (1 ,).

13. (13. × 3.5), (4.4), (3.5 × 300 100

Preanalyses for individual subjects

True visuo-motor error distribution

$$\phi_{B_i}(x,) = \frac{1}{2\pi\sigma_x^{B_i}\sigma^{B_i}} \exp\left(-\frac{x^2}{2(\sigma_x^{B_i})^2} - \frac{^2}{2(\sigma^{B_i})^2}\right). \quad (2)$$

Choice phase

(choice position), 5% 14%

(,) 1 . S.

$$f(E|\sigma_x^{B_i}, \sigma^{B_i}) = \begin{cases} \phi_{B_i}(x, \sigma_x^{B_i}, \sigma^{B_i}), & \text{if } E \text{ is on the screen} \\ 1 - \int_S \phi_{B_i}(x, \sigma_x^{B_i}, \sigma^{B_i}), & \text{if } E \text{ is outside the screen} \end{cases} \quad (3)$$

$$\begin{aligned} \sigma_x(t) &= \theta_x + \kappa_x e^{-v_x t} \\ \sigma(t) &= \theta + \kappa e^{-v t}, \end{aligned} \quad (4)$$

$$\theta_x, \kappa_x, v_x, \theta, \kappa, v$$

$$t = t_i + 15(i - 1).$$

4,

Subjects' intern I model of visuo-motor error distribution

$$\psi(x, \sigma_x, \sigma) = \frac{1}{2\pi\sigma_x\sigma} \exp\left(-\frac{x^2}{2(\sigma_x)^2} - \frac{\sigma^2}{2(\sigma)^2}\right), \quad (5)$$

$$\sigma_x, \sigma, \sigma_x^N, \sigma^N, \sigma_x^C, \sigma^C$$

$$T_1, T_2,$$

$$p_1, p_2$$

$$\begin{aligned} p_1 &= \int_{T_1} \psi(x, \sigma_x, \sigma) dx d, \\ p_2 &= \int_{T_2} \psi(x, \sigma_x, \sigma) dx d \end{aligned} \quad (6)$$

$$\begin{aligned} T_2, p_1 - p_2, \sigma_x^C, \sigma^C, \sigma_x^N, \sigma^N, \tau, \sigma_x^C, \sigma^C, \sigma_x^N, \sigma^N, \Pr(T_2) = \frac{1}{1 + e^{(p_1 - p_2)/(\tau D)}}, \quad (7) \\ D = p_1(1 - p_2) + (1 - p_1)p_2, \tau > 0 \end{aligned}$$

Exclusion of subjects

20%

20%

$$\Pr(T_2) = \frac{1}{1 + e^{(A_1 - A_2)/(\tau(A_1 + A_2))}}, \quad ()$$

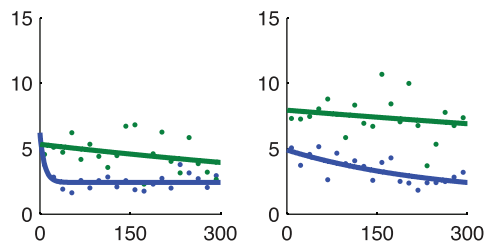
$$A_1, A_2, T_1, T_2, \tau > 0$$

$$(5)$$

$$(, , \& , 1.74, .440).$$

$$0.05$$

,



$\sigma_x^t, \sigma^t, \sigma^t, \beta^t.$
 $\beta^T = \sigma^T / \sigma_x^T.$
 $\left(\begin{array}{cc} \sigma_x^C & \sigma^C \\ \sigma_x^N & \sigma^N \end{array} \right)$

$(\beta^T > 1).$
 β^T

1.4
 12
 11

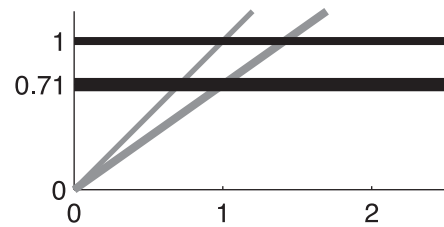
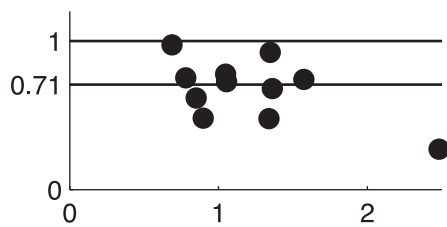
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Learning of the anisotropy estimate

Internal models at the choice and new positions

$\beta^C = 1.17$
 $\beta^T = 1.5$
 t
 $t(11) = -4.0$
 $p = 0.002.$



3 , - - 0.072. β^C β^T

1.12, $p = 0.2$. $t(11) =$, (5).

5 β^C β^T ()

0.05 β^C β^T , $r = 0.56$, $p =$

Transfer of the anisotropy estimate

$\beta^N = \beta^C / \sqrt{2}.$
 $\beta^C.$

$H_1 \quad \beta^N = 1/\sqrt{2} + \varepsilon,$
 $H_2 \quad \beta^N = 1 + \varepsilon,$
 $H_3 \quad \beta^N = 1/\sqrt{2}\beta^C + \varepsilon,$
 $H_4 \quad \beta^N = \beta^C + \varepsilon$

ε
 $\beta^N.$
 H_1
 $(\quad, H_1 \quad 2 \quad 5 \quad, \quad 5 \quad)$
 β^N
 H_1
 $1,321.$

Coordinate systems for visuo-motor error

$(\quad, \quad r = 0. \quad, p < 0.001), \quad \sigma_x^N \quad \sigma^N,$
 $(\quad, \quad r = 0. \quad 2, p < 0.001), \quad \sigma_x^T \quad \sigma^T, \quad r = 0.5 \quad, p =$
 $0.04 \quad (\quad$
 $\quad r = 0.62, p = 0.041).$
 $\sigma_x^T \quad \sigma^T$

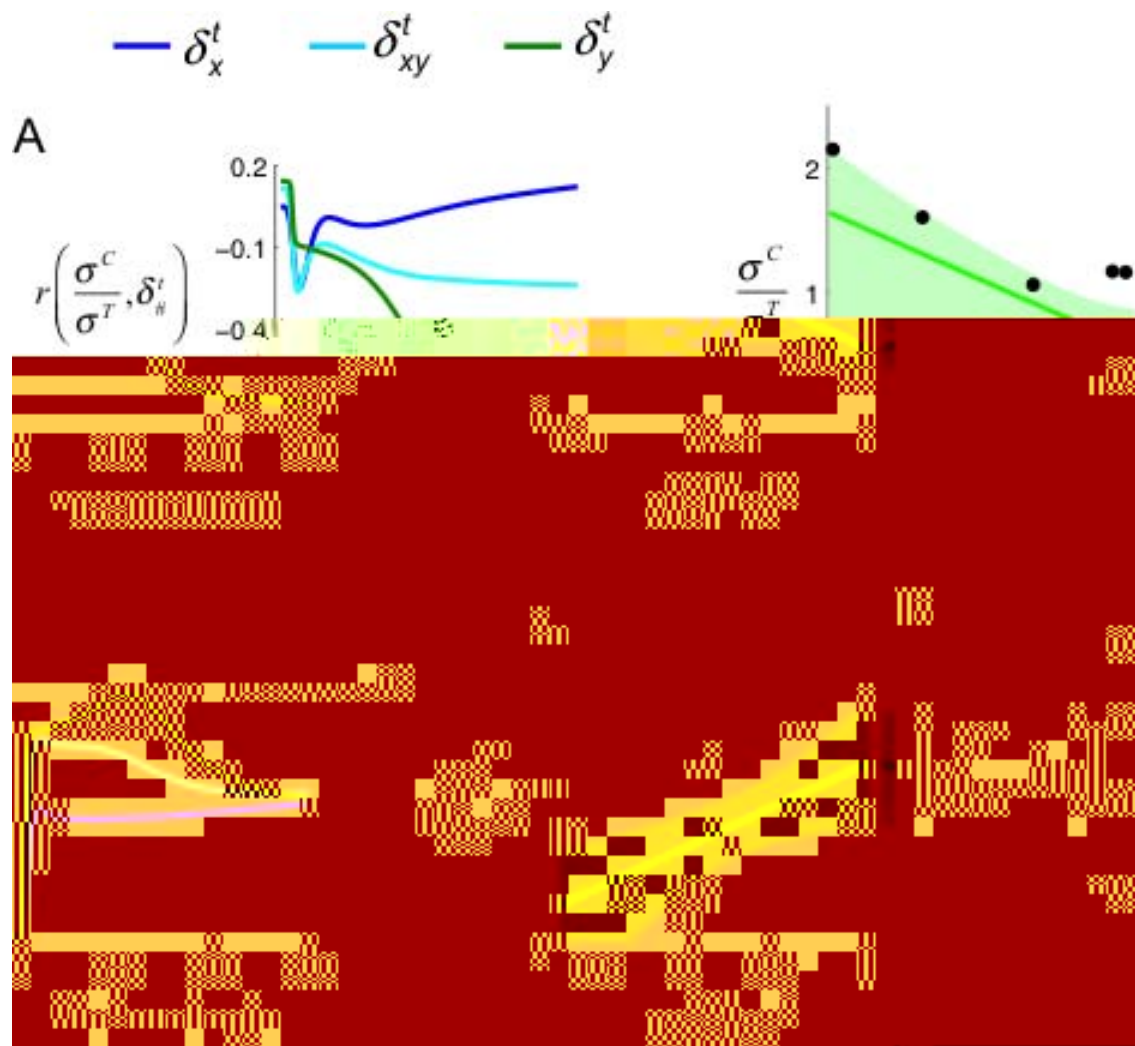


Figure 6. Standard deviations assumed in the internal model. The symbols δ_x^t , δ_y^t , and δ_{xy}^t denote the change rate of true standard deviations at trial number t , respectively, for the horizontal direction, the vertical direction, and overall (i.e., $\delta_{xy}^t = \sqrt{\delta_x^t \delta_y^t}$). (A) Learning. Left: Pearson's correlation between the misestimation of true standard deviation at the choice position (σ^C/σ^T) and the change rates. The horizontal line marks the significance level of 0.05. The correlation was significant only for the vertical change rate (green curve) in the second half of the training phase. A 75-trial range of the most prominent correlations was from trial 225 to trial 300. Right: The correlation σ^C/σ^T predicted by $\sigma_y^{300}/\sigma_y^{225}$. Each dot denotes one subject. Solid line denotes the linear prediction. Shadow denotes its 95% confidence interval. (B) Transfer. Left: Pearson's correlation between the mistransfer of standard deviation from the choice position to the new position (σ^N/σ^C) and the change rates. The horizontal line marks the significance level of .05. The correlation was significant only for the vertical change rate (green curve) in the second quarter of the training phase. A 75-trial range of the most prominent correlations was from trial 85 to trial 160. Right: The correlation σ^N/σ^C predicted by $\sigma_y^{160}/\sigma_y^{85}$. Each dot denotes one subject. Solid line denotes the linear prediction. Shadow denotes its 95% confidence interval.

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Discussion

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Ke words: perception and action, movement planning, visuo-motor uncertain , representation, transfer, choice

Acknowledgments

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Appendix

Detailed results on the variance estimate

Let r_{nin} of the variance estimate

$$\sigma^C / \sigma^T \delta_x^t (\delta^t, \delta_x^t)$$

$$t. \sigma^C / \sigma^T \delta^t$$

$$(p < 0.05).$$

$$\sigma^C / \sigma^T \delta_x^t (p > 0.41).$$

$$\sigma^{00} / \sigma^{225} \delta^t \sigma^{00} / \sigma^{225}$$

$$75- \sigma^C / \sigma^T \delta^t \sigma^C / \sigma^T \delta^t \sigma^{00}$$

$$/ \sigma^{225} (\sigma^C / \sigma^T \delta^t)$$

$$\sigma^C/\sigma^T \quad \delta^t$$

$$t (\pm 300).$$

$$\sigma^N/(\sqrt[4]{2}\sigma^C) \quad \delta^t$$

$$(p < 0.05).$$

$$5. \quad t,$$

$$\sigma^N/(\sqrt[4]{2}\sigma^C) \quad \delta_x^t$$

$$(\sigma^N/(\sqrt[4]{2}\sigma^C) \quad \delta_x^t)$$

$$(p > 0.21).$$

Transfer of the variance estimate

$$\sigma^N = \sigma^C), \quad \sigma^N = \sqrt[4]{2}\sigma^C. \quad (\sigma_x^N = \sqrt{2}\sigma_x^C,$$

$$\sigma^N/(\sqrt[4]{2}\sigma^C) \quad \delta_x^t \quad (\delta^t, \delta_x^t)$$

$$t, \quad \sigma^{160}/\sigma^{85} \quad \sigma^N/(\sqrt[4]{2}\sigma^C) \quad \delta^t$$

$$(\sigma^{160}/\sigma^{85} = 1),$$

$$(\sigma^N/(\sqrt[4]{2}\sigma^C) = 1).$$