

# S3 Appendix:

## Motor expertise facilitates the accuracy of state extrapolation in perception

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## RESPONSE MODELS WITH LIMITED EXTRAPOLATION HORIZON

In order to investigate the hypothesis that subjects may only be able to predict the pole dynamics accurately over a limited period before having to switch to a heuristics, we investigated a class of partly heuristic forward models (lh\_cVEL).

Let  $t_{noi} = 4.5s$  be the time after which the force that is applied to the cart is clamped to zero and let  $t_{occ} = t_{noi} + 0.1s = 4.6s$  be the time of the occlusion onset. Furthermore, let  $t_{resp} = t_{occ} + 0.9s = 5.5s$  be the time when the subjects have to report their current pole angle estimate  $\theta_{est}$ . For  $t_{noi} \leq t \leq t_{resp}$ , the true dynamics of the cart-pole system are described by the second-order differential equations (1) with the initial state  $s_{init} = s(t = t_{noi}) = (x(t) \quad \dot{x}(t) \quad \theta(t) \quad \dot{\theta}(t))^T$ .

$$\ddot{\theta} = F(\theta, \dot{\theta}, u = 0) = \frac{g \sin(\theta) + \cos(\theta) \left( \frac{-u - m_p l \dot{\theta}^2 \sin \theta}{m_c + m_p} \right)}{l \left( \frac{4}{3} - \frac{m_p \cos^2 \theta}{m_c + m_p} \right)} \quad (1)$$

$$\ddot{x} = G(\theta, \dot{\theta}, \ddot{\theta}, u = 0) = \frac{u + m_p l (\dot{\theta}^2 \sin \theta - \ddot{\theta} \cos \theta)}{m_c + m_p}$$

These equations describe also the dynamics that are simulated by the model PERF, which consequently extrapolates the pole angle  $\theta(t_{resp})$  without error. When assuming constant pole acceleration (cACC) or velocity (cVEL) after the occlusion occurred ( $t \geq t_{occ}$ ), the estimated pole angle  $\theta_{est}(t_{resp})$  is determined by simulating the dynamics, which are described by the differential equations in (2) and (3) with the initial state  $s_{init} = s(t = t_{occ})$ .

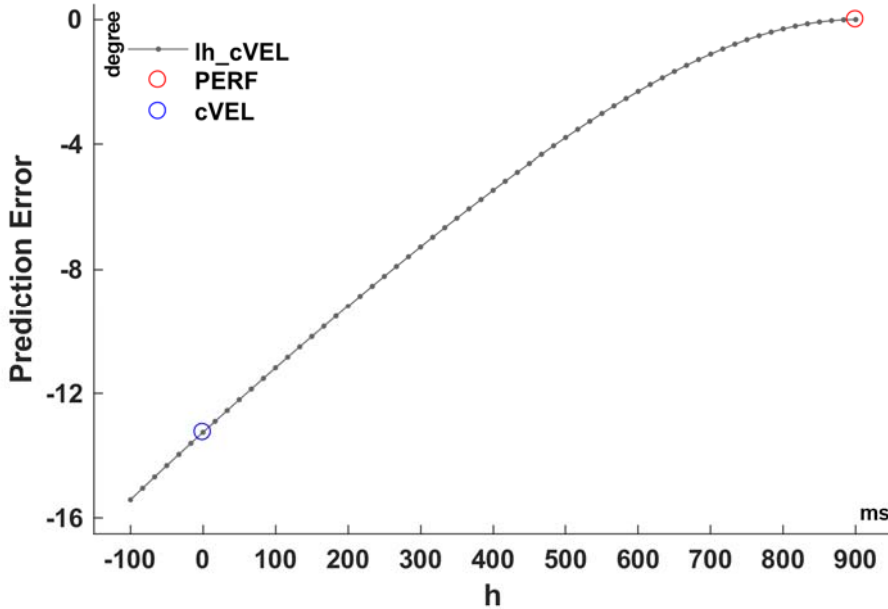
$$\ddot{\theta}_{est} = \ddot{\theta}(t_{occ}) \quad (2)$$

$$\dot{\theta}_{est} = \dot{\theta}(t_{occ}) \quad (3)$$

Our model lh\_cVEL has one parameter  $h$ ,  $-100ms \leq h \leq 900ms$ , which determines the duration of precise state extrapolation in milliseconds. It first either observes ( $h \leq 0ms$ ) or extrapolates ( $h > 0ms$ ) the state  $s(t_{occ} + h)$  by simulating the true dynamics (equation 1) using the initial state  $s_{init} = s(t = t_{occ})$ . Then, it switches to the constant pole velocity model (cVEL) and simulates the corresponding dynamics (equation 4) for  $t_{occ} + h \leq t \leq t_{resp}$  using the initial state  $s_{init} = s(t = t_{occ} + h)$ .

$$\dot{\theta}_{est} = \dot{\theta}(t_{occ} + h) \quad (4)$$

For  $h = 900ms$  the model coincides with the model PERF, which represents perfect knowledge of the pole dynamics. Correspondingly, for  $h = 0ms$  the model coincides with the model cVEL, which assumes that, the pole velocity remains constant over the time of the occlusion. We investigated 61 values of  $h$  corresponding to the 61 frames ( $\Delta t = 1/60s$ ) from 100ms before ( $h = -100ms$ ) to 900ms after ( $h = 900ms$ ) the pole occlusion. The prediction error increases with increasing value of the parameter  $h$ . This corresponds to the decreasing accuracy of the model (**Figure 1**).



**Figure 1. Prediction error as function of the extrapolation horizon ( $h$ ) averaged over all stimuli.** Notice that the prediction error monotonically increases with decreasing value of the parameter  $h$ .

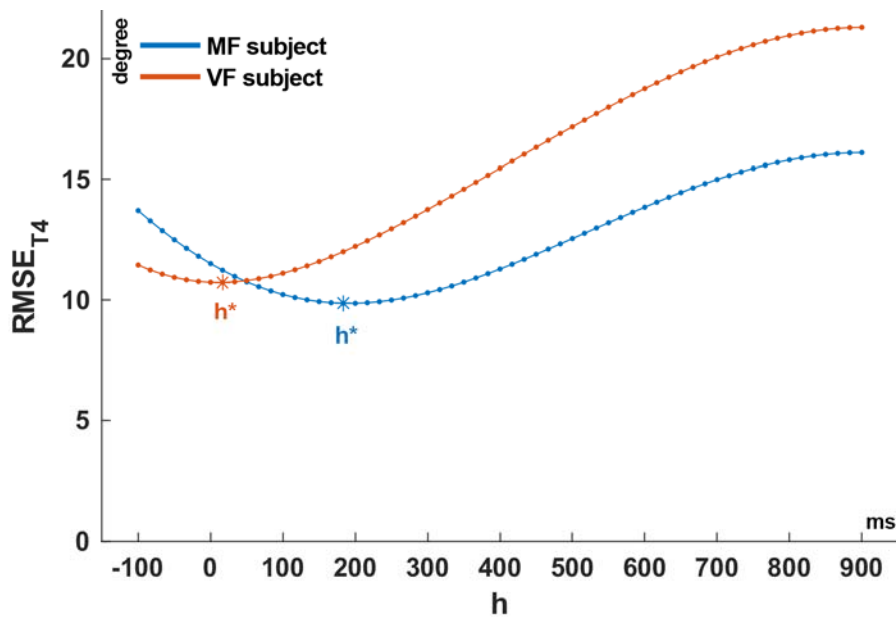
In order to determine the best fitting model ( $h_s^*$ ) for each subject ( $s$ ), we first calculated the root mean squared error ( $RMSE_{T4,s,h}$ ) between the models' ( $MDL_h = \theta_{est}(t_{resp})$ ) and subjects' ( $RSP_{T4,s}$ ) responses in block T4 for each model ( $h$ ) (Equation S1).

$$RMSE_{T4,s,h} = \sqrt{\frac{1}{40} \sum_{trial=1}^{40} (RSP_{T4,s,trial} - MDL_{h,trial})^2} \quad (S1)$$

The best fitting model ( $h_s^*$ ) for each subject ( $s$ ) was determined by minimizing the root mean squared error with respect to  $h$  (Equation S2).

$$h_s^* = \arg \min_h RMSE_{T4,s,h} \quad (S2)$$

**Figure 2** shows the root mean squared error of all investigated models in the class lh\_cVEL for two representative subjects, one from the group VF and the other from the group MF.



**Figure 2. Root mean squared error of the model class lh\_cVEL for two representative subjects.** The best fitting model ( $h^*$ ), according to the root mean squared error (RMSE) is for each of the two subjects indicated by a star. For the subject representing the group MF,  $h^*$  (extrapolation horizon) is higher (closer to the model which perfectly extrapolates the dynamic behavior of the pole:  $h = 900ms$ ) than for the subject representing the group VF.