Behavioral mechanisms underlying visually-guided control of steering

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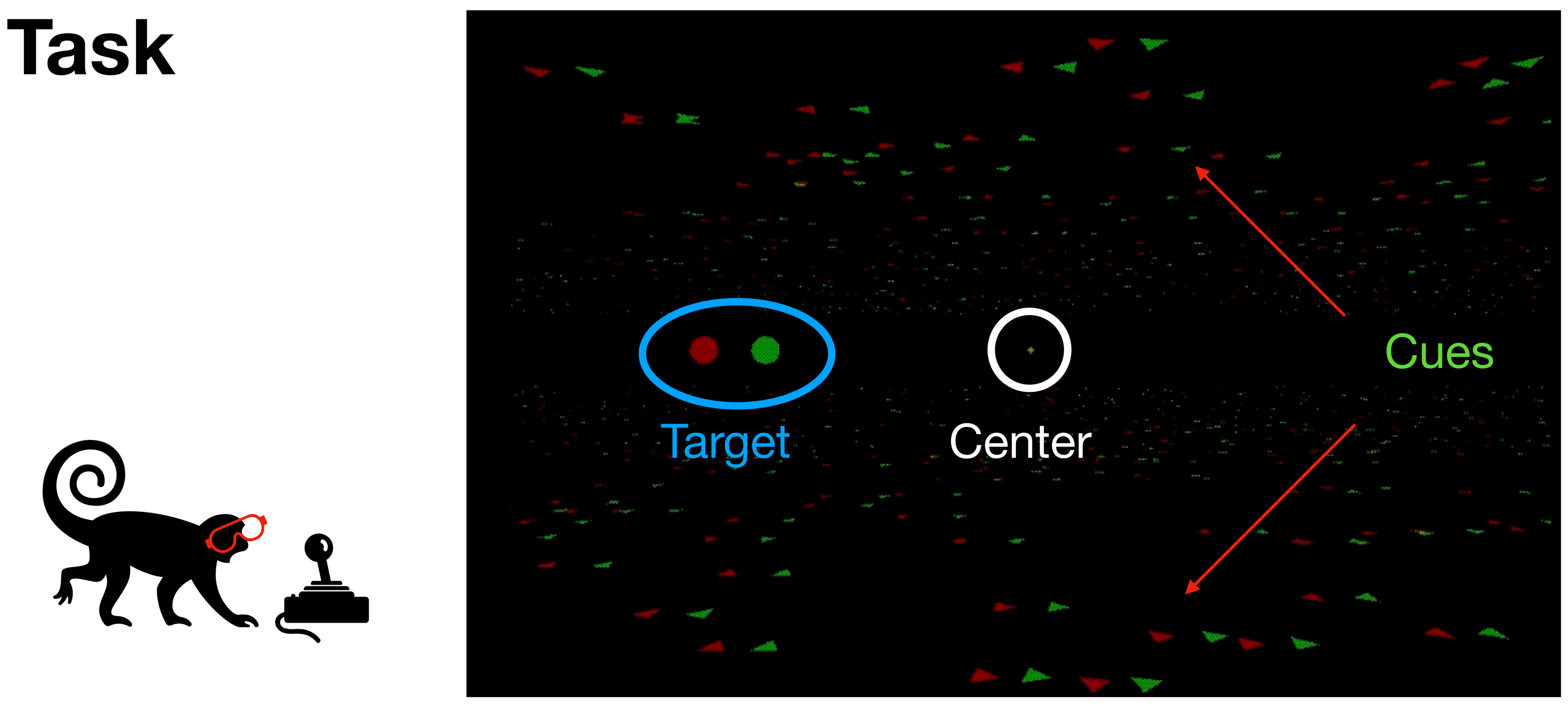
Motivation

- Navigating an environment in a goal-directed behaviour involves tracking critical variables, e.g. location and heading direction for spatial navigation.
- Visual motion processing circuits of the brain analyse global patterns of retinal image motion (optic flow) generated by movement of the observer, signals that help with navigation.
- Whereas human behavioral studies have extensively examined how optic flow contributes to goal-directed navigation, not much is known about the neural processing of optic flow that guides navigation, especially for closed-loop tasks.

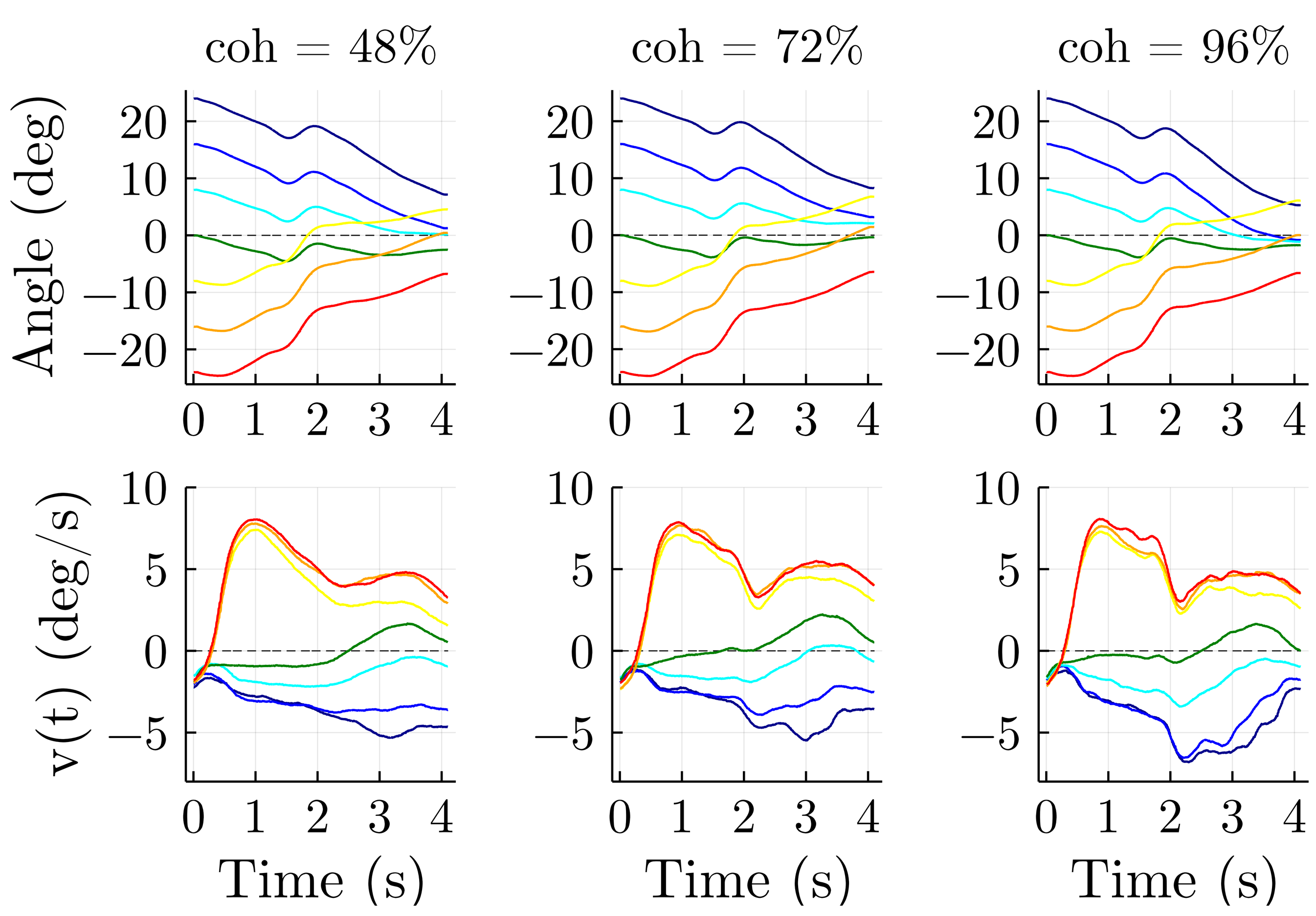
Task



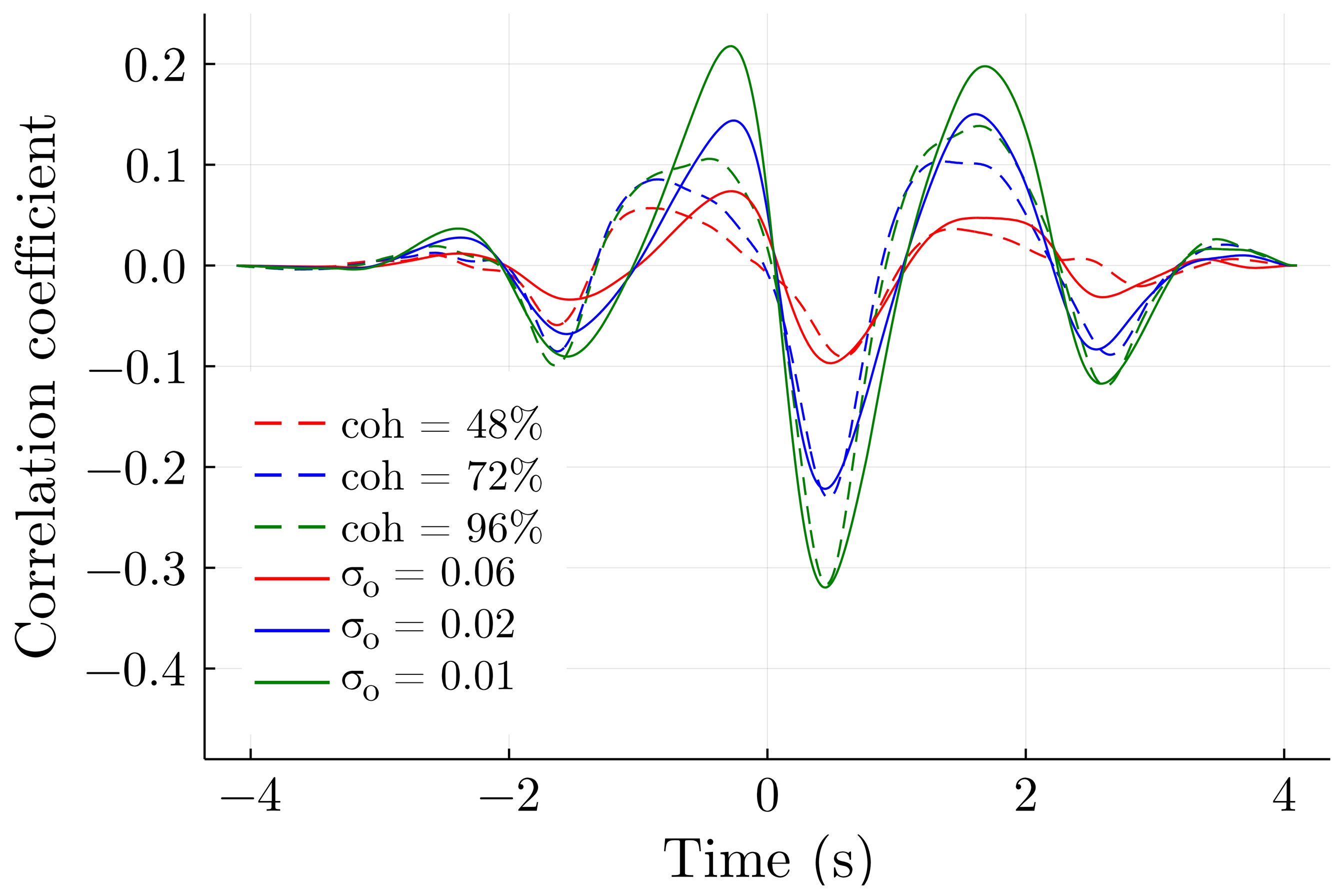
- We designed a simple fixed-duration navigation task in which a monkey needs to steer a joystick to align themselves to a cued target (like driving a car), which is not visible during steering.
- The virtual environment only provides noisy optic flow feedback in the form of a random dot motion, that reacts coherently with the monkey's steering, and whose coherence can be experimentally modulated (like driving a car in a snow storm).
- In addition, we introduce external perturbations to the angular velocity, which decouple the joystick signal from the optic flow (like there is an unpredictable wind pushing the car), making it necessary to observe the dot motion.

Experimental results

Mean trajectories



Perturbation-joystick cross correlation



Model

- We develop a minimal and interpretable stochastic optimal control model that captures important features in the data such as multiplicative noise in the control and reactive, closed-loop control in the presence of external perturbations.

System dynamics $x(t+\Delta t) = Ax(t) + Bu(t) + \xi_u Cu(t) + \xi_x(t)$

$$\begin{bmatrix}\theta(t+\Delta t)\\ v(t+\Delta t)\\ f(t+\Delta t)\\ p(t+\Delta t)\end{bmatrix} = \begin{bmatrix}1 & \Delta t & 0 & \Delta t\\ 0 & 1-\frac{\Delta t}{\tau_2} & \frac{\Delta t}{\tau_2} & 0\\ 0 & 0 & 1-\frac{\Delta t}{\tau_1} & 0\\ 0 & 0 & 0 & 1-\frac{\Delta t}{\tau_p}\end{bmatrix}\begin{bmatrix}\theta(t)\\ v(t)\\ f(t)\\ p(t)\end{bmatrix} + \begin{bmatrix}0\\ 0\\ \frac{\Delta t}{\tau_1}\\ 0\end{bmatrix} u(t) + \sigma_u\xi_u(t)\begin{bmatrix}0\\ 0\\ \frac{\Delta t}{\tau_1}\\ 0\end{bmatrix} u(t) + \sigma_p\xi_p(t)\begin{bmatrix}0\\ 0\\ 0\\ \Delta t\end{bmatrix}$$

Partial observability $o(t) = v(t) + p(t) + \sigma_o\xi_o(t)$

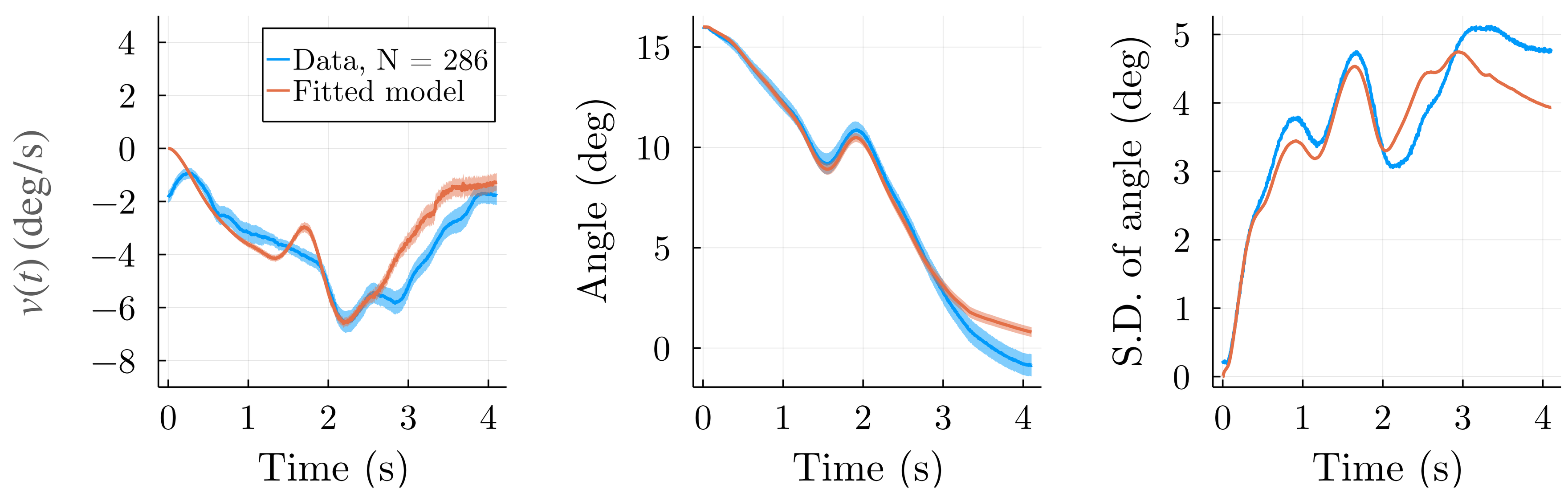
Cost function $C(u,x) = \frac{1}{2}\theta^2(T) + \sum_{t=0}^{T}\left(\frac{r}{2}u^2(t) + \frac{q}{2}\theta^2(t)\right)\Delta t$

Estimation $\hat{x}(t+\Delta t) = A\hat{x}(t) + Bu(t) + K(t)(o(t) - H\hat{x}(t))$

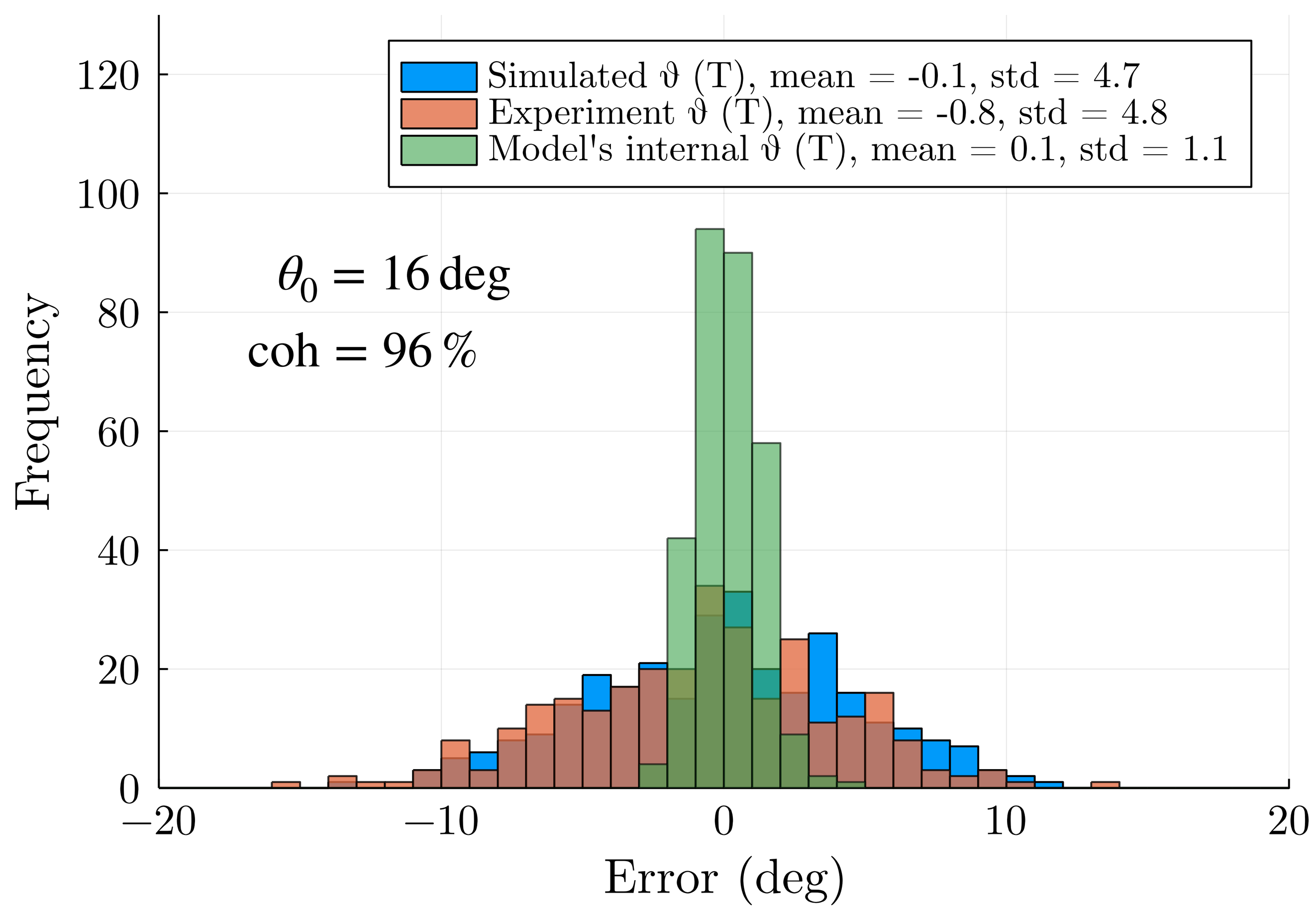
Optimal control $u(t) = -L(t)\hat{x}(t)$

Fitting model to data

We fit 7 global parameters $(r, q, \tau_1, \tau_2, \sigma_u, \sigma_p, \tau_p)$ plus the coherence σ_o, by performing a grid search over parameters and minimising distance between the mean experimental and the mean modelled angular velocity exerted by the joystick.



Future work: estimating internal states



Conclusions

- Current model can capture behaviour by modelling cost and internal dynamics such as integration of control over time. By modelling partial observability, we can manipulate relevance of experimental observations and thus probe the integration of control and observations.
- By estimating internal variables, it will be possible to correlate certain signals such as control, optic flow and heading to neural activity from relevant brain areas.