Adaptive temporal weighting across behavior and neural network models

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Motivations

Perceptual decision-making relies on the accumulation of sensory evidence over time. Classical models link this process to distinct psychophysical effects, including **primacy**-related early weighting, **uniform** integration, and **recency**-related weighting or leaky integration. However, experiments show that primates flexibly adapt weighting strategies to sensory evidence, a capacity that current models do not fully explain. We propose a two-paired **sensory** and **decision** populations model for **adaptive temporal weighting**.

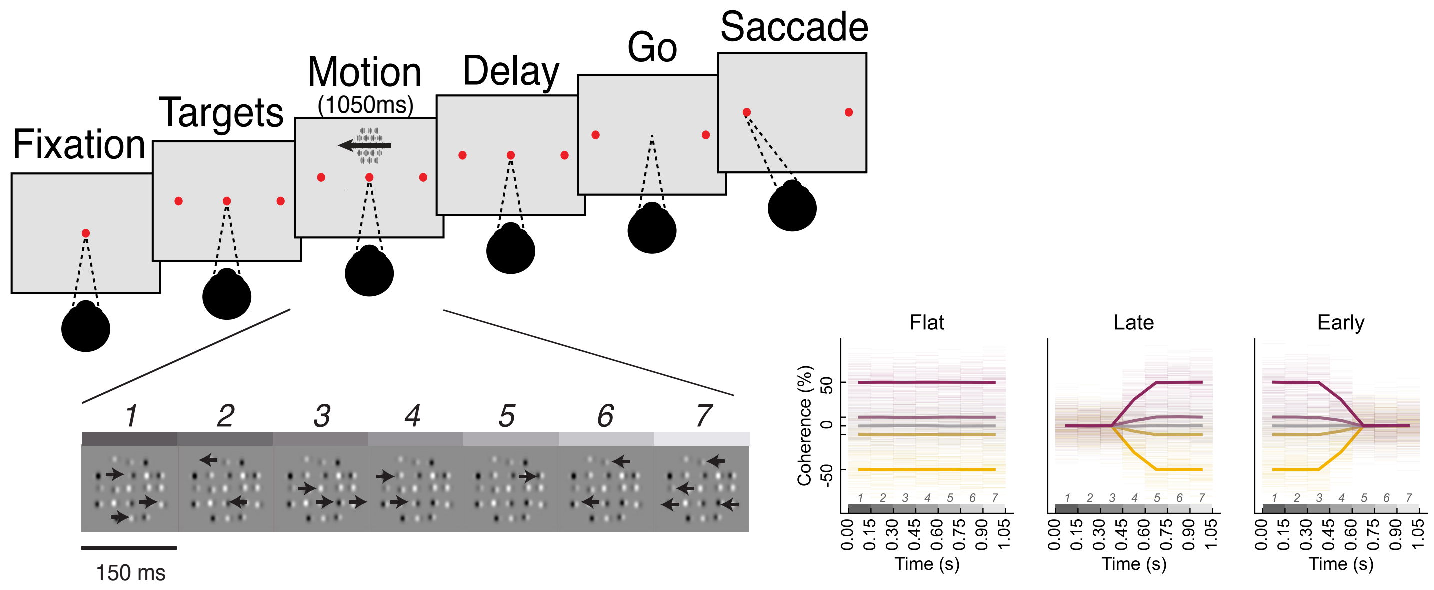

Figure 1. Perceptual decision-making task[1]. Seven pulses of motion gratings are presented at different coherency levels. The subjects are asked to indicate their choices by saccading to target locations. Timeline of sensory motion coherence in trial-averaged (thick lines) and sample trials (thin lines) for Flat, Late or Early conditions. The target direction is a temporal integration of Flat, Late or Early informative pulses.

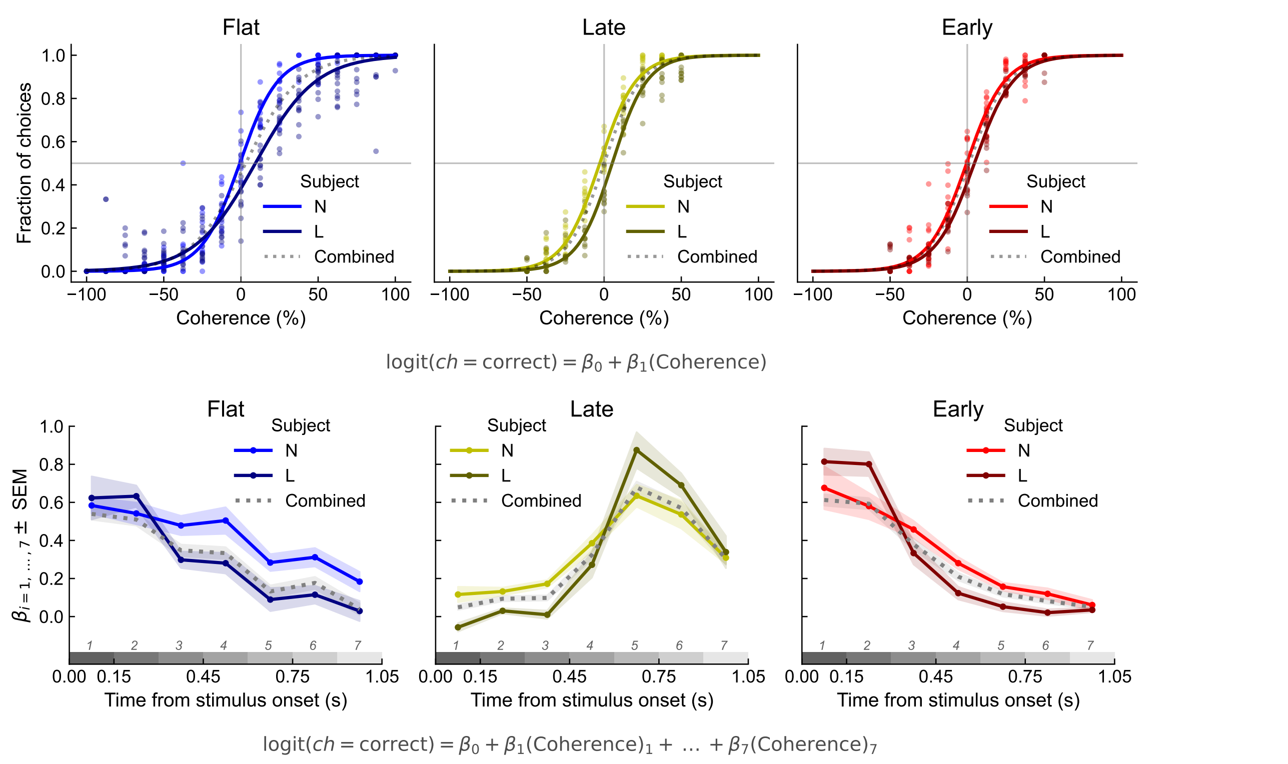

Figure 2. Behavioral characterization. Performances (top) and psychophysical kernels (bottom) for Flat (left), Late (middle), and Early (right) conditions computed via logistic fits of motion coherences and choices. Session-average performance is displayed as coherency bin dots for the two subjects. Logistic regression lines and psychophysical kernels are computed for the two subjects (solid lines) and combined (dotted).

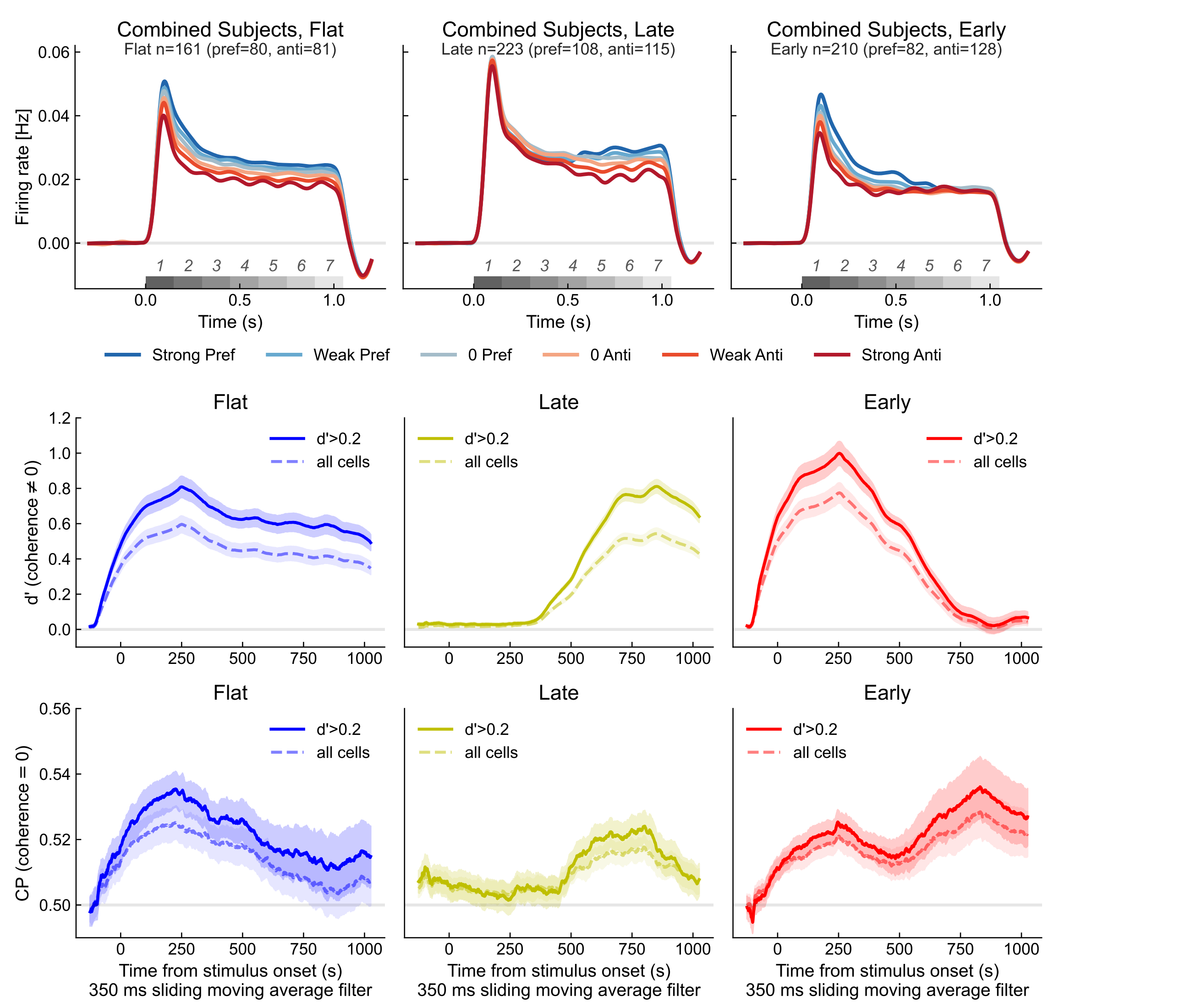

Figure 3. Adaptive temporal weighting in MT. Top: baseline-subtracted trial-average firing rate[2] (top) at different coherence levels (0, weak, strong) for preferred (strong R/L and choice R/L) and anti-preferred (strong R/L and choice L/R) tuning. Middle: moving average $d'(t)$ for firing rates aligned to preferred choice, i.e. (strong R - strong L) in preferred R, (strong L - strong R) in preferred L. Bottom: Choice Probability (CP) computed via AUC score of choice ROC analyses for firing rates in zero-coherence trials.

Network Model

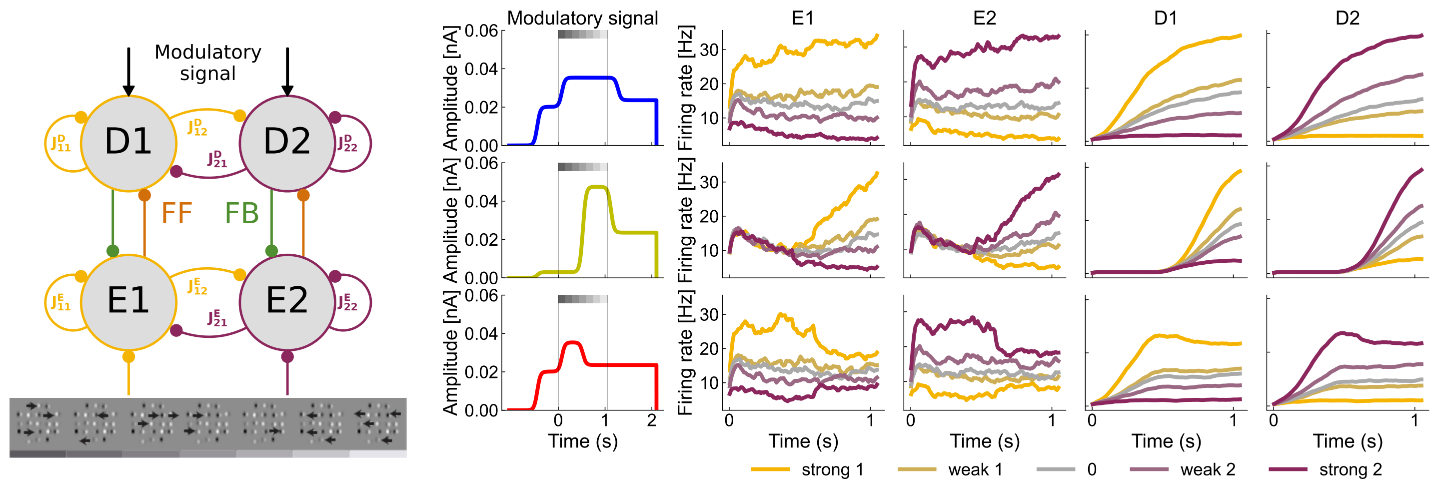

Figure 4. Two-paired sensory and decision populations model[3,4]. Model diagram (left) and example simulation outputs (right). Columns show the modulatory signal and firing rates of sensory (E1, E2) and decision populations (D1, D2) across coherence levels. Rows correspond to Flat, Late, and Early conditions.

Synaptic Dynamics

$$\frac{dS_i}{dt} = -\frac{S_i}{\tau_S} + (1-S_i)\,\gamma\,\sigma(x_i), \qquad \sigma(x) = \frac{ax-b}{1-\exp[-d(ax-b)]} \tag{1}$$

Input Currents

$$I_i = J_{\mathrm{A,ext}}\,\mu_0\big(1 \pm c(t)\big), \qquad dI_{\mathrm{N},i} = -\frac{I_{\mathrm{N},i}}{\tau_{\mathrm{N}}}\,dt + \sigma_{\mathrm{N}}\,dW_t \quad \text{(OU noise)} \tag{2}$$

$$I_{\mathrm{mod}}(t) = I_{\mathrm{baseline}} + (I_{\mathrm{peak}} - I_{\mathrm{baseline}})/(1+\exp[-b(t-a)]) \tag{3}$$

Sensory Circuit (E)

$$x_1^E = \boxed{J_{11}^E}\,S_1^E - \boxed{J_{12}^E}\,S_2^E + \boxed{J_{\mathrm{FB},1}}\,S_1^D + I_1^E + I_{\mathrm{N},1}^{\mathrm{stim}} + I_0^E + I_{\mathrm{N},1}^{\mathrm{bg}} - A_1 \tag{4}$$

$$x_2^E = \boxed{J_{22}^E}\,S_2^E - \boxed{J_{21}^E}\,S_1^E + \boxed{J_{\mathrm{FB},2}}\,S_2^D + I_2^E + I_{\mathrm{N},2}^{\mathrm{stim}} + I_0^E + I_{\mathrm{N},2}^{\mathrm{bg}} - A_2 \tag{5}$$

Integration Circuit (D)

$$x_1^D = \boxed{J_{11}^D}\,S_1^D - \boxed{J_{12}^D}\,S_2^D + \boxed{J_{\mathrm{FF},1}}\,S_1^E + I_0^D + I_{\mathrm{mod}} + I_{\mathrm{N},1}^{\mathrm{bg}} \tag{6}$$

$$x_2^D = \boxed{J_{22}^D}\,S_2^D - \boxed{J_{21}^D}\,S_1^D + \boxed{J_{\mathrm{FF},2}}\,S_2^E + I_0^D + I_{\mathrm{mod}} + I_{\mathrm{N},2}^{\mathrm{bg}} \tag{7}$$

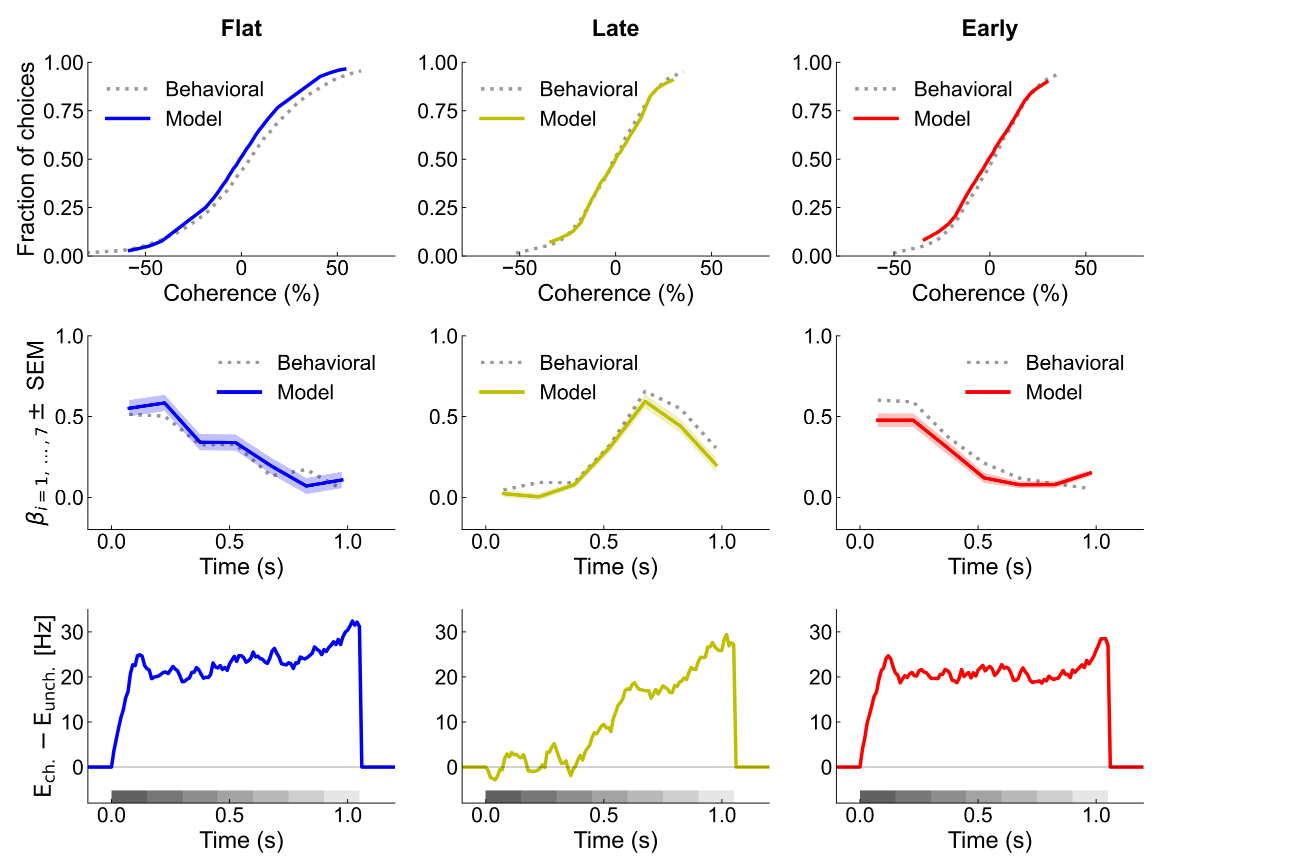

Figure 5. Simulation outputs compared to behavioral results. Choice performances (top), Psychophysical kernels (middle) and choice-tuned rate difference (bottom). Parameters fit via simulation-based inference.

Results and Future directions

- → We find that both behavioral and neural data show adaptive temporal weighting.
- → Our model allows replicating experimental findings by tuning network parameters.
- → Future stages include analyzing simulation outputs for pruning of weights.
- → Using recurrent neural network simulations we aim to show that introducing contextual modulation is a unifying mechanism for adaptive temporal integration.

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