Unsupervised Future-Predictive Learning in the Connectome-Constrained Drosophila Optical Lobe

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Abstract

Recent advances in connectome-based modeling of the fruit fly brain have enabled neural network architectures that mirror the anatomical wiring of the optic lobe (Marblestone, Wayne, & Kording, 2016). Despite the success of supervised approaches in predicting neural activity and performing optic flow estimation (Lappalainen et al., 2024), many natural settings lack explicit labels such as motion vectors. In this work, we propose an *unsupervised* learning strategy in which the input layer (R1–8) receives feedback signals to predict future visual inputs $I_{t+\Delta t}$ without any external label. We show that this approach partially reproduces ON/OFF direction selectivity in T4/T5 neurons, a hallmark of the fly visual system.

Keywords: connectome; unsupervised learning; future prediction; Drosophila; neural dynamics

Introduction

Connectome-based models of the fruit fly (*Drosophila melanogaster*) brain have garnered interest in computational neuroscience (Takemura et al., 2015; Shinomiya et al., 2019). Recent electron microscopy work has reconstructed synaptic connectivity among numerous cell types, leading to *Connectome-Constrained Deep Mechanistic Networks* (DMNs) (Lappalainen et al., 2024), which integrate anatomical knowledge with differentiable neural dynamical systems. Although supervised motion-vector training can reproduce aspects of the fly optic lobe, real organisms rarely have explicit velocity labels. This gap motivates the question of whether the connectome alone and unsupervised visual time-series can yield biologically relevant representations (Richards, Lillicrap, Beaudoin, ..., & Kording, 2019).

To investigate this, we modify the DMN from (Lappalainen et al., 2024) by removing external flow labels and focusing on *future-prediction* of visual input. Our results show partial ON/OFF direction selectivity in T4/T5 neurons, yet fail to fully differentiate subtypes such as T4a vs. T4b, which experimentally prefer orthogonal directions (Maisak & et al., 2013).

Methods

Connectome-Constrained DMN

We build upon the DMN originally proposed by (Lappalainen et al., 2024), which encodes the connectome of 64 cell types in the fly visual system. Each neuron follows a leaky integration model:

$$\tau_i \frac{dV_i}{dt} = -(V_i - V_{0,i}) + \sum_j w_{ij}\,\phi(V_j),$$

where V_i is the membrane potential of neuron i, $V_{0,i}$ is its resting potential, and $\phi(\cdot)$ is a threshold-linear nonlinearity. The weights w_{ij} reflect the measured number of synapses between the cell types of neurons i and j, scaled by a learned unit synapse strength. Each cell type thus shares parameters: a membrane time constant τ_i, resting potential $V_{0,i}$, and a sign determined by neurotransmitter profiles.

In the original DMN, a decoding sub-network was trained to output optic flow by minimizing a mean-squared error against measured flow fields. By contrast, in this work we remove such external flow labels and modify the loss function to focus on future frame prediction.

Unsupervised Future-Prediction Objective

Let I_t be the input image (brightness distribution) at time t, derived from visual data frames. During forward propagation in the DMN, the activity in the input layer (R1–8) is given by $I_t + B_t$, where B_t is feedback from higher layers. We define a loss to predict the future input $I_{t+\Delta t}$:

$$\mathcal{L} = \frac{1}{N}\sum_t \left\| (I_t + B_t) - I_{t+\Delta t} \right\|^2. \tag{1}$$

Thus, the network must learn internal representations that reproduce time-shifted versions of the input solely from self-consistency. We use standard backpropagation through time (BPTT) with the Adam optimizer.

Training Procedure

Dataset (Sintel). We use short 24 Hz, 19-frame video sequences from the MPI-Sintel database. Each sequence is upsampled to 50 Hz (40 frames). Additionally, frames are split vertically and randomly rotated (in 60° steps from 0° to 300°) with a 50% chance of horizontal flipping, thereby enriching the dataset with diverse spatio-temporal transformations (Lotter, Kreiman, & Cox, 2017).

Loss Function Setup. In Eq. (1), we set $\Delta t = 3$, so the network predicts the brightness 3 frames ahead. The activity in R1–8 is defined as $(I_t + B_t)$, with B_t computed by the DMN's recurrent connections.

Hyperparameters. Training is performed for 10,000 epochs with a batch size of 16. Synaptic strength scale factors and neuron-specific parameters are randomly initialized; the Adam optimizer is used with a fixed learning rate (e.g., 10^{-4}).

Training Configuration: MovingEdge Stimuli

To probe direction selectivity post-training, we employ the *MovingEdge* dataset from `flyvis.datasets.moving_bar.MovingEdge`. This dataset generates ON/OFF edges traveling across the visual field at angles from 0° to 330° in 30° increments. Each stimulus lasts 2 s (1 s pre-stimulus, 1 s post-stimulus), rendered at 200 Hz. Bar speed, size, and offset follow `flyvis` defaults to ensure stimuli match the biological scale for fly receptive fields.

Results

T4/T5 Neurons Show Partial Direction Selectivity

After training the DMN on the future-prediction task (without motion labels), we tested responses to the *MovingEdge* stimuli, focusing on T4 and T5 neurons known for strong ON/OFF direction selectivity. T4 subtypes (a–d) are typically ON-selective, and T5 subtypes (a–d) are OFF-selective.

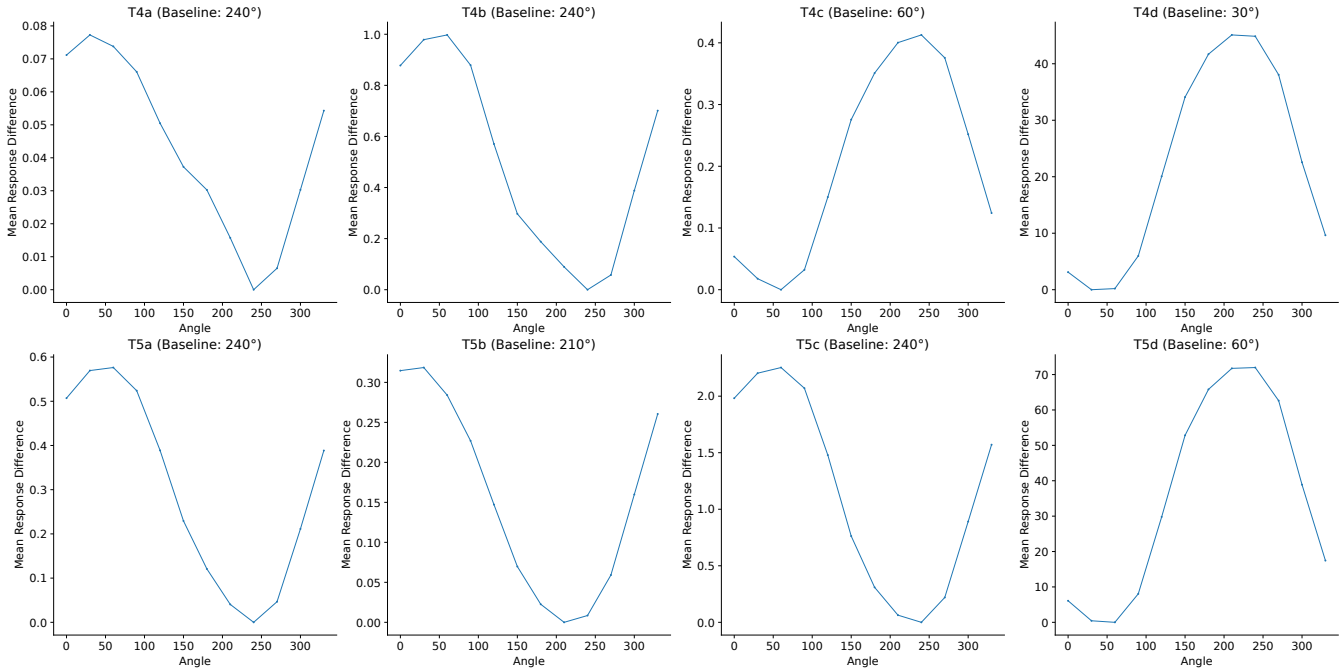

Figure 1: Example tuning curves for T4/T5 subtypes (a–d) under MovingEdge stimuli. The vertical axis shows the baseline-corrected mean response, and the horizontal axis shows motion angles in 30° increments. The network reproduces coarse ON/OFF segregation but does not clearly partition T4 subtypes by 90° steps, as documented in some experimental studies (Maisak & et al., 2013).

Membrane potentials were measured from -0.5 s to $+1.5$ s around stimulus onset. For each subtype, the condition with the lowest mean activity (the *baseline sample*) was subtracted from other conditions to yield *difference curves*. Final tuning curves were generated by averaging these differences over time and plotting them against stimulus angles.

Figure 1 shows that the model segregates ON versus OFF responses (T4 for bright edges, T5 for dark). However, the tuning curves lack the clear 90° separation reported experimentally (Maisak & et al., 2013), indicating that the model only partially replicates the biological direction preference.

Discussion

Our findings demonstrate that an unsupervised future-prediction scheme enables the DMN to acquire basic ON/OFF direction selectivity for T4/T5 neurons. This suggests that connectome constraints combined with time-series self-consistency can yield rudimentary motion tuning without explicit motion labels. However, the tuning for T4 and T5 subtypes lacks the distinct 90° separation seen experimentally, possibly because (1) the predictive loss does not strongly enforce precise directional axes, (2) random initial conditions may cause convergence to local optima, and (3) simplified modeling assumptions (e.g., omission of electrical synapses or glial effects) might limit fine-scale tuning (Nern, Scheffer, Schlegel, ..., & Rubin, 2025). Overall, our results highlight the promise of unsupervised, connectome-based approaches while underscoring the need for further refinements to capture the nuanced features of real neural circuits (Richards et al., 2019).

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