Efficient coding of visual motion signals in area MT and smooth pursuit.

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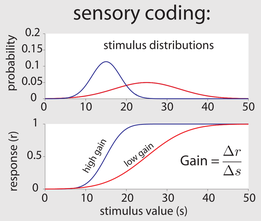
1. Introduction:

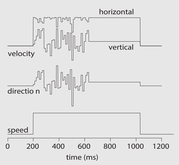
Performance in sensory-motor behaviors guides our understanding of many of the key computational functions of the brain: the representation of sensory information, the translation of sensory signals to commands for movement, and the production of behavior. Eye movement behaviors have become a valuable testing ground for theories of neural computation because the neural circuitry has been well characterized and eye movements can be tightly coupled to cortical activity (Osborne et al., 2005-9). Here we show that smooth pursuit eye movements, and the cortical sensory signals that mediate them, demonstrate the hallmarks of efficient sensory coding. Barlow (1961) proposed that neurons should adapt their sensitivity as stimulus conditions change in order to maintain efficient coding of sensory inputs. Evidence for efficient coding of temporal fluctuations in visual stimulus has been observed in the retina (Wark et al., 2009) and H1 (Brenner et al., 2000; Fairhall et al., 2001). We asked whether adaptation to stimulus variance generalizes to higher cortical areas and whether such adaptation impacts performance of visually-driven behavior. Specifically, we have studied the impact of dynamic fluctuations in motion direction on the gain of smooth pursuit and found neural correlates of pursuit adaptation in cortical area MT.

2. Experiments:

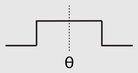
Barlow's hypothesis of efficient sensory coding:



Stimulus design:

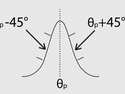


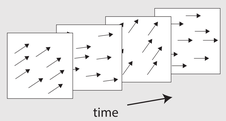
Stimuli: Stochastic motion perturbations (in direction or velocity) drawn from a uniform distribution



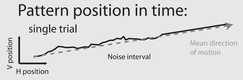
Pursuit Experiment: perturbation is applied to translation of target across screen

MT Experiment: motion perturbation applied to within aperture motion of a random dot kinetogram in the RF





Pattern position in time:

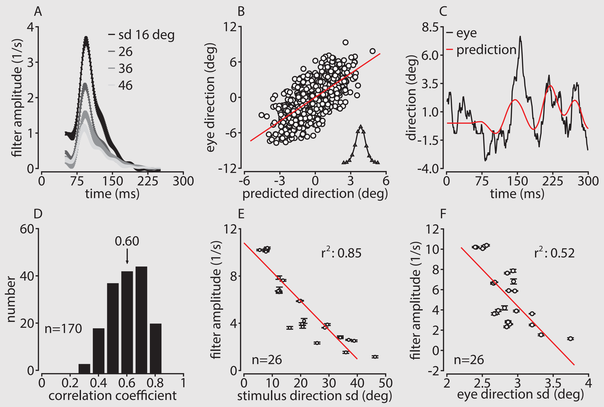


Extracellular single unit recording in awake, fixating monkeys

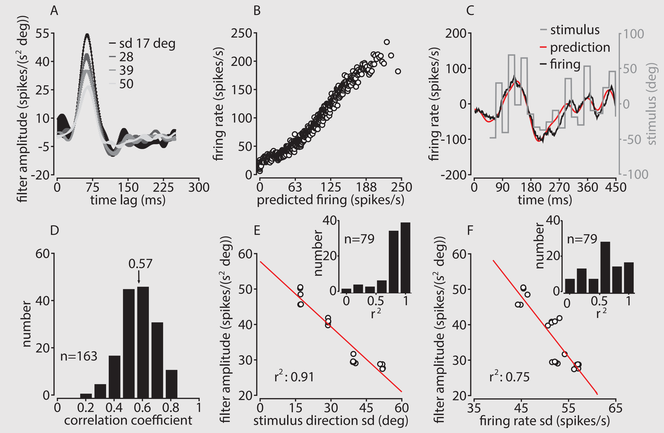
3. Linear analysis: Response gain scales inversely with motion variance for pursuit and MT neurons

$$\hat{e}(t) = \int_{-\infty}^{t} d\tau h(\tau) s(t-\tau)$$

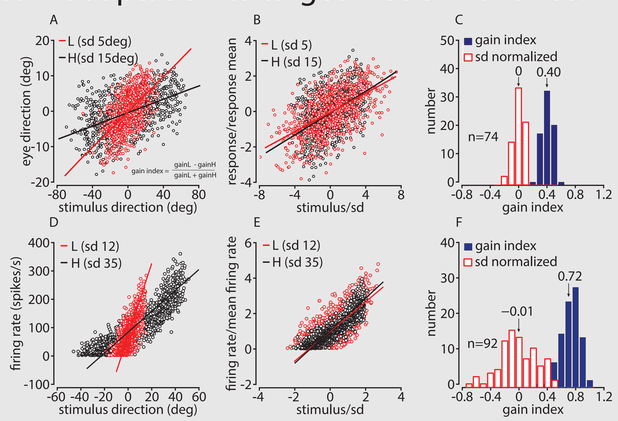
Pursuit:



MT neurons:

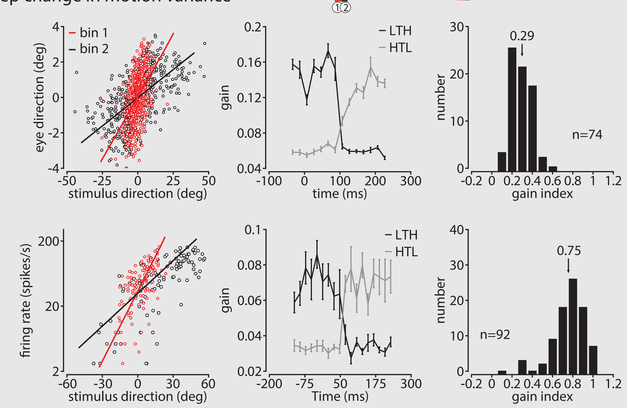


4. Gain adaptation to target motion variance:



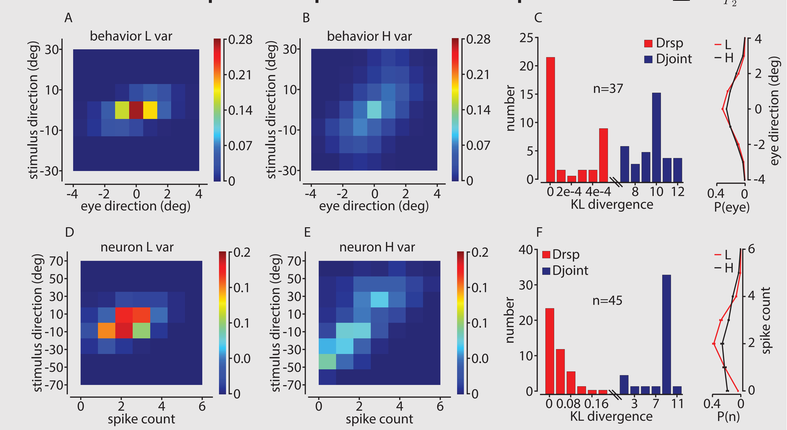
5. Dynamics:

step change in motion variance

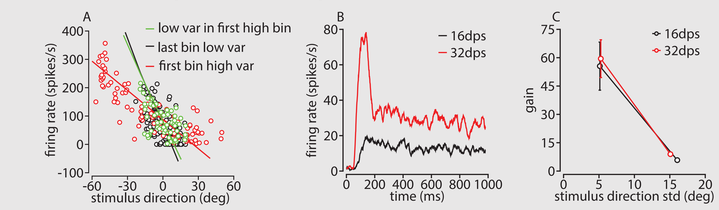


6. Rescaled input-output relationships:

$$D_{KL}(P_1||P_2) = \sum P_1 ln \frac{P_1}{P_2}$$

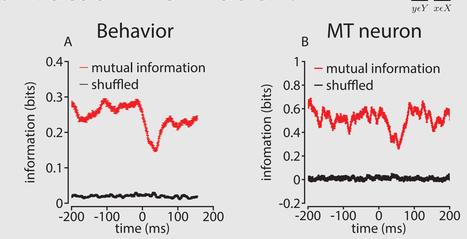


7. Gain adaptation depends on stimulus not rate:



8. Mutual information:

$$I(X;Y) = \sum_{y \in Y} \sum_{x \in X} p(x,y) log_2 \left(\frac{p(x,y)}{p(x)p(y)}\right)$$



Adaptation maintains stimulus information in pursuit behavior and MT neurons

Pursuit and MT neurons show indentical adaptation effects

9. Discussion:

Pursuit demonstrates that the brain encodes time-varying motion signals efficiently. Changes in both the linear gain and in the information encoded about target motion are consistent with the system preserving information via gain adaptation. When target motion variance is low, pursuit becomes more sensitive to perturbations and vice versa such that the information encoded about motion remains constant. These results demonstrate a behavioral benefit for efficient sensory coding. Physiology data show that adaptation in MT cortical neurons drives adaptation in pursuit. MT neurons, like pursuit, become less sensitive to target direction fluctuations as motion variance increases, consistent with Barlow's theory of sensory efficiency. Furthermore, this gain adaptation rescales rapidly after a step change in motion direction variance. We compared the eye direction distribution (or firing rate) in a 20 ms window preceding a step to that immediately following a step. The gain change is already apparent in the first time window after the step as a shift in the distribution of response vs stimulus values. These data suggest that feature selective cortical areas are themselves capable of efficient sensory coding and that efficiencies in cortical coding are relevant to behavioral performance.

1. Barlow HB, 1961. 2. Osborne LC and Lisberger SG, 2009 3. Osborne LC et al, 2005. 4. Fairhall AL et al., 2001. 5. Brenner et al., 2000. 6. Wark B et al, 2009. 7. Wark B et al, 2007.

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