A Dynamic Model for Decoding Direction and Orientation in Macaque's Primary Visual Cortex

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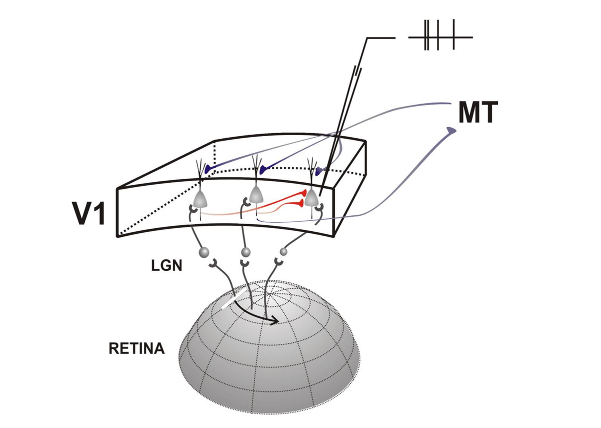
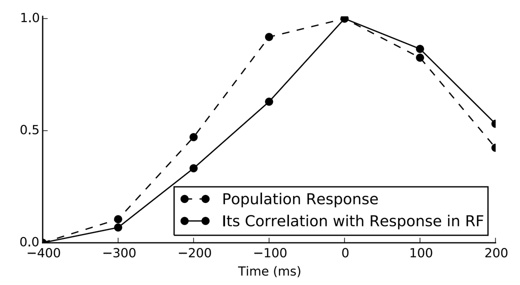
1. Motivation

1. When an oriented moving bar reaches the classical receptive field (cRF) of V1 neurons, how are directional and orientational (tuning) information dynamically encoded in their activity?
2. How could this information be decoded from a V1 population, within and outside the cRF (while approaching or passing the RF) ?

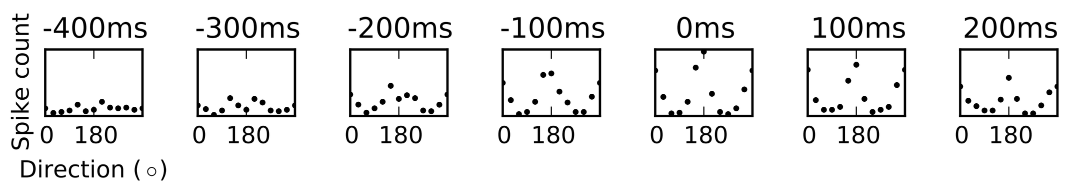
2. Stimulation Paradigm



- *Awake* macaque monkeys,
- Stimulus: *oriented, moving* bar, 12 directions.



- *Extracellular* recordings in area *V1* (67 cells).



3. Decoding Approach [1]

1. Definition of a model for the inter-trial variability of spike counts. We use the Poisson model, which needs only one parameter, its mean μ_0:

$$P(k) = \frac{\mu_0^k e^{-\mu_0}}{k!} \qquad (1)$$

2. Estimation of the tuning function on the stimulus' parameters (orientation, direction, ...) : f(ϑ)= mean(k | ϑ) such that :

$$P(k|\vartheta) = \frac{f(\vartheta)^k e^{-f(\vartheta)}}{k!} \qquad (2)$$

3. Pooling of the population information assumes conditional independence:

$$P(Y|\vartheta) = \Pi_{i=1}^{N} P(k_i|\vartheta), Y = [k_1, k_2..k_N] \qquad (3)$$

4. Bayes' rule. $P(\vartheta|Y) = \frac{P(Y|\vartheta)P(\vartheta)}{P(Y)}$
5. Maximum likelihood paradigm

   -The evidence term $P(Y)$ is a normalization term independent of $\vartheta \rightarrow P(Y)$=cst

   -There is no prior knowledge on $\vartheta \rightarrow \forall(\vartheta_1, \vartheta_2), P(\vartheta_1) = P(\vartheta_2)$

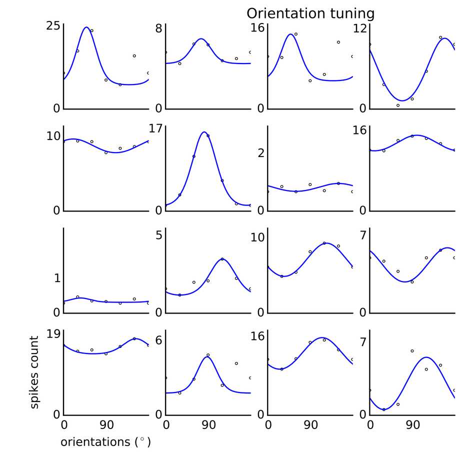
   $\rightarrow$ Maximizing the posterior $P(\vartheta|Y)$ is equivalent to maximizing :

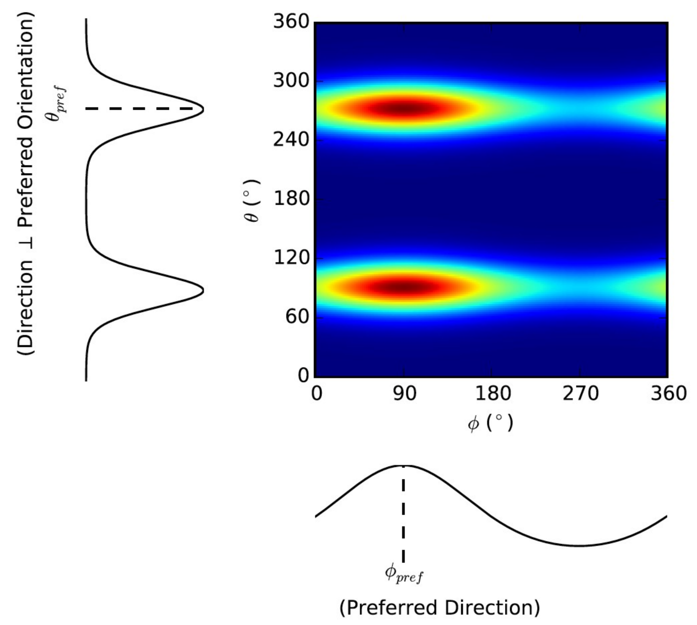
$$L(\vartheta) = P(Y|\vartheta) = \Pi_{i=1}^{N} \frac{f_i(\vartheta)^{k_i} e^{-f_i(\vartheta)}}{k_i!}$$

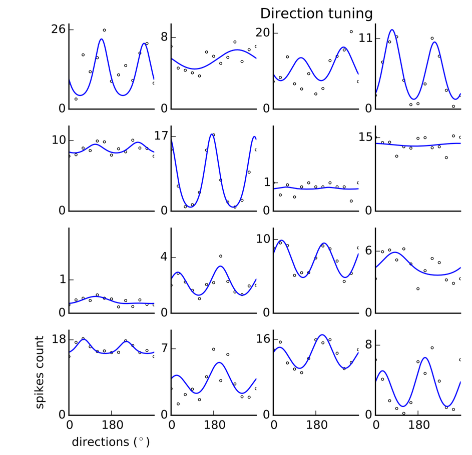
6. Accuracy is computed using a 100-fold Leave One Out cross-validation scheme.

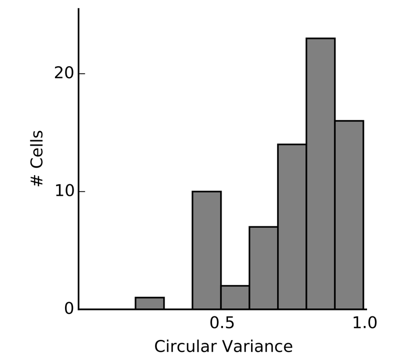
4. Generative Tuning Model

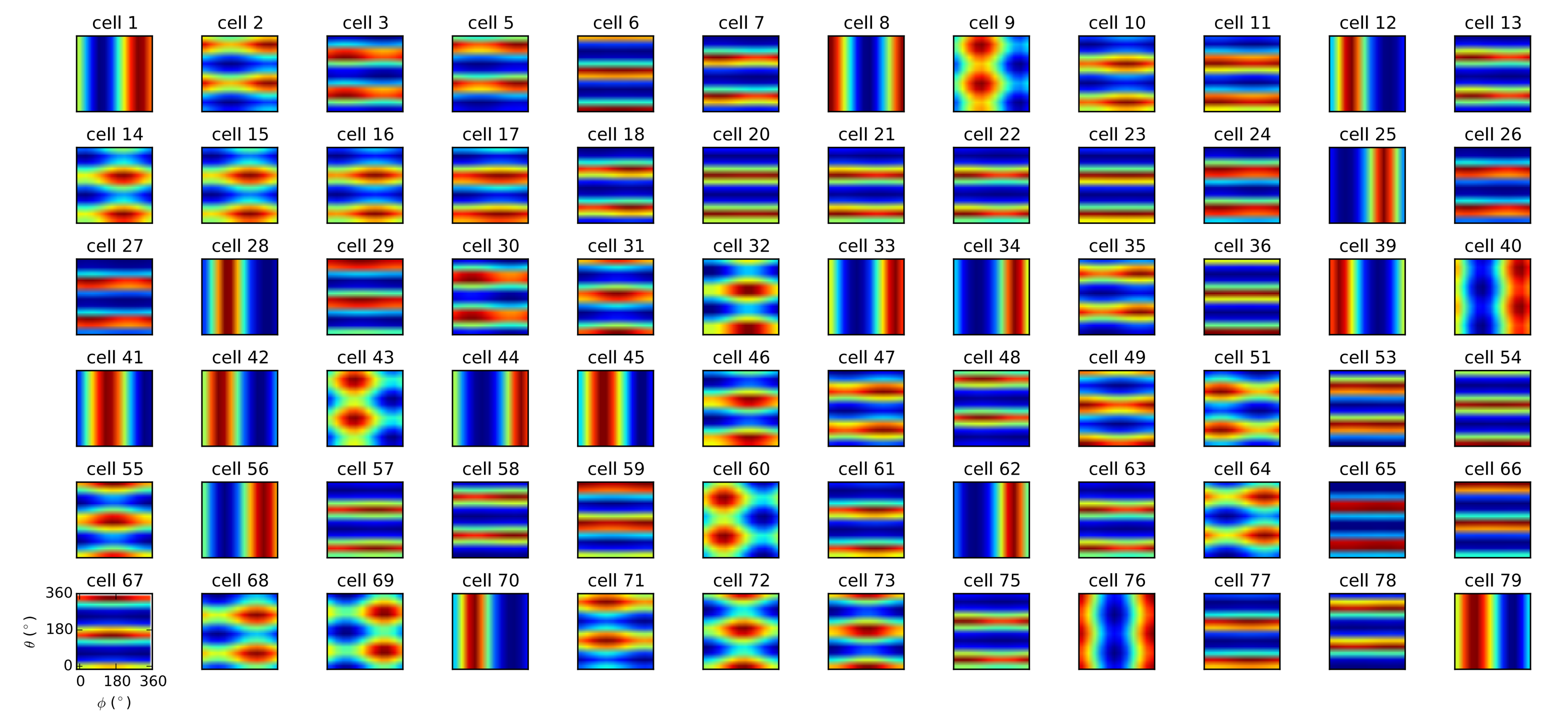
$$f(\phi, \theta) = R_0 + (R_m - R_0) \cdot e^{\kappa_\theta \cdot (\cos(2(\theta - \phi_0)) - 1)} \cdot e^{\kappa_\phi \cdot (\cos(\phi - \phi_0) - 1)}, \text{D}\perp\text{O} \rightarrow \phi = \theta$$

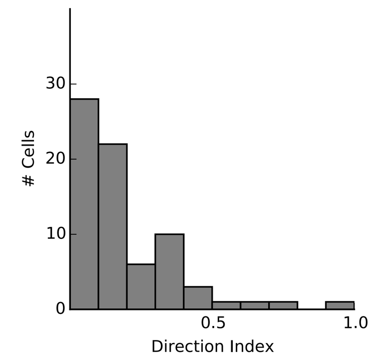








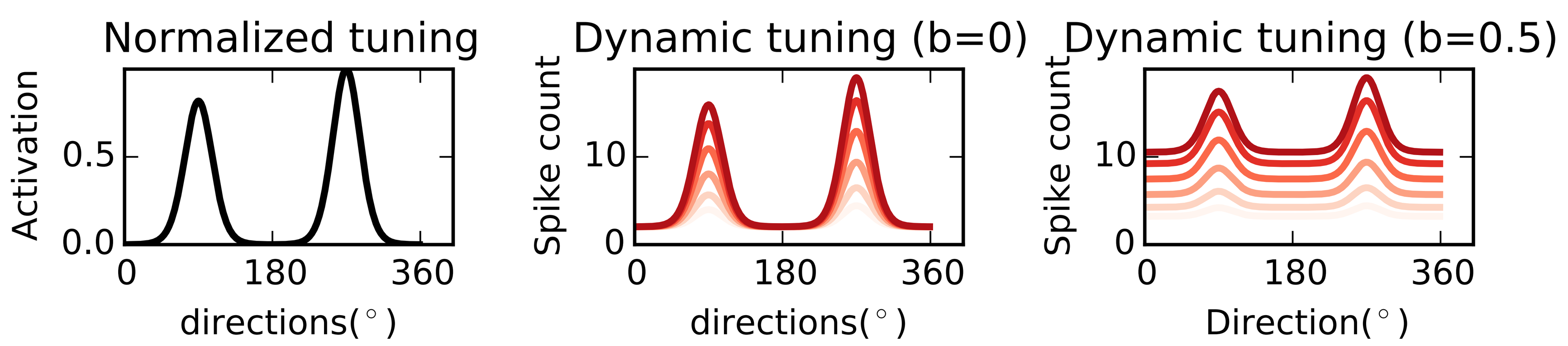


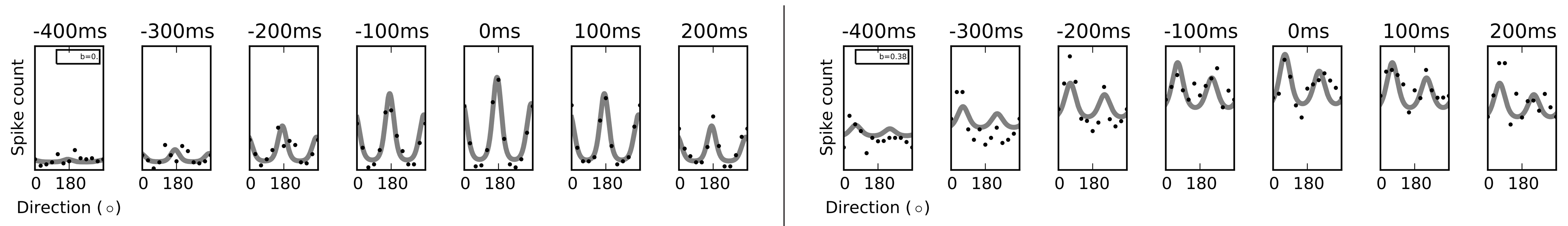


5. Generative Model of Dynamic Tuning

$$\mathbf{f}(\phi, \theta, \mathbf{t}) = \mathbf{R_0} + (\mathbf{R_m} - \mathbf{R_0}) \cdot \mathbf{A}(\mathbf{t}) \cdot (\mathbf{b} + (\mathbf{1} - \mathbf{b}) \cdot \mathbf{e}^{\kappa_\theta \cdot (\cos(\mathbf{2}(\theta - \phi_0)) - \mathbf{1})} \cdot \mathbf{e}^{\kappa_\phi \cdot (\cos(\phi - \phi_0) - \mathbf{1})})$$

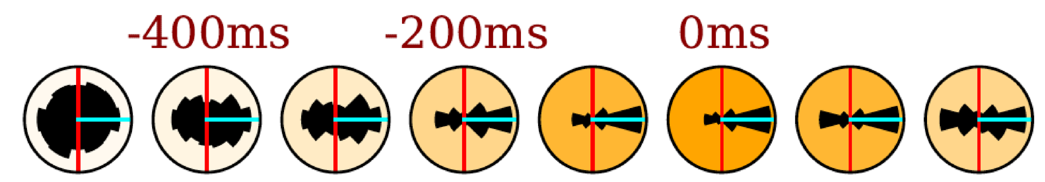
with a **Gaussian activation** profile: $A(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(t-\mu)^2}{2\sigma^2}}$ and a **constant offset-to-gain ratio** : b





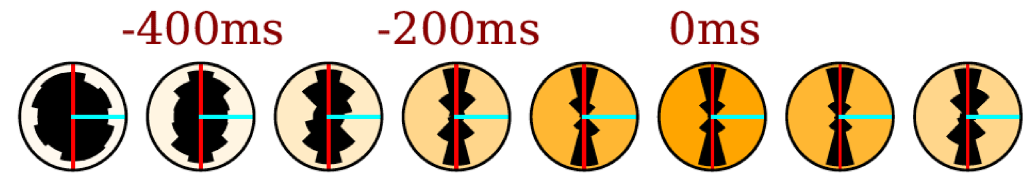
6. Dynamic Decoding of θ and ϕ

Decoding direction orthogonal to orientation :

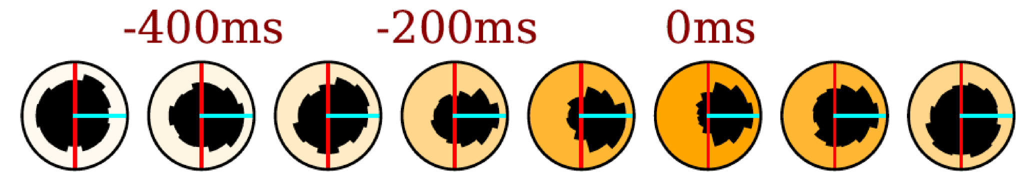


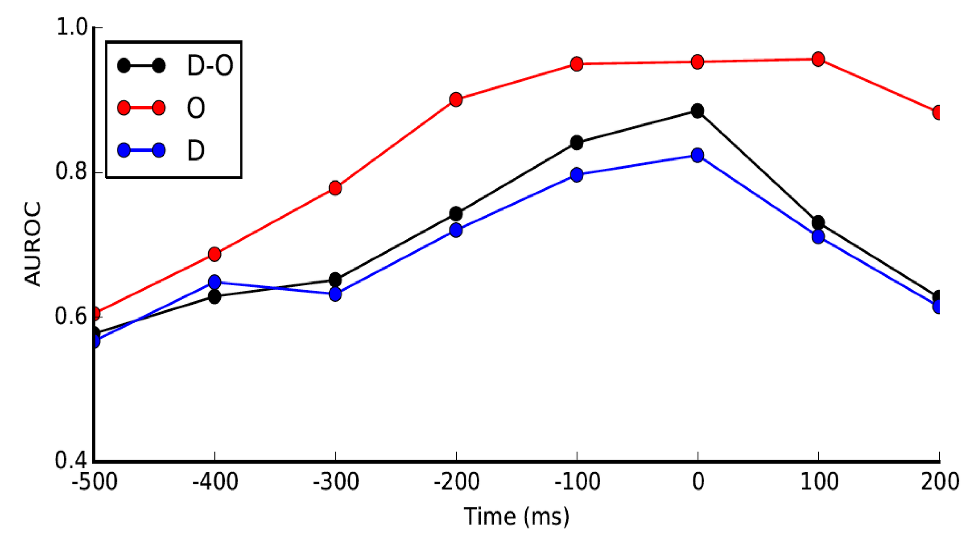
Decoding using separable direction and orientation :

Orientation



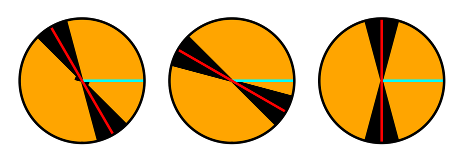
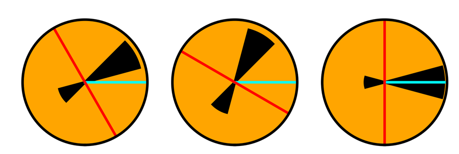
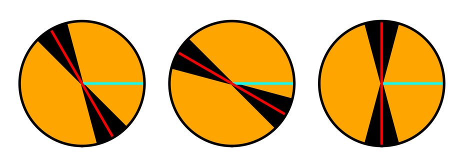
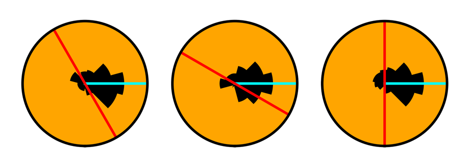
Direction





7. Predictions on Surrogate Data

Using the tuning curves, we generated surrogate spike rasters for $\phi = 0$ and $\theta \in \{\pi/6, \pi/3, 0\}$:

Orientation Tuning	
	
	Direction Tuning
	
Joint O-D Tuning	
	

References

[1] M. Jazayeri and J.A. Movshon. Optimal representation of sensory information by neural populations. *Nature Neuroscience*, 9(5):690–696, 2006.

Acknowledgment

This work was supported by "BrainScaleS" (EC FP7-269921) and "FACETS-ITN" (FP7-237955). More on http://invibe.net/LaurentPerrinet/Publications/Taouali16odd.