Predicting the relationship between sensory neuron variability and perceptual decisions

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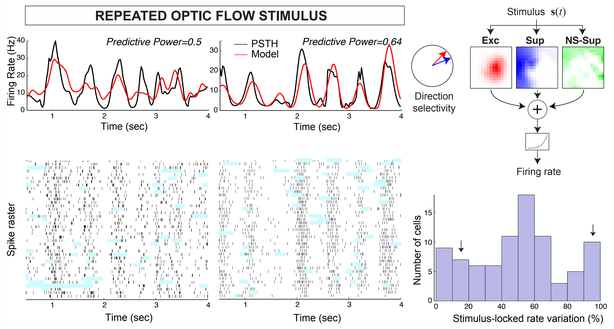
Motivation

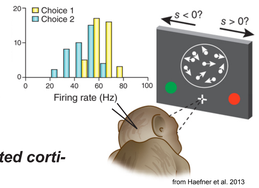
While it is well understood that visual cortical neurons receive only a fraction of their inputs from upstream visual areas [1,2], a majority of studies of visual processing – both experimental and computational – necessarily focus on the role of feed-forward processing in vision. However, much recent work has described the possibility of inferring details of the network state from a common element of extracellular recordings, local field potentials [3-6]. In this work, we evaluate the impact of ongoing network activity on response variability of MT in both passive fixation conditions and during a motion discrimination task

Response variability of MT neurons



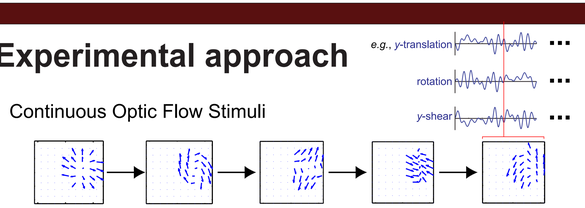
Only ~50% of the firing rate variation is stimulus locked in a passive fixation task. Previous studies have shown that part of the response variability can be explained by ongoing network activity [4-5, 7].

Response variability of MT is also related to perceptual decision in a motion discrimination task [8].



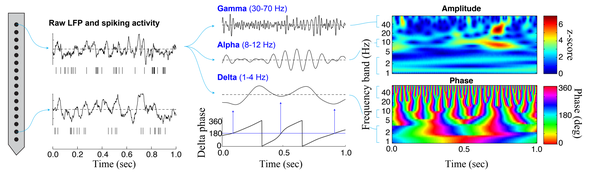
Can we explain spontaneous and decision-related cortical variability with ongoing network activity?

Experimental approach



Evolution of each optic flow component is independent low-passed Gaussian noise. A circular aperture is moving around slowly to explore the spatial profile of MT receptive fields.

Extracellular recordings were made in area MT in an awake macaque during a simple fixation task (*e.g.*, see [10]). Eye position was monitored at 500Hz with an infrared eye tracker.

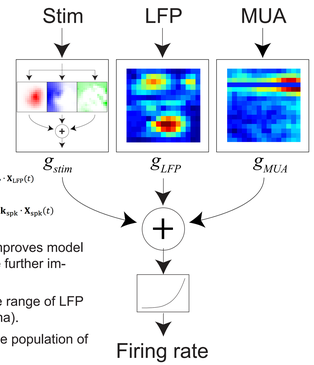


A Bayesian spike removal algorithm is applied to the raw LFP to remove artifactual correlations between spikes and LFPs ([9]).

Time frequency analysis fo the LFPs was done using the continuous wavelet transform with a complex Morlet mother wavelet. Instantaneous phase and amplitude at each frequency were then given by the phase and modulus of the wavelet coefficients.

Modeling framework

Neural response is modeled with a unified nonlinear framework using both stimulus (left, [10]) and network activity inferred from the LFP (middle) and MUA (right).

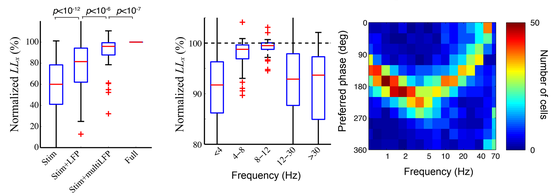


Contribution of LFP:

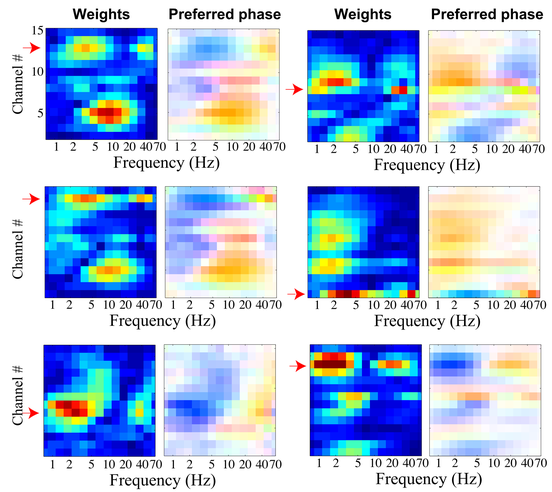
$$g_{LFP}(t) = \sum_f w_f \{A_{s,f}(t)\cos[\phi(f,t) - \phi_f^0]\}$$
$$= \sum_f A_{s,f}(t)[\alpha_f \cos\phi(f\ t) + \beta_f \sin\phi(f,t)] = \mathbf{k}_{LFP} \cdot \mathbf{x}_{LFP}(t)$$

Contribution of MUA: $g_{spk}(t) = \sum_{d,t} k_{d,t} r_d(t-\tau) = \mathbf{k}_{spk} \cdot \mathbf{x}_{spk}(t)$

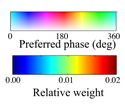
- Inclusion of LFP signals significantly improves model performance. Adding MUA provides little further improvement.
- Model performance depends on a wide range of LFP frequency bands (delta, beta, and gamma).
- Consistent phase preference across the population of cells.



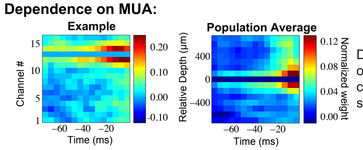
LFP modeling across cortical depth



LFP from the same electrode contributed most to predicting single unit spiking, but there was also contribution from other depths, particularly in the low frequency range.

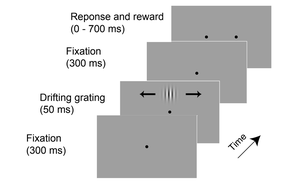


Dependence on MUA:

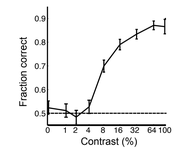


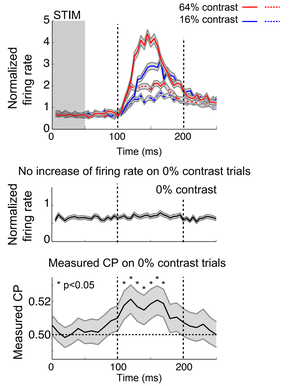
Dependence of single unit activity on MUA was localized to nearby channels, consistent with previous studies [11].

Motion discrimination task



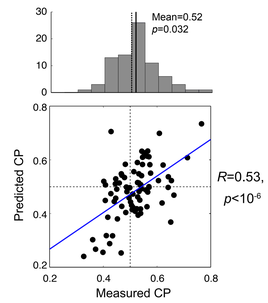
Psychometric function:





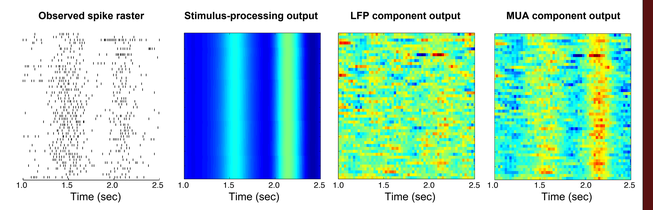
Significant CP's were only observed at the typical response latencies, although there is no increase of firing rate.

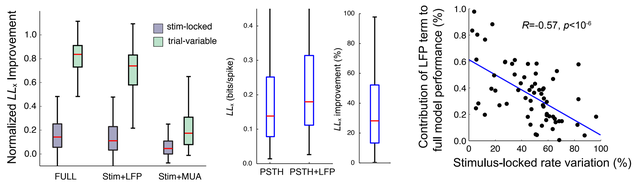
Prediction of choice probability



Predicted CP was calculated using predicted response from the LFP model.

Network inputs predict variability





- Trial-variable component of the LFP signal contributes most to the model performance improvement
- Contribution of LFP to predicting spiking activity was larger for units with more variability

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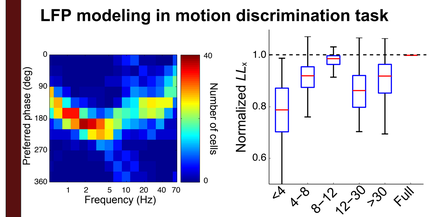
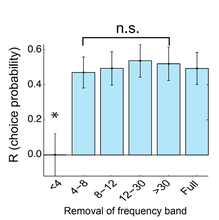
Choice probability of MT neurons predicted by delta-band phase

LFP modeling in motion discrimination task

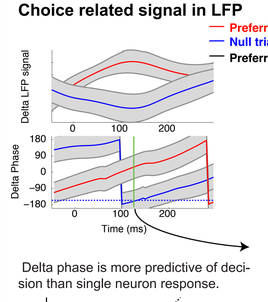


Phase preference and dependence of model performance across frequency bands were similar as the passive condition

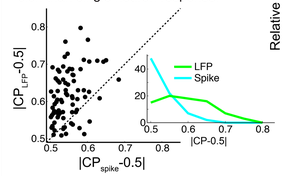


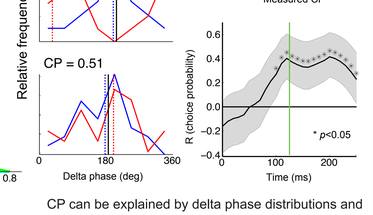
Only removal of delta band affects the ability to predict CP

Choice related signal in LFP



Delta phase is more predictive of decision than single neuron response.





CP predicted by delta phase

CP can be explained by delta phase distributions and the preferred delta phase of the neuron.

Conclusions:

1. Only a fraction of cortical neuron response is stimulus driven. Part of the response variability can be explained by ongoing network activity.

2. Consistent dependence on LFP phase was observed across MT neurons and across task conditions.

3. Correlations between neuron activity and behavior (choice probability) can be predicted by low-frequency LFP components.

4. New modeling framework for incorporating network influences into stimulus processing.

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