Modulation of stimulus processing by network activity across cortical depth in area MT

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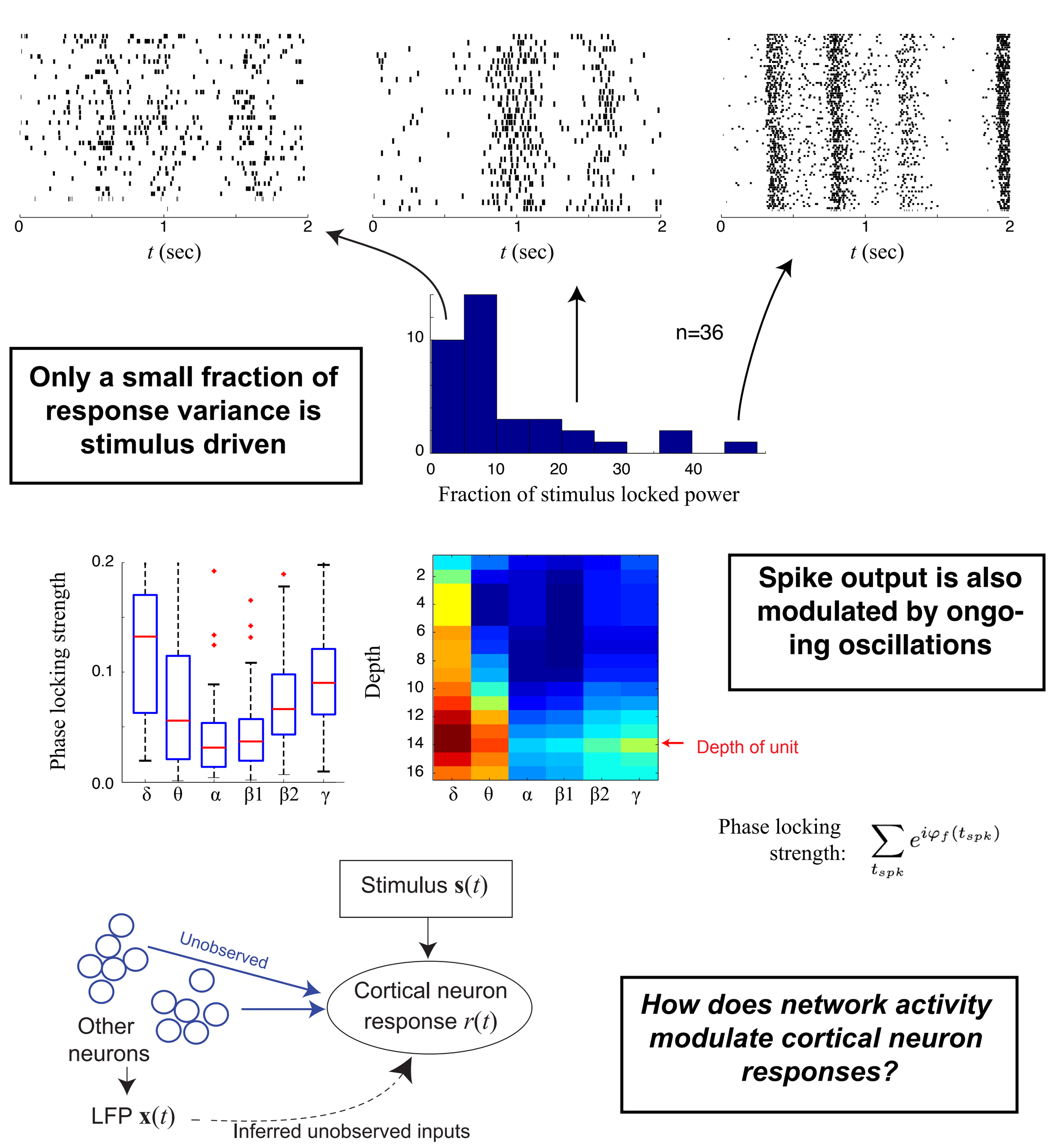
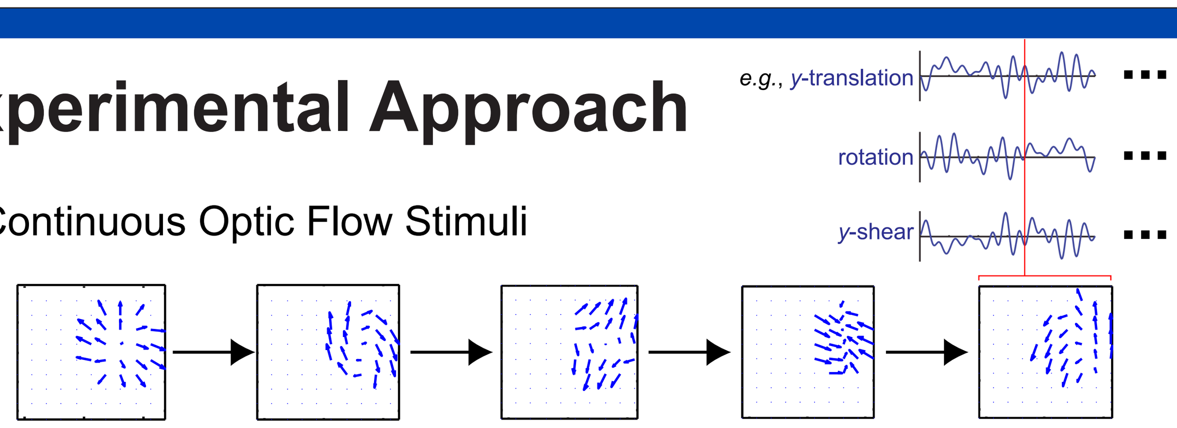
Motivation

Visual cortical neurons receive only a fraction of their inputs from upstream visual areas [1,2], and recent work has explored the possibility of inferring details of the network state from a common element of extracellular recordings, local field potentials [3-6]. Here, we use nonlinear modeling to understand the contributions of stimulus-driven inputs and network modulation in explaining the response of MT neurons.



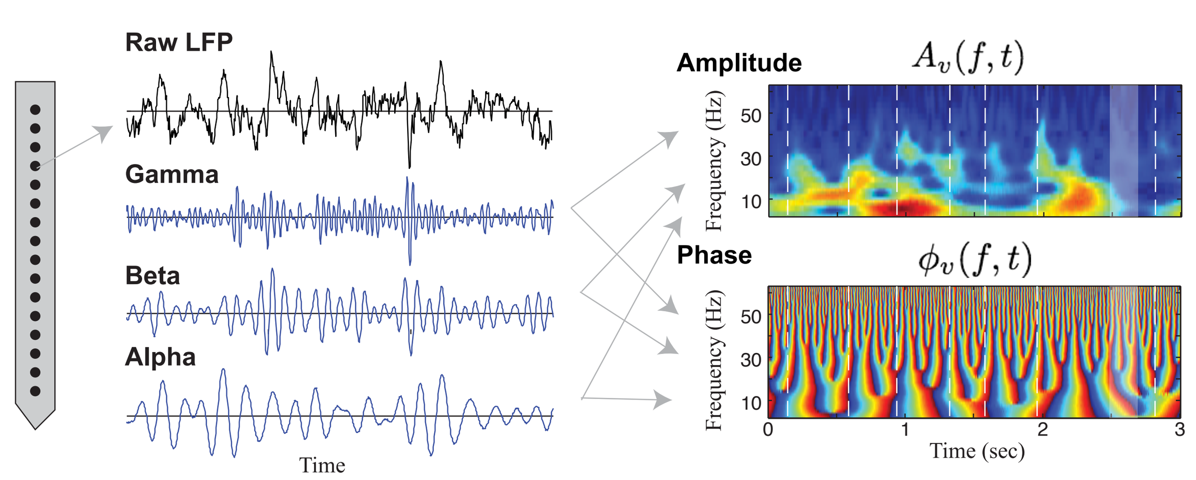
Experimental Approach

Continuous Optic Flow Stimuli



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 field.

Extracellular recordings were made in area MT in an awake macaque during a simple fixation task (*e.g.*, see [3]). Eye position was monitored at 500Hz with an infrared eye tracker.

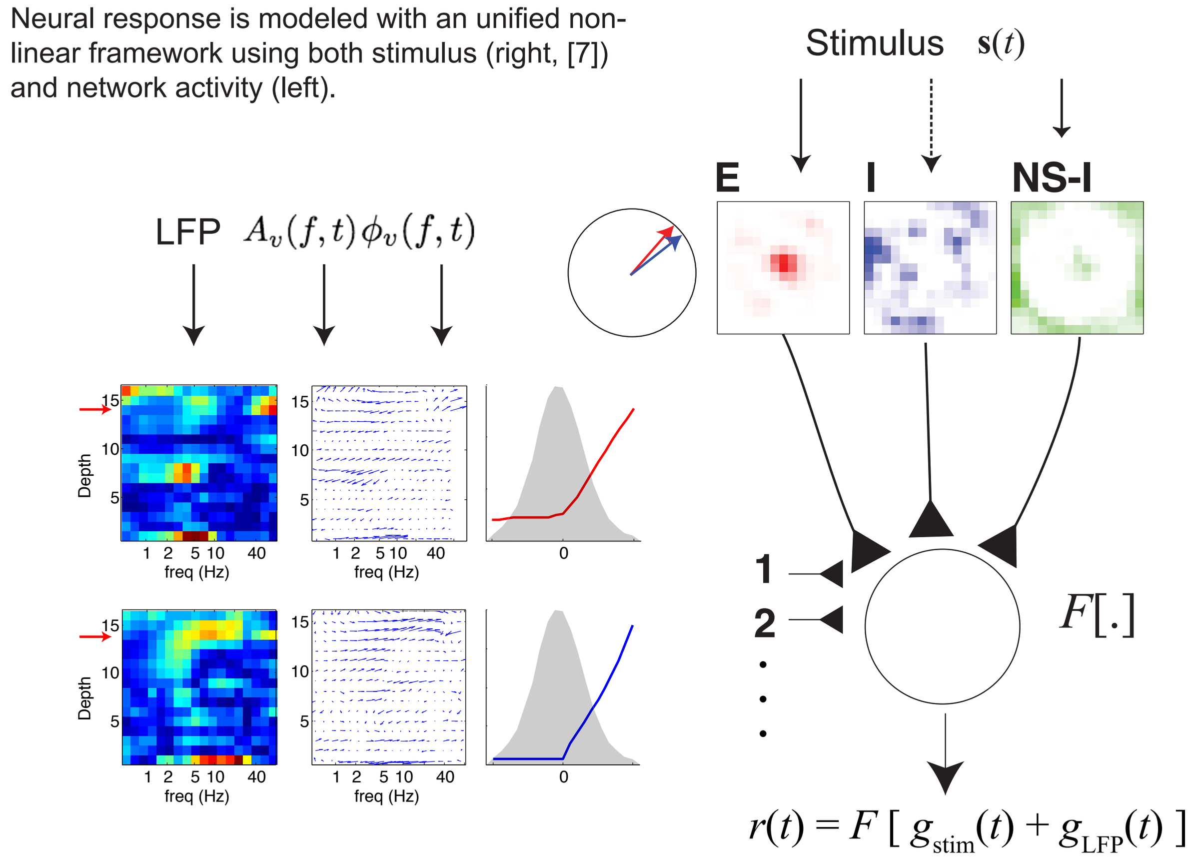


A Bayesian spike removal algorithm is applied to the raw LFP to remove artifactual correlations between spikes and LFPs ([4]).

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

Modeling Framework

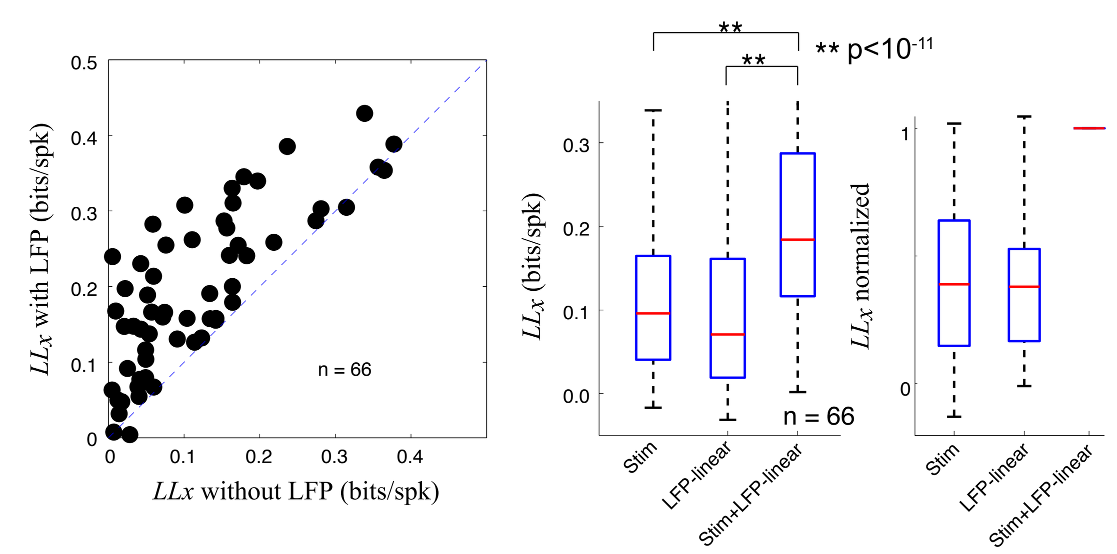
Neural response is modeled with an unified nonlinear framework using both stimulus (right, [7]) and network activity (left).



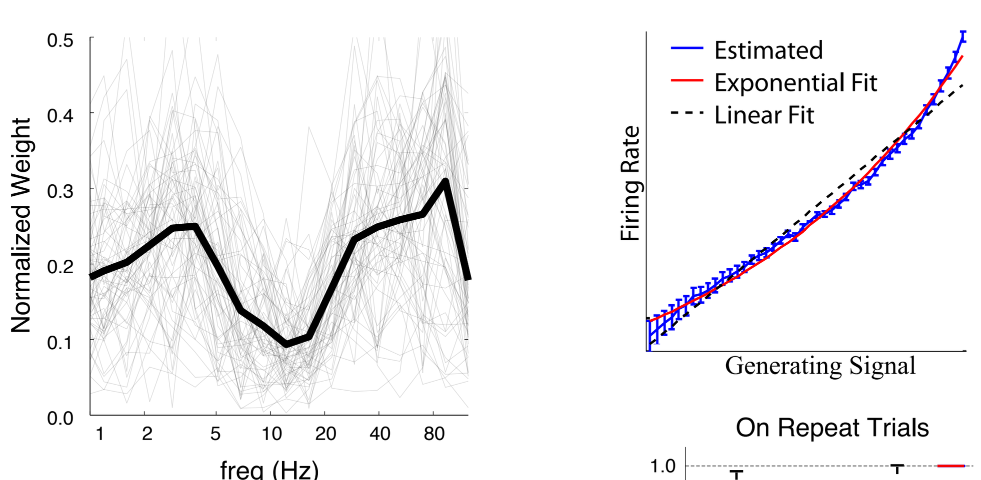
$$r(t) = F\,[\,g_{\text{stim}}(t) + g_{\text{LFP}}(t)\,]$$

$$g_{\text{LFP}}(t) = \sum_f w_f \{A_v(f,t)\cos[\phi(f,t) - \phi_f^0]\} = \sum_f A_v(f,t)\,[\alpha_f \cos\phi(f,t) + \beta_f \sin\phi(f,t)]$$

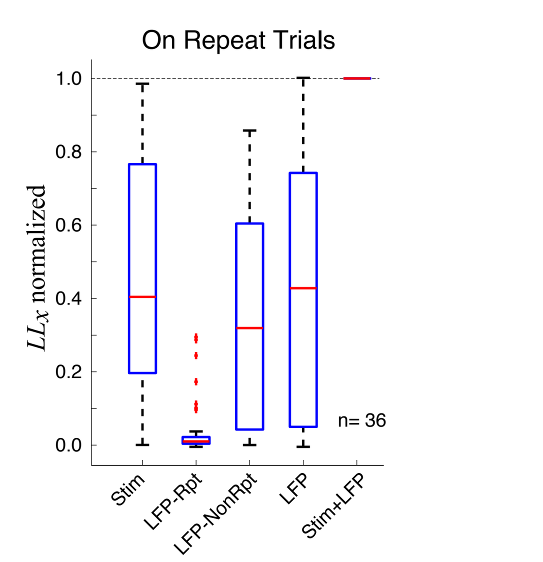
First-order LFP phase model



Doubled performance with LFP included!



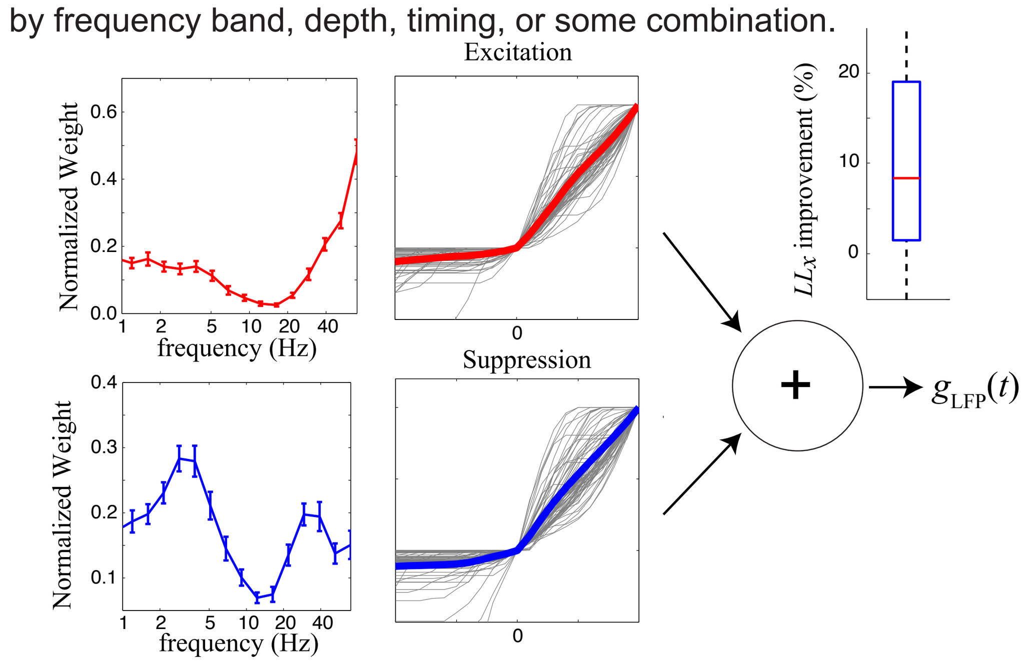
The model identifies two distinct frequency bands that is most predictive of spikes. This is consistent with the traditional metric of phase lock strength.



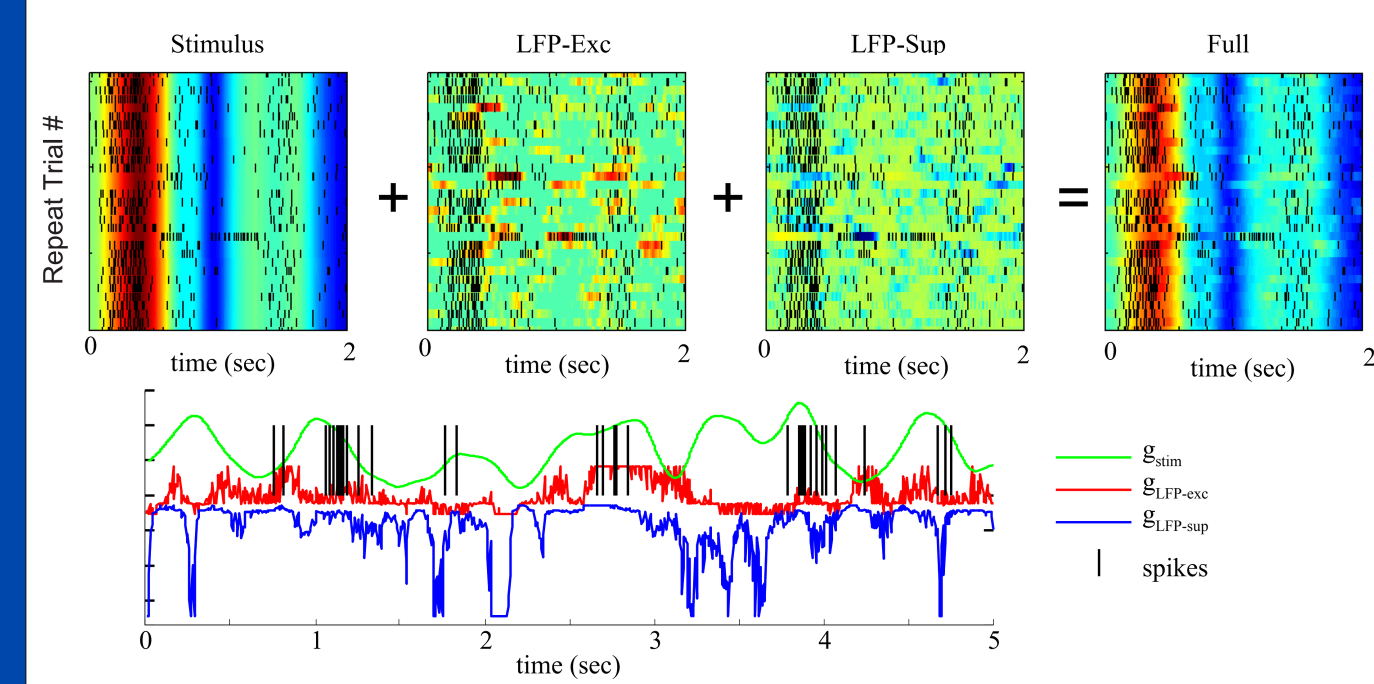
The LFP-based signal is largely not stimulus locked: it is this non-repeatable part of LFP that contributes to the prediction

Nonlinear LFP model

Linear LFP models only capture the "average" feature modulating neuronal responses. However, just as cortical neuron selectivity depends on multiple nonlinear inputs, one might expect multiple nonlinear inputs to be represented in the LFP, which could be distinguished by frequency band, depth, timing, or some combination.

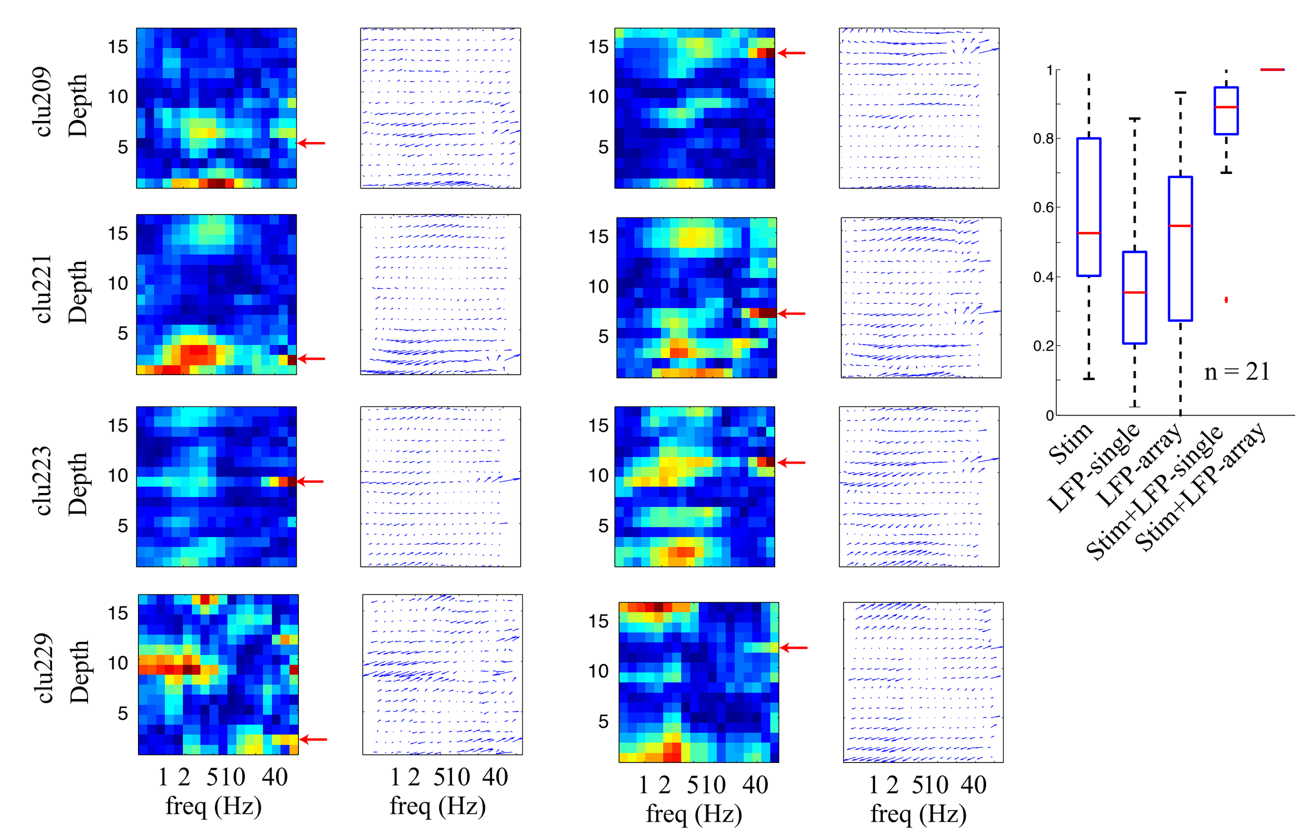


Model Prediction:



LFP modeling across cortical depth

Modulatory inputs into given cortical areas are layer specific ([10]), the most "informative" LFP signal may not be from the same electrode.



The high frequency LFP from the same electrode is most useful.
Neural response depend on low frequency LFP from distinct recording sites ,
This depth profile is consistent within experiment.

Conclusions:

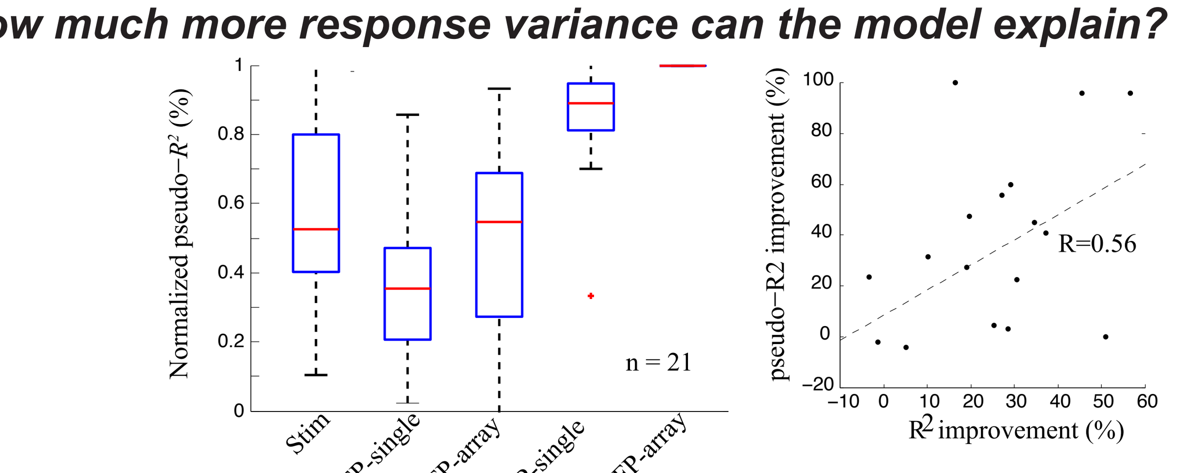
1. Only a fraction of MT neuron responses are predictable form the stimulus. Including network activity (LFPs) improves model predictions by a factor of two.

2. Two distinct frequency bands, gamma (>30 Hz) and delta (1-4 Hz), are most predictive of spiking. Their effects are best modeled by separate excitatory and suppressive nonlinear inputs respectively.

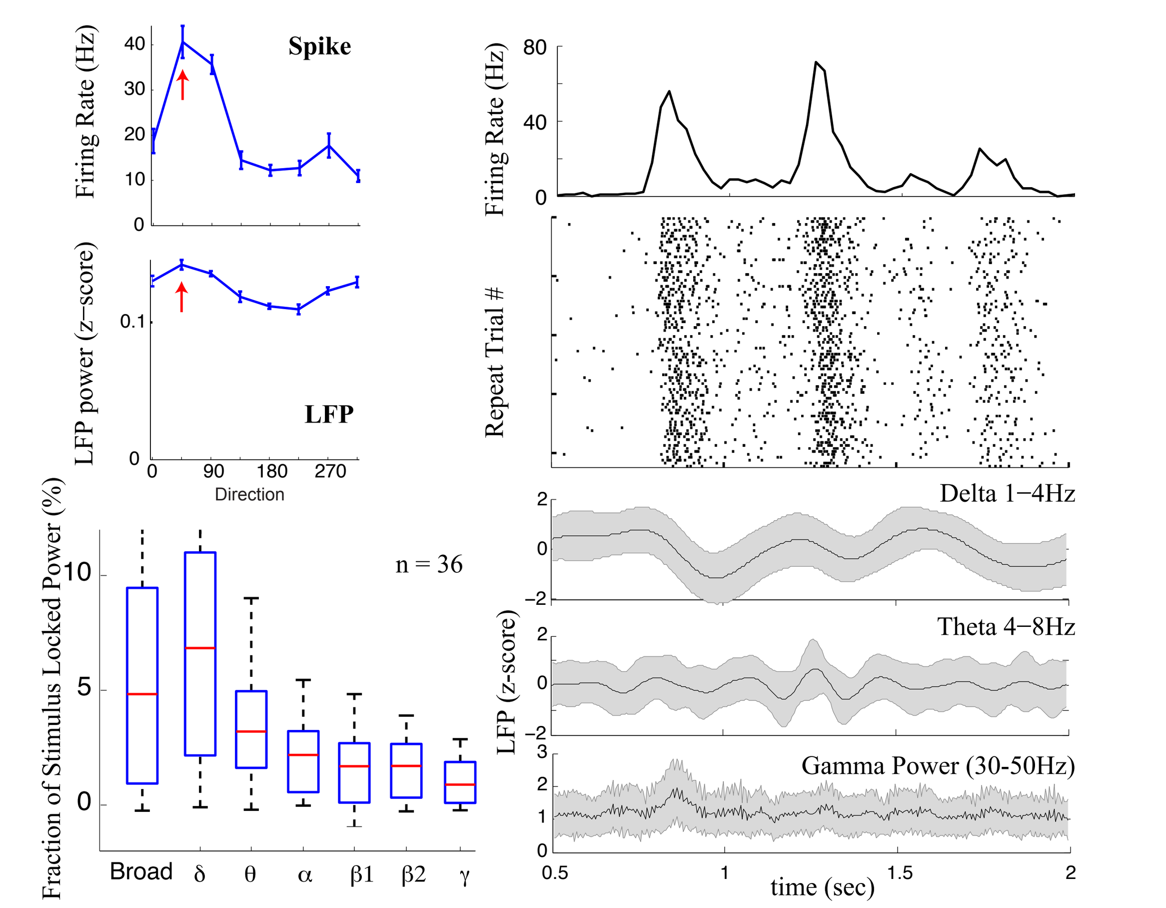
3. Neural responses depend on LFPs measured across cortical depths. Simultaneously recorded neurons depend on low-frequency LFPs with similar depth profiles, suggesting common modulatory inputs.

4. MT LFPs are only weakly dependent on the stimulus, and they can be used to capture largely stimulus-independent modulatory effects on single-neuron responses.

How much more response variance can the model explain?



Stimulus dependence of spike and LFP



LFP has similar stimulus preference as spikes, but is much less stimulus dependent

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