Cognitive control of speed-accuracy trade-off in a neural model of two-stage decision making

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Introduction

Decisions are faster and less accurate when conditions favour speed (vice versa for accuracy)
Speed-accuracy trade-off (SAT) reveals a cognitive control mechanism for decision processing
See Standage, Blohm and Dorris, Front Neurosci, 2014

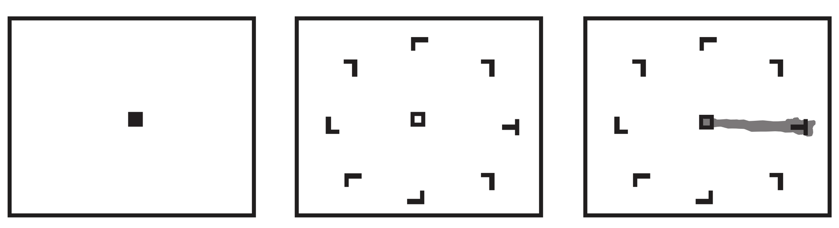
SAT is well characterized by the principles of bounded accumulation
A higher decision bound favours accuracy at the expense of speed (and vice versa)
... but what is the implementation of the bound in brain circuitry?
See Standage, Wang and Blohm, Front Neurosci, 2014

Electrophysiological data recorded from monkeys performing an SAT task reveal neural mechanisms
i.e. SAT condition-dependent modulations of neural activity
Heitz and Schall, Neuron, 2012; Heitz and Schall, Phil Trans R Soc B, 2013

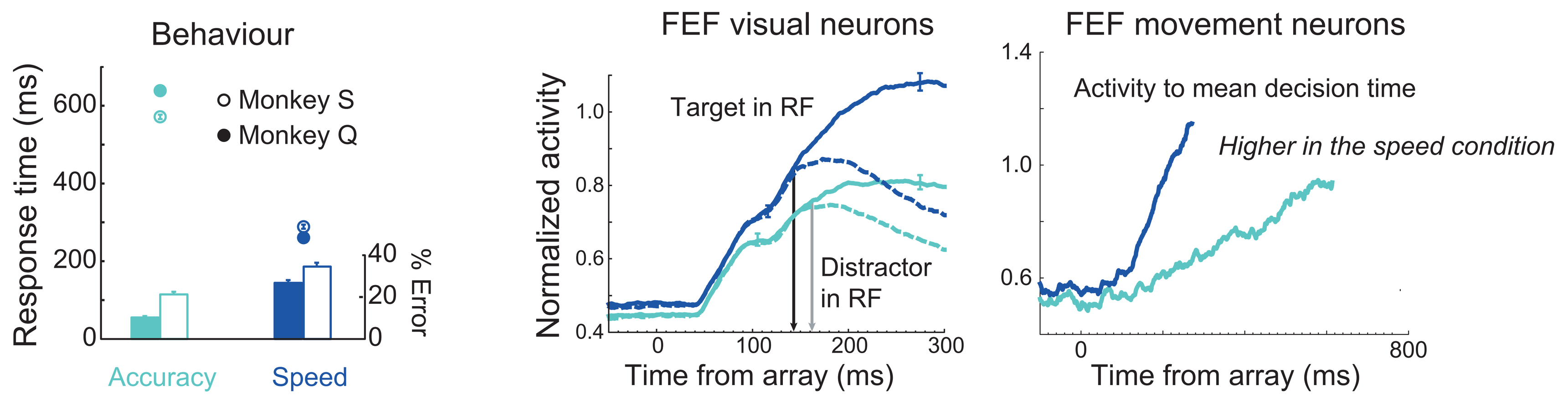
We invesitgate the neural basis of SAT by attempting to account for 10 neural modulations
Neural-circuit model of 2-stage decision making
If we can account for the data, we can make predictions for experimental testing

Background

Heitz and Schall, Neuron, 2012



Monkeys performed an 8-choice visual search task under speed and accuracy conditions

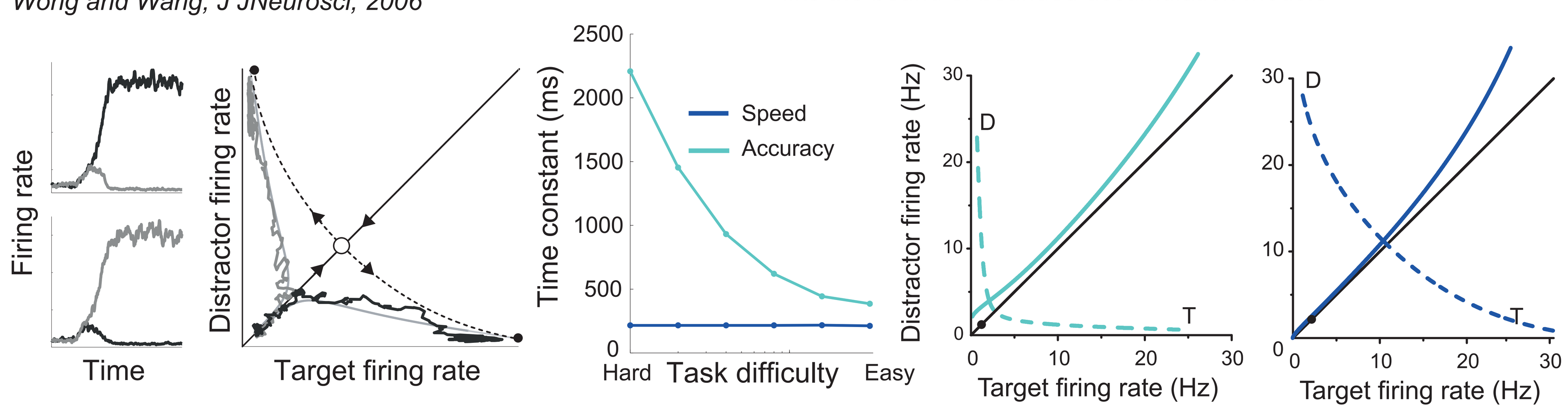


Under speed conditions (vice versa for accuracy)
Visual neurons showed **(1)** higher baseline, **(2)** higher response magnitude and **(3)** earlier target-in / target-out separation
Movement neurons showed **(4)** higher baseline, **(5)** higher rate of rise and **(6)** higher peak rate

Neural dynamics of decision making and SAT

Network state is drawn toward an unstable saddle point along a stable manifold (solid) and is repelled along an unstable manifold (dashed) toward an attractor state
Wong and Wang, J JNeurosci, 2006

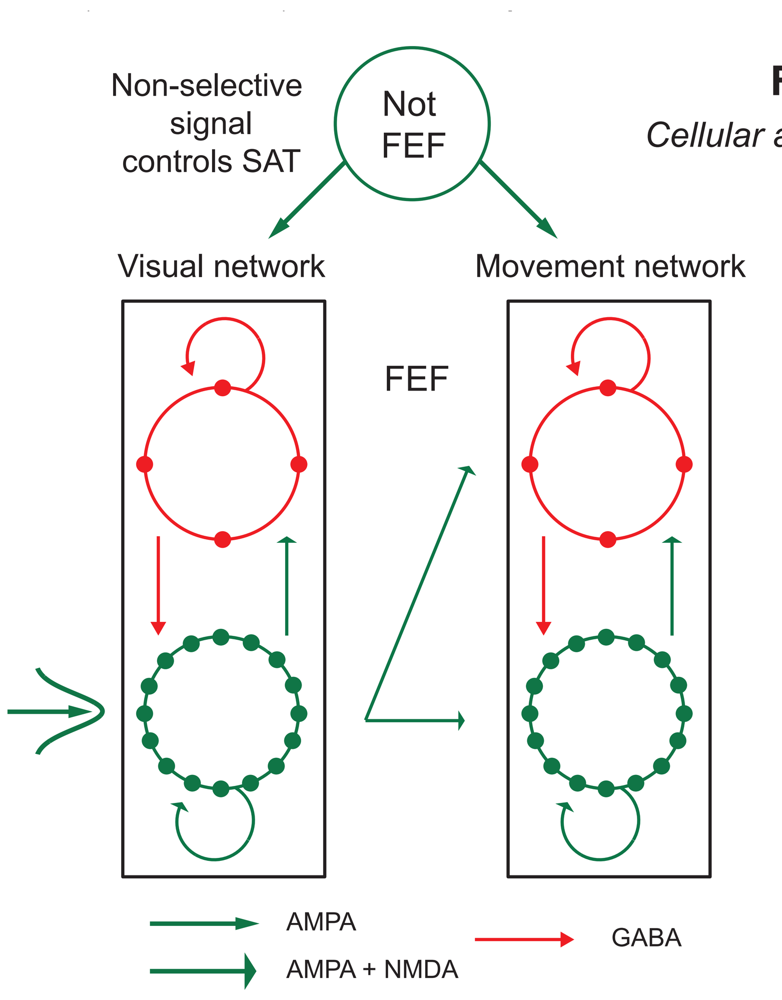
The time constant of the unstable manifold of the saddle decreases with increasing non-selective excitation
i.e. it decreases under speed conditions, like the bound of bounded accumulation models



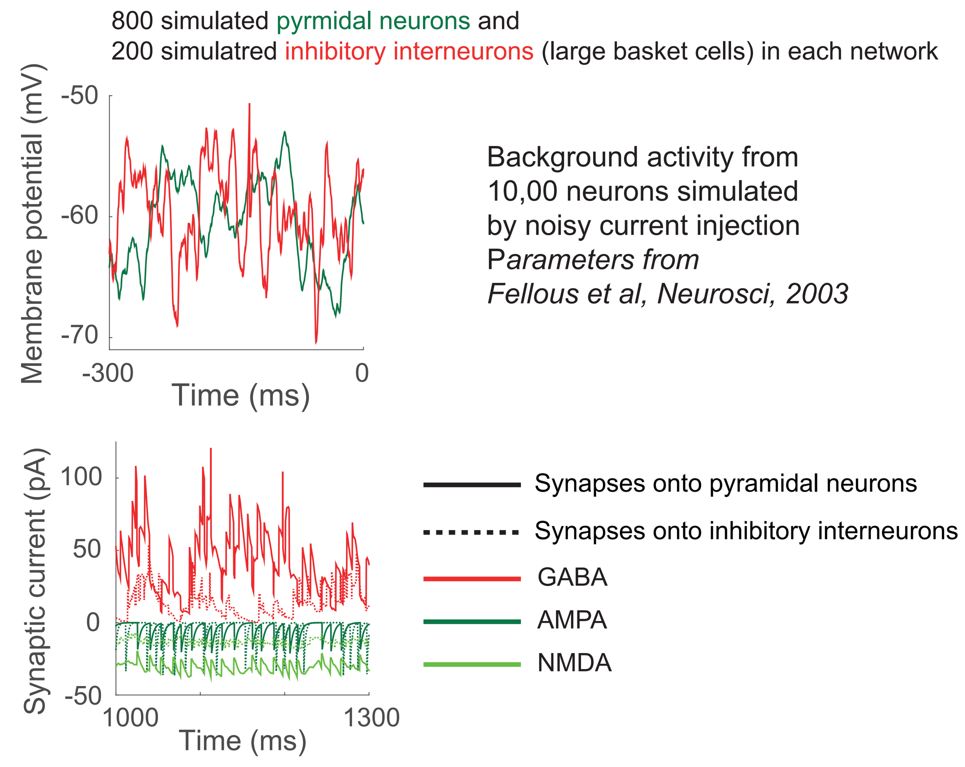
Stronger non-selective excitation pushes the stable manifold closer to the midline, further decreasing accuracy
Standage, Wang and Blohm, Front Neurosci, 2014

Methods

FEF model
Cellular and synaptic resolution

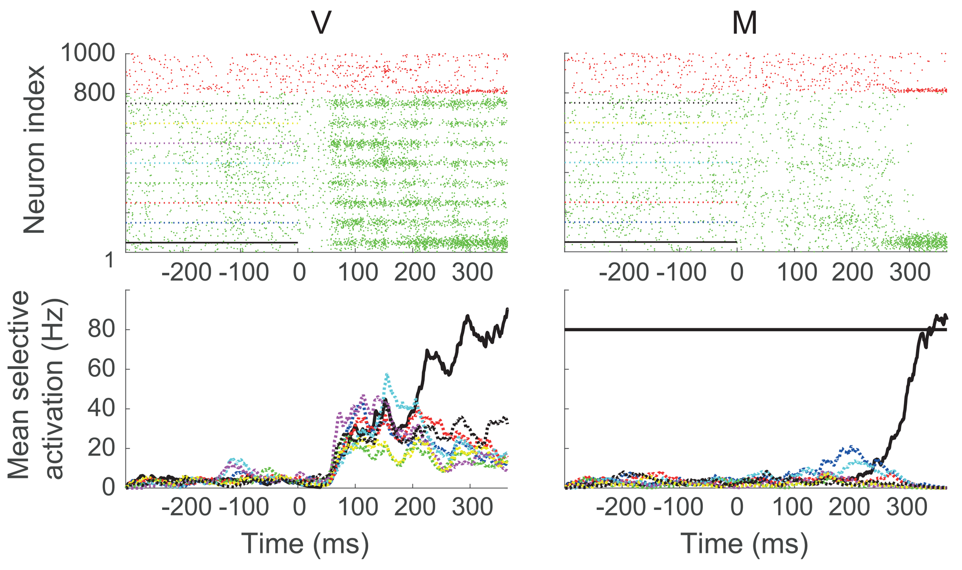


800 simulated pyrmidal neurons and 200 simulatred inhibitory interneurons (large basket cells) in each network

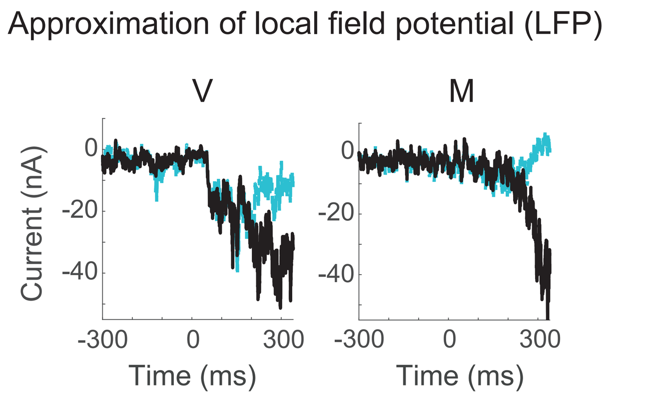


Background activity from 10,00 neurons simulated by noisy current injection
Parameters from Fellous et al, Neurosci, 2003

Example trial (speed condition)



Approximation of local field potential (LFP)



Sum all synaptic currents onto target and distractor populations
... 25 pyramidal neurons either side of response field centre

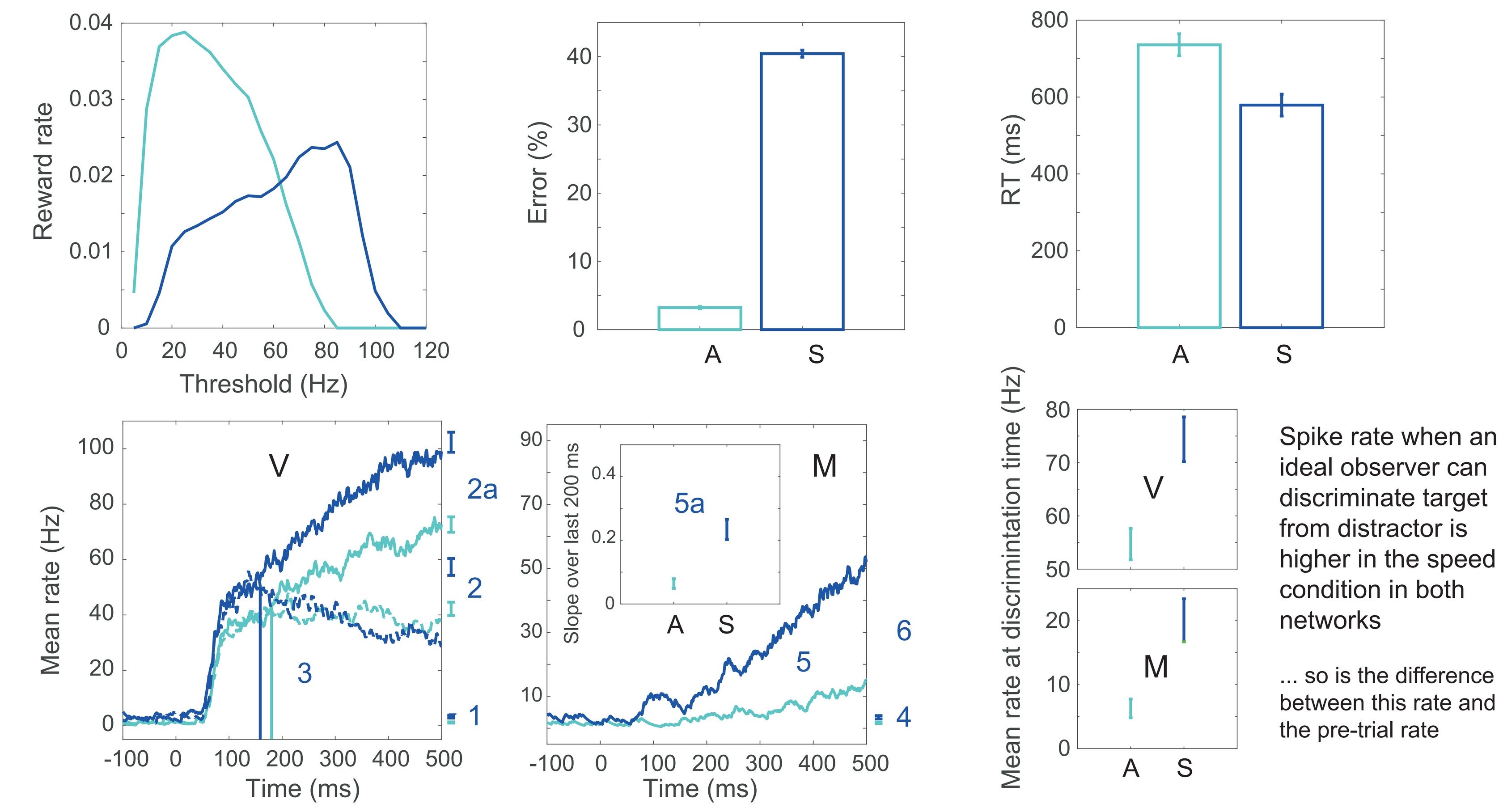
Results

100 simulated trials in the speed and accuracy conditions

Simulated behavioural data

Reward rate is maximized with a higher "decision threshold" in the speed condition
r r = number of accurate trials / (total RT + 1200ms)

Reaction times are longer than in the data

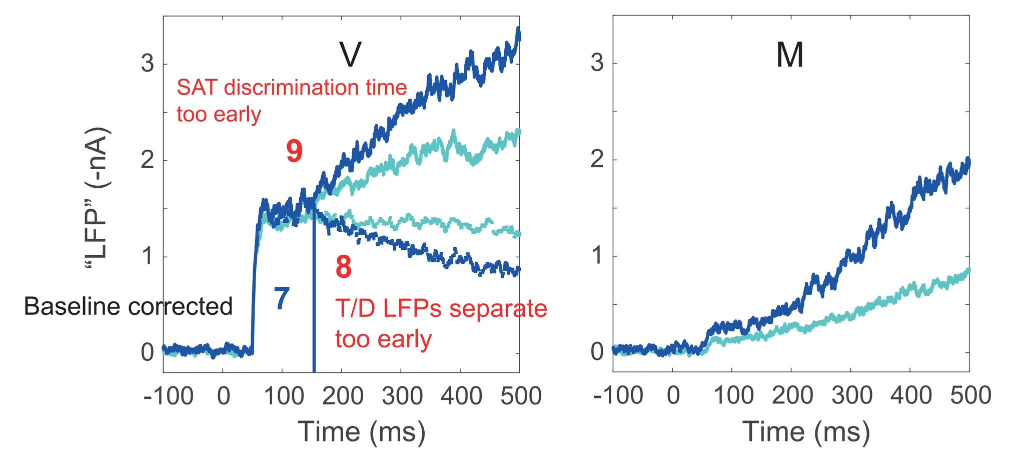


Spike rate when an ideal observer can discriminate target from distractor is higher in the speed condition in both networks

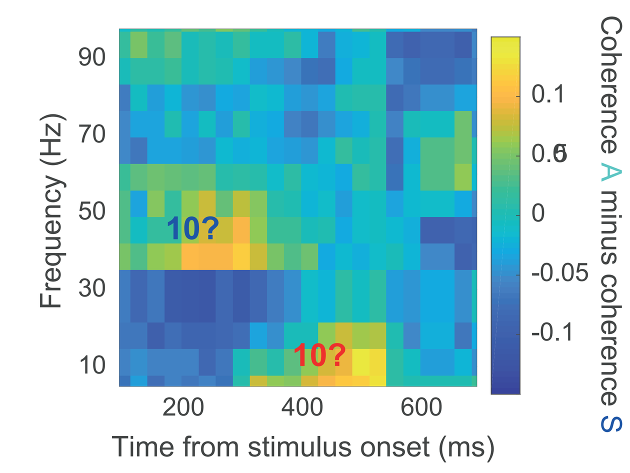
... so is the difference between this rate and the pre-trial rate

Heitz and Schall, Phil Trans R Soc B, 2013

Visual LFP showed **(7)** earlier stimulus response, **(8)** later target selection and **(9)** earlier speed-accuracy discrimination than visual neurons ...

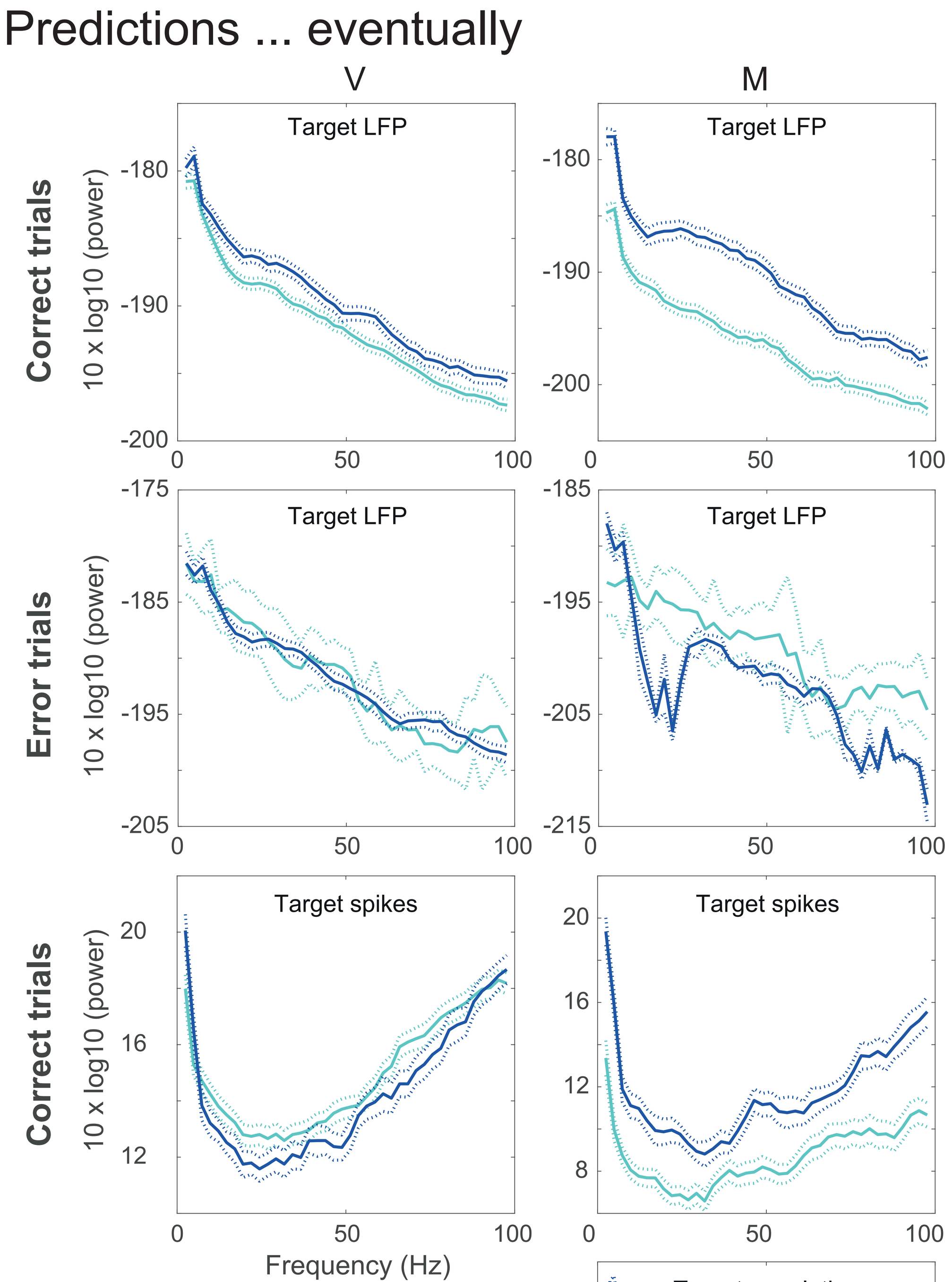


... and **(10)** spike-field coherence was greater in the Gamma range in the accuracy condition during early and late task epochs, and was greater in the speed condition at less than ~10Hz



Heat map shows results for one set of parameter values that may (or may not) be promising ...

Predictions ... eventually

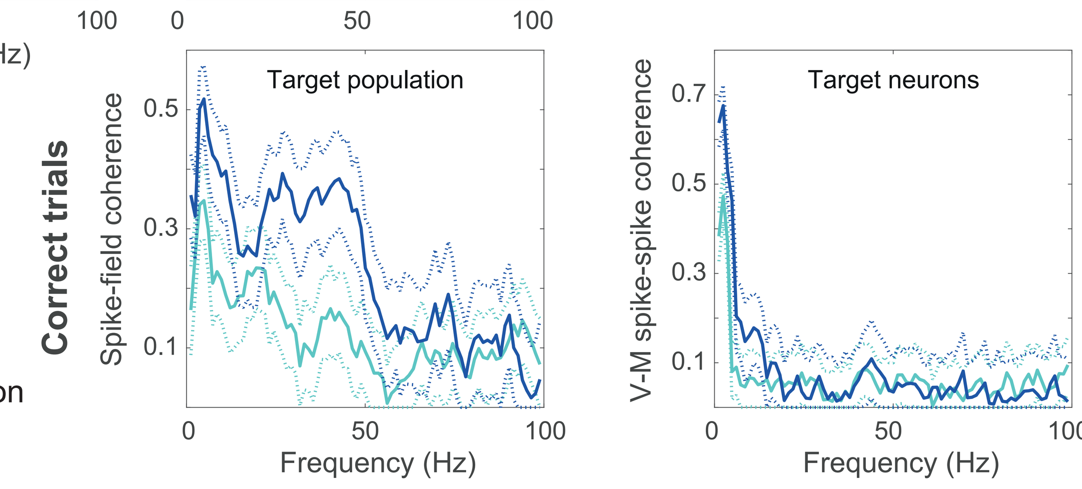


On correct trials, baseline-corrected LFP power in the target population is higher in the speed condition in almost all frequencies in both networks
An index of the strength of recurrent dynamics ?

... but not on error trials

On correct trials, relative spike power in target neurons differs between networks by speed/accuracy condition (but not on error trials)

On correct trials, spike-field coherence in the low Gamma band in the movement network and visual-movement spike-spike coherence in the low theta band are greater in the speed condition among the target population



Conclusions and future work

Our FEF model addressing the FEF data by Heitz and Schall (2012, 2013) shows the neural signatures of our simplified model *(Standage, Wang and Blohm, 2014)*
Bound is implemented by the time constant of the unstable manifold of the saddle
... but the model does not yet account for all the data

Higher pre-trial spike rates in the speed condition do not adjust a "threshold-baseline difference"
They reveal a cognitive signal controlling neural dynamics
Where from?

We need to choose model parameter values more systematically to account for the data
One parameter set shown here

Supported by Marie Sklodowska-Curie Actions and the Natural Sciences and Engineering Research Council of Canada