A Recurrent Network Mechanism of Time Integration in Perceptual Decisions(Wang Model)

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Objective for neurobiologists is to uncover the underlying neural mechanisms responsible for the time it takes to react in cognitive tasks. Recent studies involving non-human primates have identified neural firing patterns associated with simple decisions[3]. For instance, in an experiment involving visual motion discrimination, researchers observed that neurons in the lateral intraparietal (LIP) cortex of monkeys exhibited spike firing that correlated with response time and choice[4]. The spike activity in LIP neurons gradually increased from the onset of a random dot motion stimulus until the monkey made a choice through a rapid eye movement. This increase in neuronal activity and the monkey's response time were both longer when the percentage of coherent motion (motion strength) in the stimulus was lower. These findings suggest that LIP neurons may play a role in accumulating uncertain visual information prior to making a perceptual decision.[2]

[1]Speed and accuracy of making decisions based on perception are influenced by the level of difficulty of the task. According to the article, when the proportion of randomly moving dots that are moving coherently (motion strength) is lower, both neuronal activity and the time it takes to respond increase. Furthermore, the article suggests that the decision-making process is closely tied to the local dynamics within the "decision space" of the system, specifically around an unstable saddle steady state that separates the regions where the two alternative choices are more likely. This offers a precise and measurable explanation for how performance and response time are affected by the difficulty of the task.

By creating a visual representation called a two-parameter state diagram, the researchers were able to identify and distinguish between two specific patterns of network behavior associated with decision-making processes and working memory. They discovered that there exists a limited region within the parameters where competition occurs, leading to a categorical decision because the only stable states are those representing the available choices. Additionally, they noticed that the network can enter this region and engage in competition as long as an appropriate stimulus is present, regardless of whether the network is at rest or in a state characterized by a single or multiple stable states. This valuable insight allowed the researchers to classify and differentiate the various modes of network behavior associated with decision computation and working memory.

The study presents a cortical network model of decision-making that is grounded in biophysical principles and encompasses a large number of spiking neurons. This model can be viewed as a circuit composed of interconnected neural populations, with mutual inhibition serving as an effective means of coupling them. The model relies on recurrent excitation, which is crucial for generating reverberating dynamics that facilitate winner-take-all competition. Notably, the recurrent excitation is primarily influenced by slow and saturating synaptic dynamics associated with NMDA receptors. In contrast to a previous model's assumption of cross-inhibition along the feedforward input pathway, the reciprocal inhibition between neural pools selective to different choices is achieved through feedback inhibition within the local circuit.

Results

1. part A

A. Generating Figure 2 of the Article. Figure 2 of the article displays the time course of two different coherence levels, c'. By observing the figure, we can see that as the coherence level (c') increases, the neural population's ramping activity, specifically the one associated with the saccadic target's response field (RF), becomes steeper. Consequently, when the coherence level is higher, the decision time is shorter. This outcome is expected since higher external inputs lead to steeper ramping activities, resulting in faster accumulation of sensory evidence prior to making a decision. It is worth noting that when viewing motion with lower coherence levels, there is an initial time period lasting hundreds of milliseconds (indicated by a black horizontal bar) where the two activity traces are indistinguishable before eventually diverging. You can see the created figure in Fig. 1. parameters are as in figure 2.

B. Generating Figure 6.A of the Article. When the value of μ_0 is reduced, neurons require more time to gather and process information from a less intense stimulus. Consequently, the time it takes to make a decision increases steadily and without exception.

Based on Figure 3 and Figure 4 show chronometric curves of Wang model and real data separately. We can observe that in lower coherencies the variance is more than variance in actual data and the difference increases while coherency decreases. And we observe that totally higher variances in Wang Model which can be logical because totally reaction times are higher than real data. Also mean reaction time in Wang model is mostly higher than our data. It is important to highlight that the decision time remains finite despite all divergences.

Please provide details of author contributions here.

[1] A.O.(Author One) and A.T. (Author Two) contributed equally to this work (remove if not applicable).

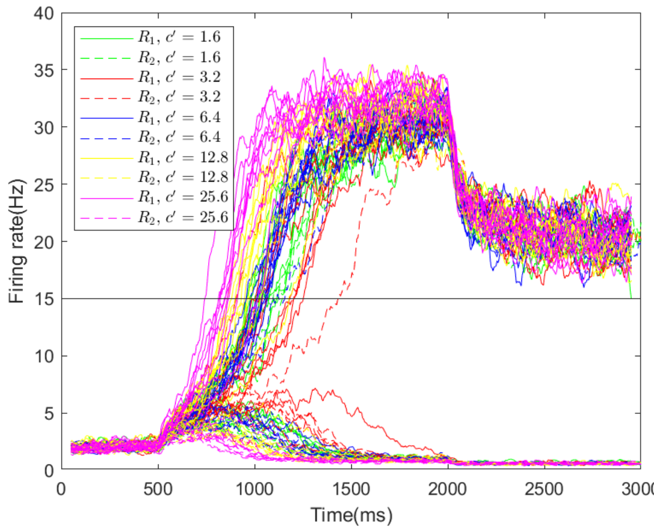

Fig. 1. Temporal progression with five distinct levels of motion strength. In the experiment, motion coherence was set at 1.6%, 3.2%, 6.4%, 12.8% and 25.6% with 5 sample trials conducted for each level. The firing rates of the neurons exhibit an upward trend (shown by bold traces) when saccades are directed towards the receptive field (RF) of the neuron. Conversely, a downward trend (indicated by dashed traces) is observed when saccades are made away from the RF. The rate of increase in firing rates is more pronounced for higher levels of coherence. A fixed threshold of 15 Hz is used as a criterion. Once the firing rate surpasses this threshold, a decision is reached, and the time taken from the onset of the stimulus (0 ms) until the threshold is crossed is defined as the decision time.

```
correctness = TD==SR;
Tnmda = 100;    % NMDAr
Tampa = 2;      % AMPAr
gamma = 0.641;
dt = 0.5;
mu0       = 30.0;       % External stimulus strength
thresh    = 15;         % Decision threshold
noise_amp = 0.02;       % Noise amplitude into selective populations
N_trials  = 50 ;        % Total number of trials
Tstim     = 1500;
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Fig. 2. parameters to generate figure 1

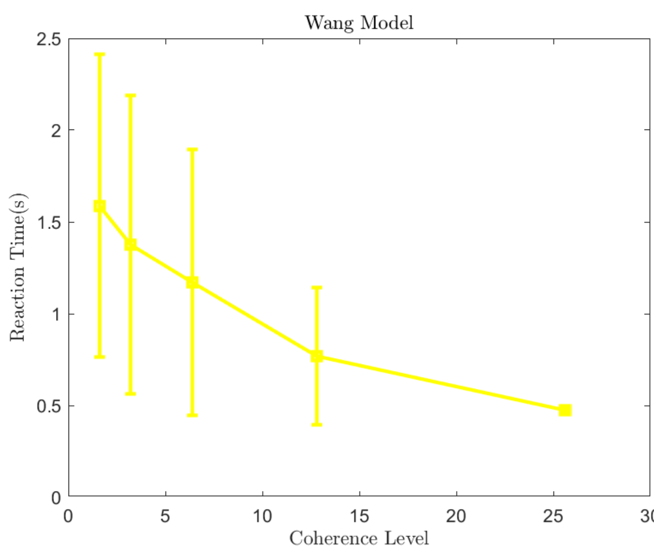

Fig. 3. Wang Model chronometric curve(Note that we have assumed 400ms for non-decision time)

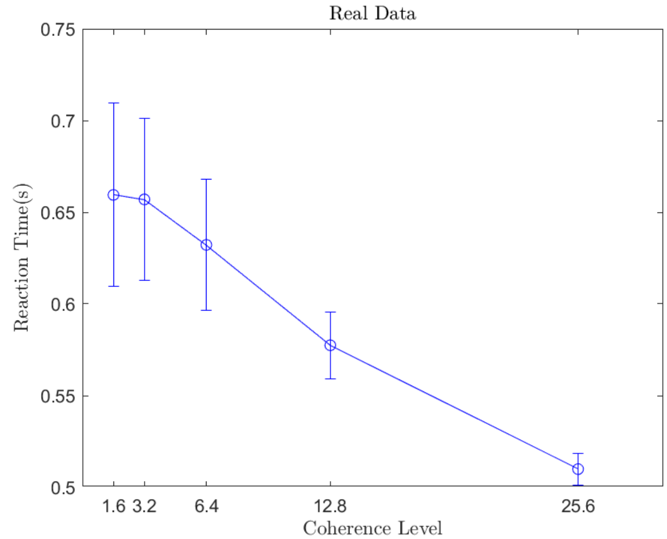

Fig. 4. Real Data chronometric curve

C. Generating Figure 7.D of the Article. Through investigation of the resource article, they discovered that when the AMPA:NMDA ratio is heightened at the recurrent synapses, the neural activity exhibits a considerable increase in speed (Figure 7A of the article). This amplified activity leads to a steeper ramping pattern, resulting in shorter decision times (Figure 7B). However, it is important to note that this enhanced speed comes at the cost of a significant decline in decision performance (as depicted in Figure 7C of the article). Upon fitting the psychometric function with a Weibull function, we made an interesting observation: the threshold (α) exhibits an increase in value as the AMPA:NMDA ratio is heightened. Furthermore, the trend of shorter reaction times not only holds true in relation to the coherence level (as depicted in Figure 7B), but also in relation to the stimulus amplitude (as illustrated in Figure 7D).

Here we have implemented figure 7D of the article to show the above discussion.

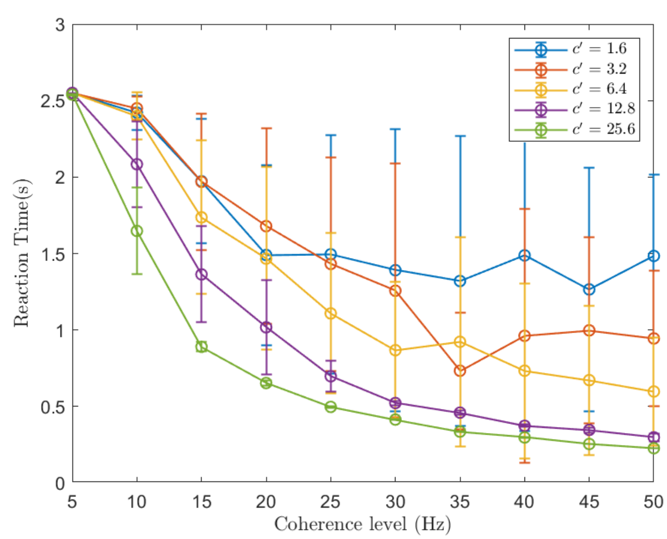

Fig. 5. Real Data chronometric curve

D. Generating Figure 11.C&D of the Article. As the value of W_+ increases, the reaction time decreases. In other words, there is an inverse relationship between w+ and reaction time, where higher values of w+ correspond to shorter reaction times. We can somehow see this in figure 6.

Also as the value of w+ increases, there is a noticeable decrease in the accuracy of performance. This means that as W_+ becomes larger, the ability to accurately perform tasks or achieve desired outcomes diminishes. It should be noted that when c is large, the decision time becomes less influenced by W_+. This occurs because the system is highly drawn towards the correct attractor, resulting in a reduced sensitivity to changes in W_+. However, despite the decreased sensitivity to w+, the performance actually worsened when a larger value of w+ was used, as depicted in Figure 11D of the article. We have showed this discussion in figure 7.

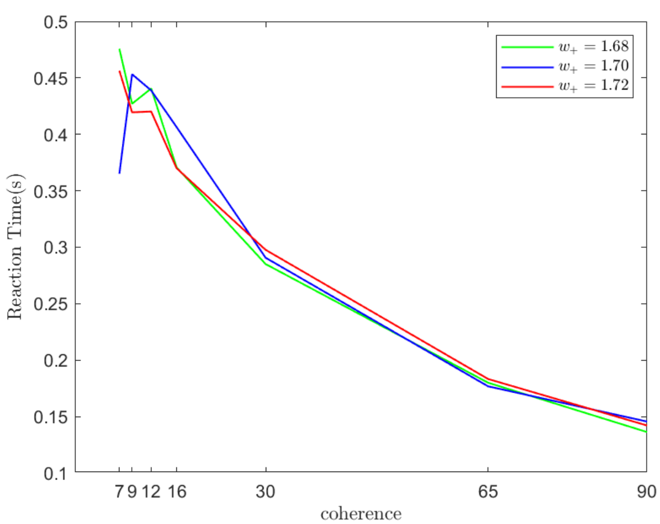

Fig. 6. Reaction time per coherence for different values of W_+

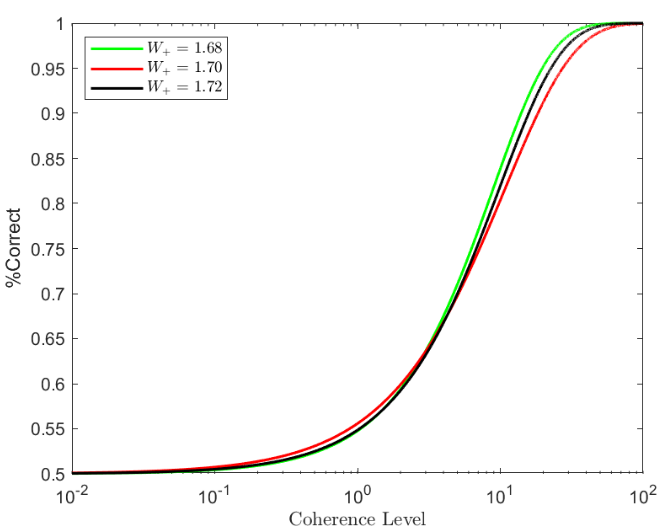

Fig. 7. Performance per coherence for different values of W_+

2. part B & C

A. Squared Error. To do this part we manually change the parameters below in a logical range:

$$Tnmda1 \in [90, 110] Tampa1 \in [0.5, 6] Thresh \in [10, 25]$$

Then we calculate SE of Wang Model Accuracy relative to real data. We considered 5 different point for each parameter and three heat maps have been plotted to show sum of error over each dimension(Figure 8-9-10).

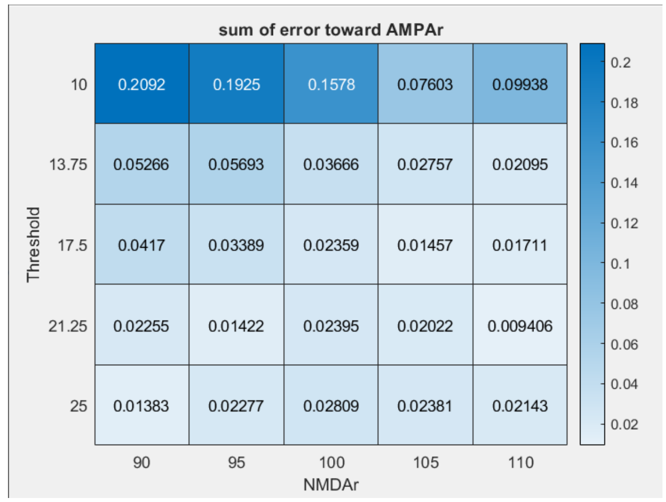

Fig. 8. Heat map of sum of errors over AMPAr

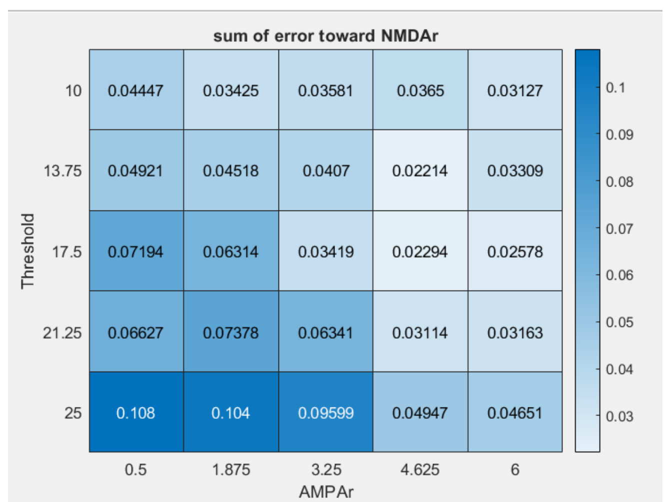

Fig. 9. Heat map of sum of errors over NMDAr

By calculating minimum of minimum squared errors we obtain the parameters in figure 11 and we Do sections A and B of the first part of results with these parameters(figure 12-13). By comparing fig 12 and fig 1 we observe better classifying in coherence.

B. Find best Parameters by Intuition. By considering the heat maps in figures 8-9-10 we can conclude that with NMDAr in

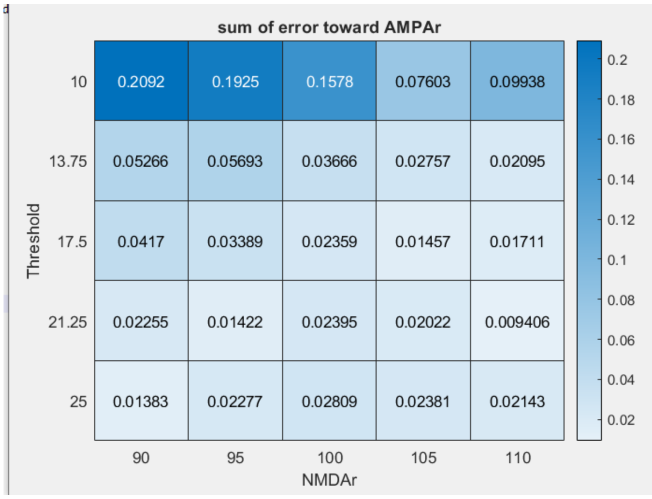

Fig. 10. Heat map of sum of errors over AMPAr

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Tampa =

    3.2500


Tnmda =

   100


thresh =

   17.5000
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Fig. 11. Parameters which corresponds to minimum error

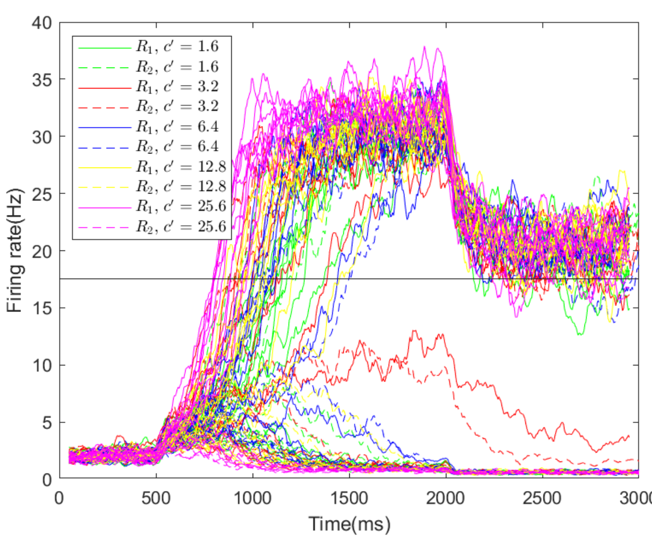

Fig. 12. Time course with 5 different coherence levels which corresponds to minimum error

range [105,110] and threshold near the range [13, 18] and almost all AMPAr in these ranges, we can have less error. Now we want to set gamma in a way that we see better accuracy and firing rate trajectory over time. We plot temporal pro-

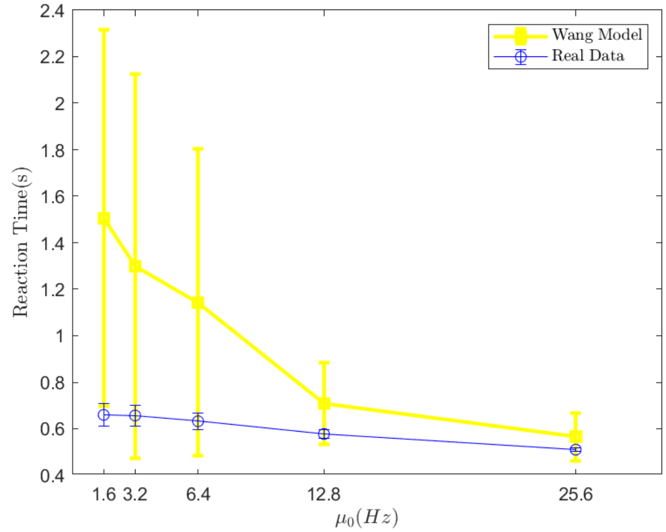

Fig. 13. chronometric curves for real data and minimum error

gression per different values of gamma. Figures 14 15 16 17 show this attempt which correspond to gamma = 0.3, 0.8, 0.6, 0.7 respectively. We can observe that better responses are obtained by gamma around 0.65.

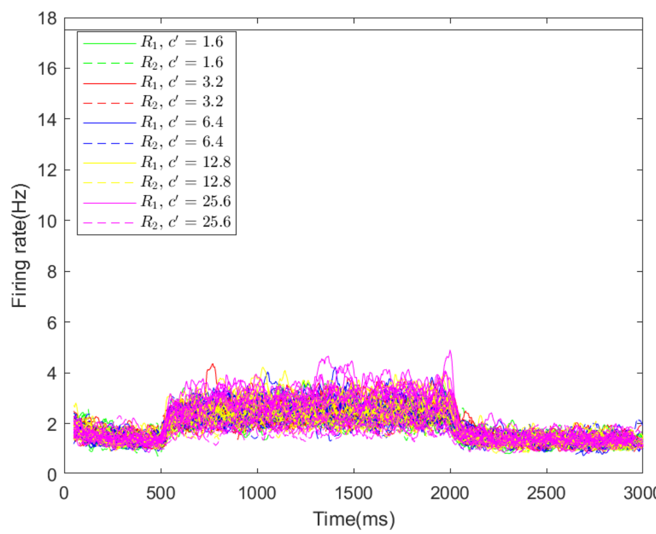

Fig. 14. Time course with 5 different coherence levels gamma = 0.3

Then by considering heat maps we change AMPAr to find the best one.(figures 18, 19, 20 respectively correspond to AMPAr = 4.25, 4.75, 4.5) As you see AMPAr equal to 4.25 gives better time progression.

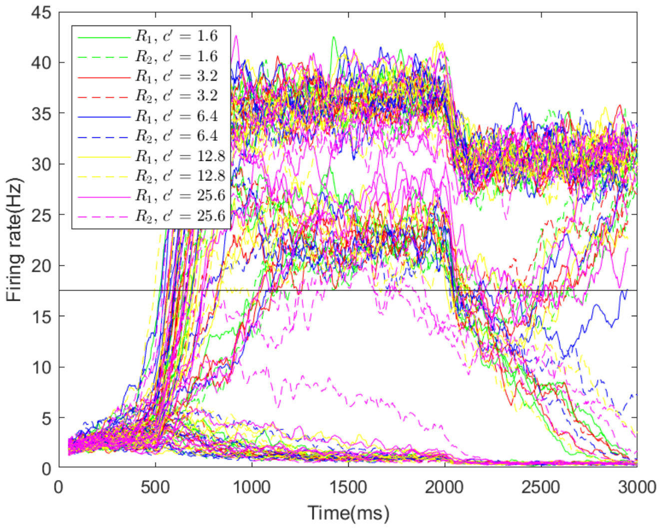

Fig. 15. Time course with 5 different coherence levels gamma = 0.8

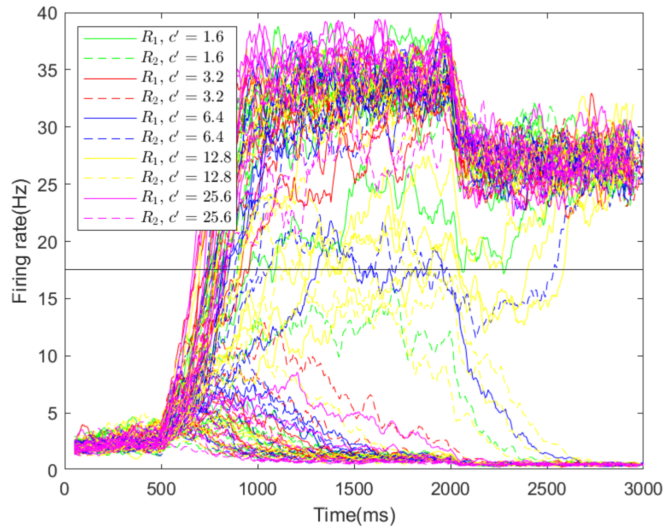

Fig. 17. Time course with 5 different coherence levels gamma = 0.7

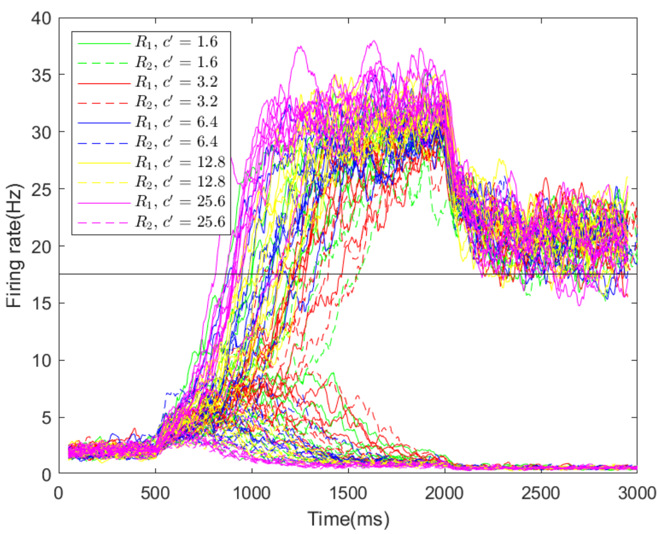

Fig. 16. Time course with 5 different coherence levels gamma = 0.6

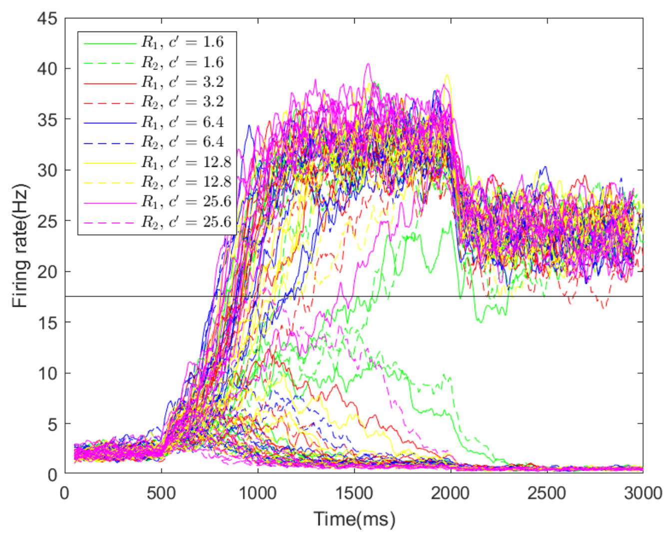

Fig. 18. Time course with 5 different coherence levels AMPAr = 4.25

3. Psychometric Curves with best parameters

Here we plot Psychometric Curves corresponding to previous parts. Figure 21 shows the curve with parameters Tampa = 3.25, Tamda = 100, thresh = 17.5, gamma = 0.6 and Figure 22 shows the curve with parameters Tampa = 4.25, Tamda = 100, thresh = 17.5 and , gamma = 0.641.

References

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4. Romo and Salinas, 2001; Schall, 2001; Shadlen and Gold, 2004)

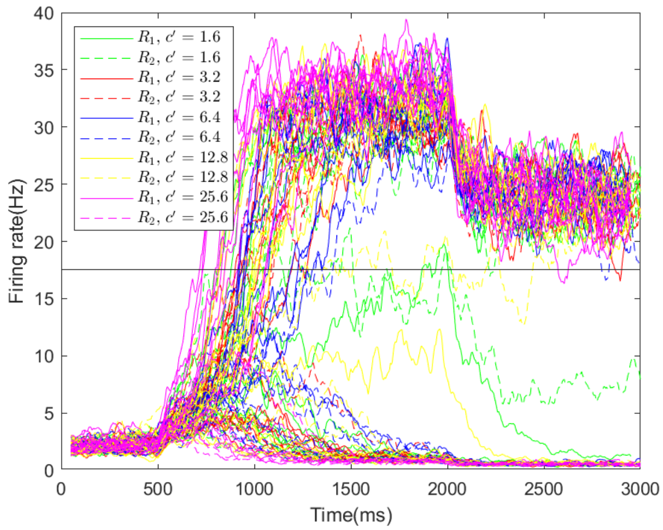

Fig. 19. Time course with 5 different coherence levels AMPAr = 4.75

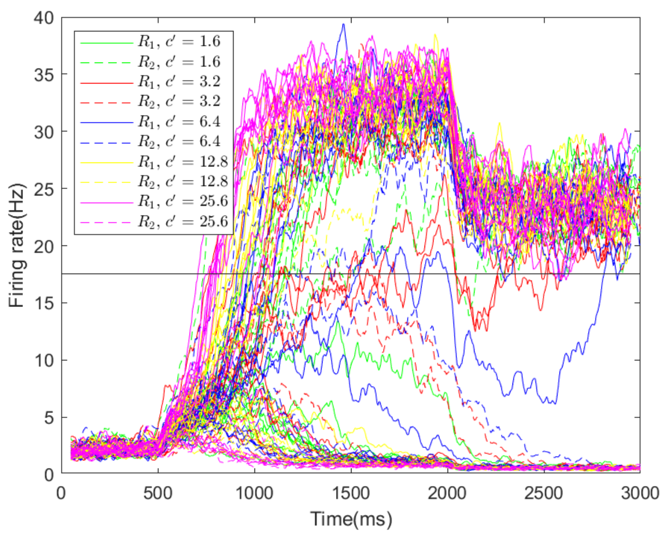

Fig. 20. Time course with 5 different coherence levels AMPAr = 4.5

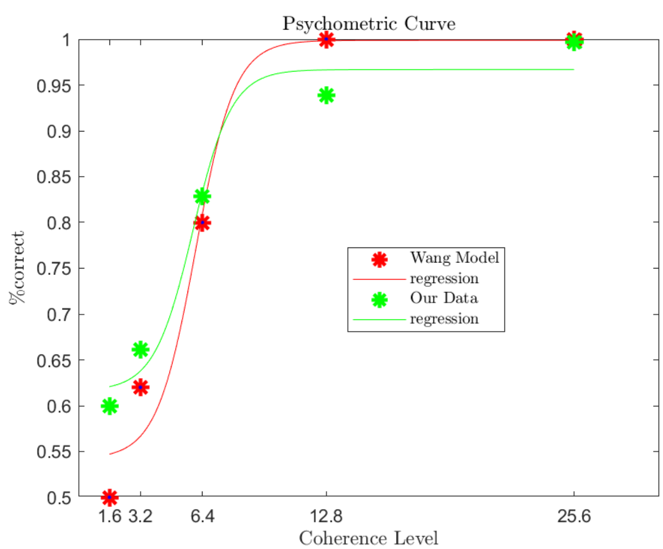

Fig. 21. Psychometric Curves corresponding to Tampa = 3.25, Tamda = 100, thresh = 17.5, gamma = 0.6

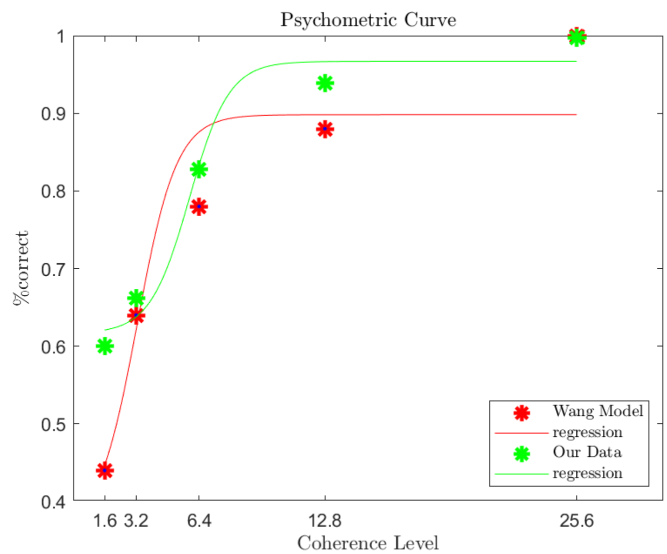

Fig. 22. Psychometric Curves corresponding to Tampa = 4.25, Tamda = 100, thresh = 17.5 and , gamma = 0.641