ASSIGNMENT 2

"Exploring the Two-Variable Model for Decision-Making Processes in Neural Populations: Parameter Tuning and Optimization for Accurate Psychometric and Chronometric Fitting"

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Abstract:

Decision making is a complex cognitive process that involves the integration of sensory information, cognitive factors, and emotional states in the brain. Recent advances in neuroscience have led to the development of computational models designed to better understand the underlying mechanisms of decision making in the brain. One such model is designed by Wong et.al. Their team conducted a study investigating the cellular and circuit basis of decision making in the brain. Using data from physiological studies on monkeys performing a visual motion discrimination task, the team developed a simplified two-variable version of a biophysically realistic cortical network model to elucidate the temporal accumulation of sensory evidence and its correlation with reaction time. Their model suggests that slow time integration in decision making is achieved through excitatory reverberation primarily mediated by NMDA receptors, and identified two distinct modes of network behavior that instantiate decision computation by winner-take-all competition with or without attractor states for working memory. The team's work provides a rigorous and quantitative explanation for the dependence of performance and response time on task difficulty, and offers a biophysically plausible framework for studying perceptual decision making in the brain.

Introduction:

As we have studied and it has been shown, the decision making process is thought to be start in LIP. In fact, research has shown that the spike activity of neurons in the lateral intraparietal area (LIP) of the brain slowly increases for hundreds of milliseconds after the onset of a random dot motion stimulus until a decision is made and a saccadic eye movement is produced. This increase in activity, as well as the monkey's response time, was found to be longer when the percentage of random dots moving coherently was lower. These findings suggest that LIP neurons may be involved in accumulating uncertain visual information before a perceptual decision is made. Lots of teams have done research and attempted proposing a computational model which mimics the process and demonstrates the previously shown effects in humans' decision making system. In this report, one successful model is discussed and some results of this model are reconstructed.

Material & Methods:

There are some models and articles simulating this process. Wang conducted a study on decision making using a biophysically based cortical microcircuit model. The model includes slow excitatory reverberation between spiking neurons that produces attractor dynamics, as well as recurrent feedback inhibition via interneurons that underlies winner-take-all behavior. However the complexity of the model - which consists of thousands of spiking neurons that interact in a highly nonlinear manner - makes it difficult to fully analyze and understand. To address this issue, a mean-field approach was employed to construct a reduced version of the model with only two dynamical variables. Despite its simplified nature, the model reproduces many of the behaviors of Wang's original spiking neuron model.

The team proposed a more simplified approach to analyzing large homogeneous populations of neurons. They assumed a constant driving force for the synaptic currents and that the variance of the membrane potential is mainly contributed by external input to each neuron. Contributions from recurrent connections were averaged out due to all-to-all connectivity and the long time constant of NMDA receptors. The resulting fixed standard deviation of fluctuations can be applied more generally to similar models of neural populations, offering a straightforward and efficient method for studying neural network dynamics.

the biophysically based cortical microcircuit model proposed by Wang (2002) was simplified through several steps. Firstly, a meanfield approach was used to reduce the number of spiking neurons from 2000 to four neural units, with a total of 11 dynamical variables. This allowed for the mean activity of the population to be represented by a single unit, with firing rates determined by input currents. Secondly, the linear input-output relation (F-I curves) of the cells was simplified by fitting the F-I curve of the spiking neuronal model with a simple function, linearizing the F-I curve for I cells, and assuming constant activity of NS cells. Finally, it was assumed that all fast variables of the system reach steady states earlier than that of NMDAR, resulting in a final reduced two-variable model consisting of two neural units endowed with self-excitation and effective mutual inhibition. These simplifications were made to make the model more tractable and amenable to analysis, while still capturing the essential dynamics of the original biophysically based cortical microcircuit model. Fig.1 shows the schematic of final simplified model.

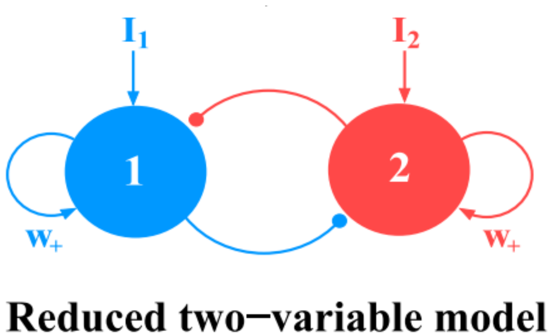

Figure 1- Simplified final scheme used in this computational model

Parameters:

In this model, Decisions were made based on the activity of two competing neural populations, with a fixed threshold of θ = 15 Hz. The decision time was defined as the duration it took for the activity of the "winning" population to increase from its initial (spontaneous) state to the decision threshold. The reaction time was then calculated by adding the decision time to a fixed nondecision time constant, which reflected a combination of sensory input latency and motor response. For their model, a fixed nondecision time constant of 100 ms was chosen. (I increased this to 400 ms in my work because the nondecision time for humans is about 350 to 500 ms).

In this report I used the MATLAB version of this model. I modified the MATLAB function the way that the function gets the desired parameters of the assignment as its inputs so that I could modify them in order to construct the desired figures.

The modified wong function takes coherency, mu0 and jn as its inputs. Jn is the parameter to fixate the w_+ parameters in the model and mu0 is introduced in the equations in order to define how important and effective the coherency of the signal is in the calculations. The outputs of this function are the two trajectories assigned to the two choices. I defined another function called RT_calc in order to calculate the reaction times assigned to the trajectories and the accuracy of decision.

Results:

1. **Reconstruction of desired figures**

I introduced the necessary modifications to the parameters in order to reconstruct the figures asked for. The results are mentioned followingly.

-Figure 2 of the article:

As mentioned in the article, I plotted the firing rate vs. time for choice trajectories in two different coherency percentages 0.0% and 51.2%. I plotted them both separately and together. First two plots in Fig.2 show the firing rate – time graph for two coherencies separately and the third one represents these two graphs together.

From the plots, it is obvious that when the coherency level increases, the reaction time

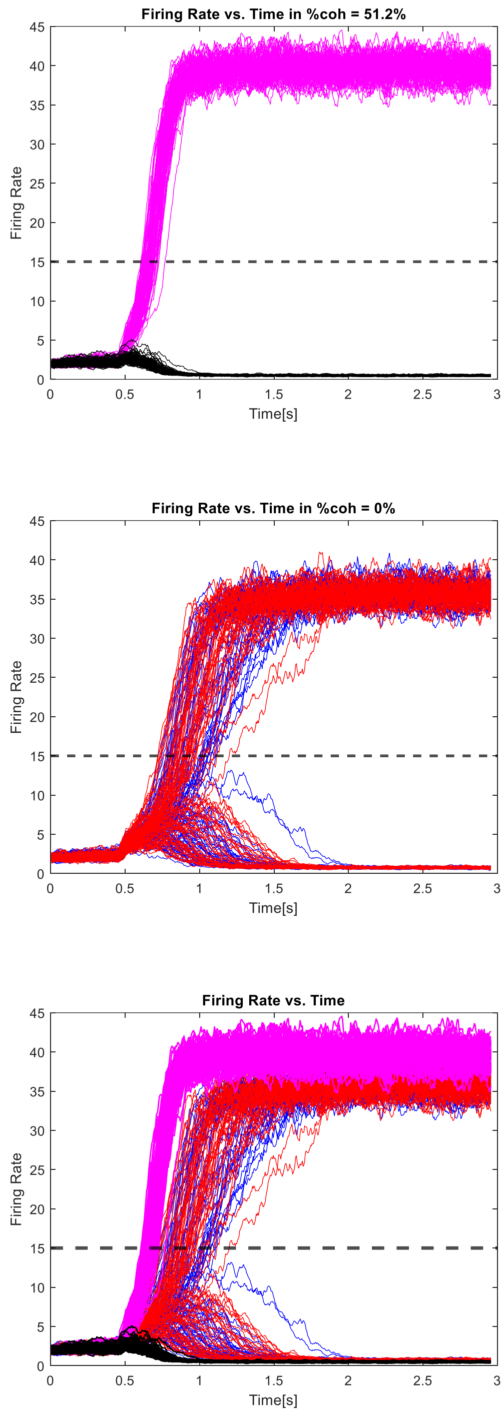

Figure 2- Reconstruction of figure 2 of the original article: Firing rate vs. time for choice trajectories in different coherency levels

decreases and the two population (choice trajectories) are separated faster. As a consequence, it could be concluded that decisions are made faster and more confidently when the evidence is stronger for one choice. This conclusion is reasonable and it is expected in humans' behavior.

-Figure 6.A of the article:

In this part the relation between reaction time and mu0 parameter is desired to be plotted. Fig.3 illustrates the relation. The coherency level is set to be 0.0% in this part of experiment in order to investigate the relation between reaction time and mu0 only.

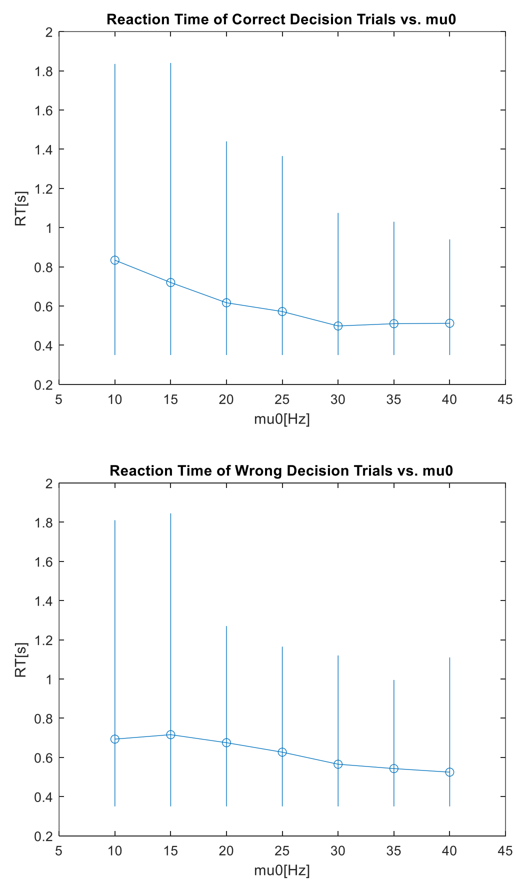

Figure 3- Reaction time vs. mu0: up: RT-Time plot for the trials in which the model has resulted in correct choice, Down: RT-Time plot for trials in which model has resulted in wrong choice. In both plots %coh is set zero.

Fig.3 shows that in correct trials, there exists a reduction trend in reaction time as mu0 increases. When the value of mu0 is decreased, neurons in the model take longer to accumulate information from a weaker stimulus, resulting in an increase in decision time. This relationship is monotonic, meaning that as x is further decreased, the decision time continues to increase. This suggests that the parameter x plays a critical role in determining the speed and accuracy of decision-making in the model, with smaller values leading to slower and less precise decisions. Also it should be mentioned that as mu0 increases, the variation in reaction time also decreases meaning that all reaction times approximately vary a little and it also indicates the increase in confidence level. The second plot shows that there is no such trend in incorrect trails and this way the conclusions get more reliable.

-Figure 11.C and 11.D of the article:

In this part first the relation between reaction time and the coherency level in different w_+ values is discussed and secondly, the way w_+ affects the accuracy-coherency plot is mentioned. Figure 11.C in the article indicates that a larger w_+ results in faster decision-making across all values of coherency level. However, it is important to note that for larger coherency values, the decision time was less sensitive to changes in w_+ because the system was strongly attracted toward the correct attractor. These findings could be seen in the reconstructed figure (Fig.4).

The variations in all regenerated figures are all because of small number of iterations that I defined in code for producing the results. Figure 11.D in the article shows that despite the faster decision time associated with larger w+ values, performance in the model was worse. The mentioned trend could be seen in the regenerated plot too (Fig.5). This suggests a trade-off between decision speed and accuracy,

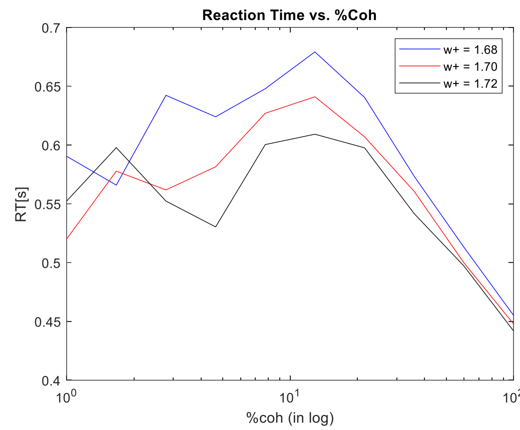

Figure 4- Reaction time vs. coherency level. The horizontal axis is in logs. Mu0 is set to be constant 30

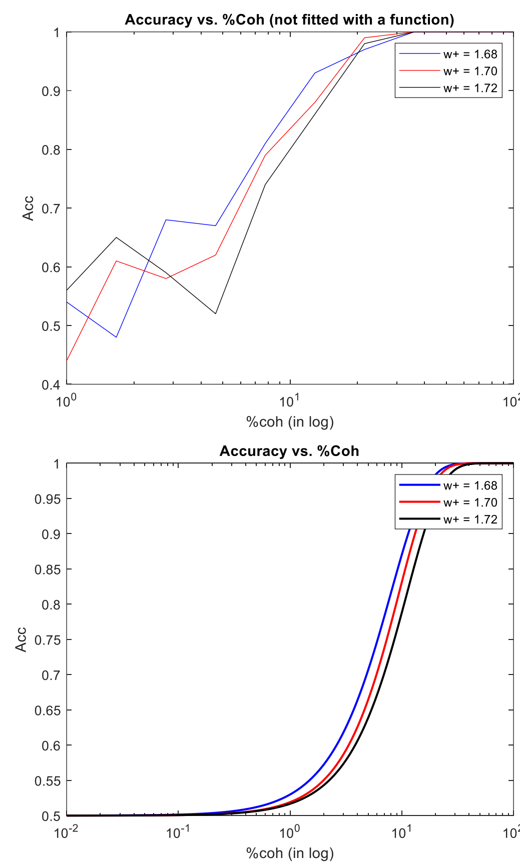

Figure 5- Accuracy vs. coherency level in different w_+ values. Up: the plot is generated from connecting the points. Down: the plot is generated by fitting a function to the resulted accuracies vs. coherency

where increasing w+ can lead to faster decisions but at the cost of decreased performance.

These results demonstrate the complex interplay between different parameters in determining the outcome of decision-making processes, and highlight the need for a comprehensive understanding of the underlying mechanisms in order to optimize performance in neural systems.

2. Manual Parameter Tuning the Model for Accurate Psychometric and Chronometric Fitting

In this section, I first modified the given data and generated the reaction time and coherency vectors and then attempted to adjust the parameters of the Wong model (mu0 and jn) to fit the provided behavioral data. I used a for loop to calculate the model's performance 100 times and then calculated the mean of the results. I tested mu0 values in the range of 30 to 40 and jn values in the range of 1.5 to 2, based on the typical values used in the article. I gradually increased these variables from their lower limit and experimentally adjusted them to obtain the following results:

The values obtained for mu0 and jn through the manual tuning process were mu0 = 36 and jn = 1.72 and the psychometric and chronometric fittings are shown in Fig.6. However, this method of parameter tuning is not always efficient or feasible, especially when dealing with complex models or large amounts of data. Therefore, other methods such as optimization algorithms or machine learning techniques may be employed to automate the parameter tuning process and improve the efficiency and accuracy of the model fitting. These methods can help to identify the optimal parameter values or explore the parameter space more efficiently, leading to a better understanding of the underlying neural mechanisms and more accurate predictions of behavior.

3. Algorithmic Parameter Tuning the Model for Accurate Psychometric and Chronometric Fitting

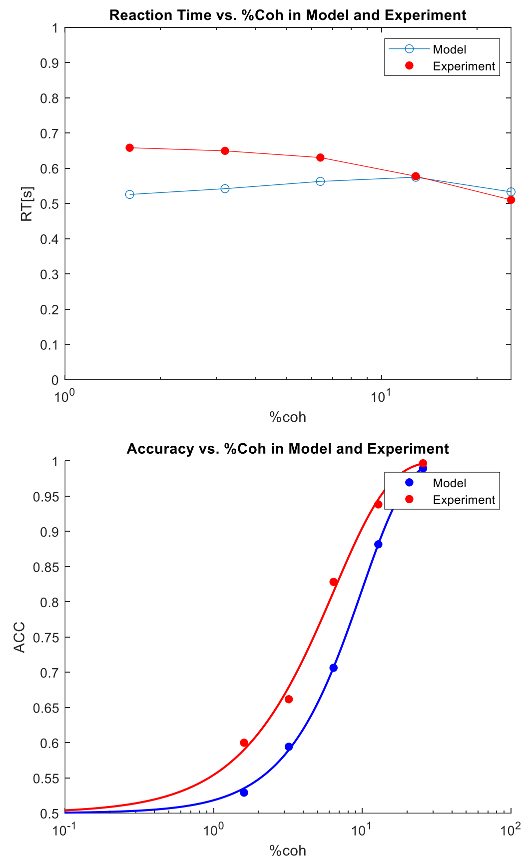

Figure 6- Up: Reaction time vs. coherency level for experimental data and the model. Down: Accuracy vs. coherency level for the experimental data and the model

In the next step, I used a genetic algorithm to optimize the parameters of the Wong model (mu0 and jn) to fit the behavioral data. The genetic algorithm is a type of optimization algorithm that mimics the process of natural selection to find the optimal solution to a problem. It works by generating a population of candidate solutions (in this case, different combinations of mu0 and jn), evaluating their fitness (how well they fit the behavioral data), and then iteratively selecting and recombining the best solutions to create a new generation of candidates.

Using the genetic algorithm, I was able to efficiently search the parameter space and find the optimal values of mu0 and jn that best fit the behavioral data. This approach is more automated and less dependent on manual adjustments, and can provide a more efficient and accurate way to optimize model parameters.

By using the genetic algorithm approach to optimize the parameters of the Wong model, the optimal values were found to be jn = 1.6779 and mu0 = 36.0011. The resulting graphs using these parameter values are shown in Figure 7, and demonstrate a better fit to the behavioral data compared to the manually tuned parameters.

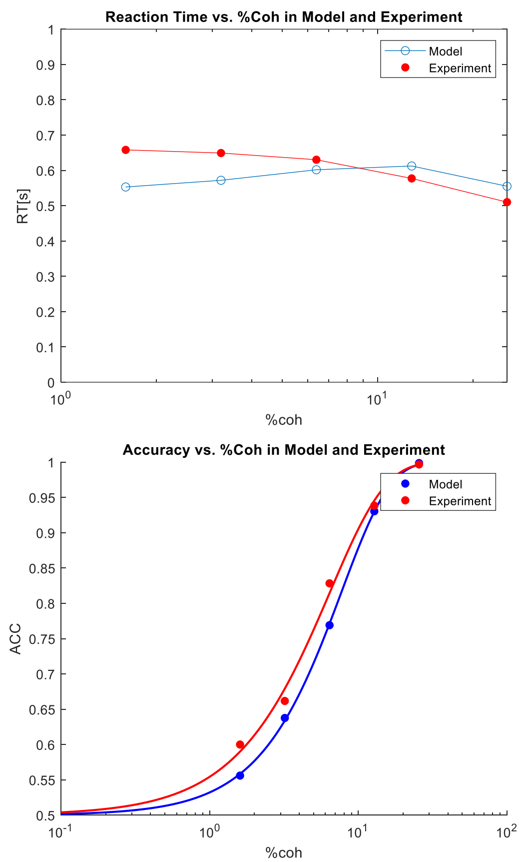

Figure7- using optimal mu0 and jn from algorithmic tuning process. Up: Reaction time vs. coherency level for experimental data and the model. Down: Accuracy vs. coherency level for the experimental data and the model

4. Effect of Threshold in Reaction Time and Accuracy

In this additional section, I investigated the effect of threshold on the performance of the model. The results showed that increasing the threshold led to a slight increase in accuracy, with a more pronounced effect at lower coherence levels. However, overall, the reaction time was only minimally affected by changes in the threshold. These findings suggest that while the threshold can have some impact on the accuracy of the model's predictions, its effect may be limited in certain conditions.

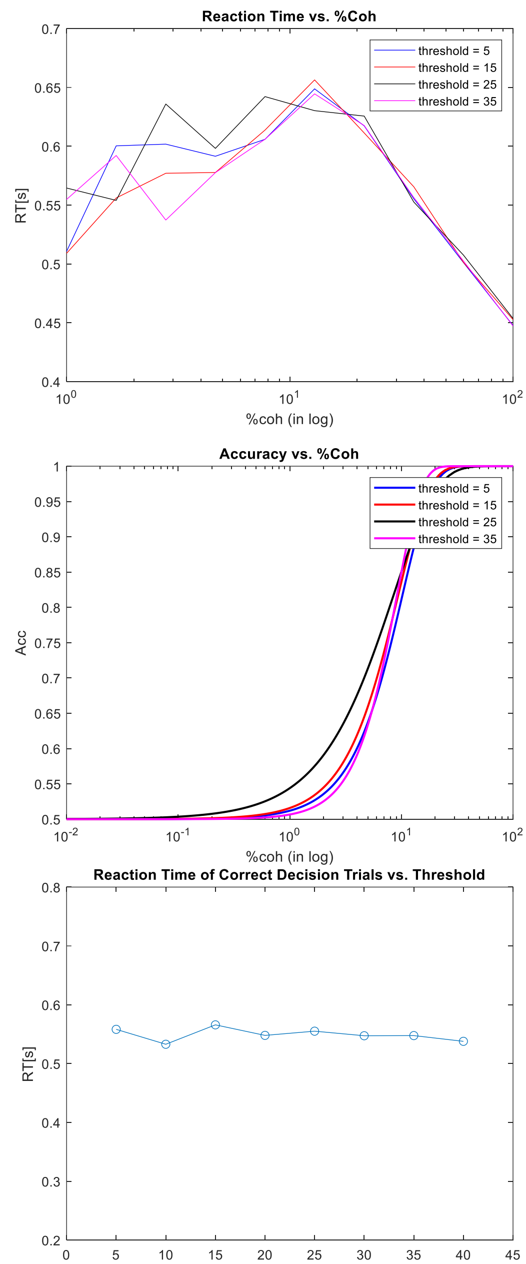

Figure 8- Up: Reaction time vs. coherency level in different threshold values. Middle: Accuracy vs. coherency level in different threshold values. Down: Reaction time vs. threshold in constant 0.0% coherency.

Further investigation is needed to determine the precise relationship between the threshold and model performance, and to explore the potential mechanisms underlying this relationship.

Discussion:

The study of the two-variable model for decision-making processes in neural populations provides valuable insights into the underlying neural mechanisms involved in these cognitive processes. By using computational models, we can simulate and investigate the behavior of neural populations and gain a better understanding of their dynamics and decision-making capabilities.

In this report, we discussed the various parameters of the two-variable model, including the excitatory and inhibitory synaptic conductance, time constants, self-excitation strength, and mutual inhibition strength. We also explored the impact of these parameters on decision-making processes and how they can be adjusted to improve the performance of the model.

Furthermore, we discussed the process of manual parameter tuning and the limitations associated with this approach. We then introduced the genetic algorithm as an automated and efficient method for optimizing the parameters of the Wong model and achieving a better fit to the behavioral data.

Overall, the study of computational neural models provides a powerful tool for investigating the complex dynamics of neural populations and their role in decision-making processes. By refining these models and optimizing their parameters, we can gain a deeper understanding of the underlying mechanisms and develop more accurate and realistic models of neural dynamics. This can lead to a better understanding of cognitive processes and inform the development of new treatments for various neurological and psychiatric disorders.

References:

- A Recurrent Network Mechanism of Time Integration in Perceptual Decisions. Kong-Fatt Wong and Xiao-Jing Wang