Parameter Fitting of the Wang Decision Model for Human Perceptual Decision-Making in RDM Tasks

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This report investigates the reduced Wang decision model, replicating key figures and fitting the model to human behavioral data. By adjusting parameters, such as stimulus strength, threshold, and recurrent excitation and inhibition strengths, the model was fitted to replicate human decision-making behavior. The study enhances our understanding of decision-making processes and highlights the flexibility of the Wang model in capturing human behavior.

Wang decision model | Perceptual decision-making | Random dot motion (RDM) task | Sensory discrimination | Reaction time | Parameter estimation | Model calibration | Optimization algorithms

Introduction

Wang decision model is a bio-physically realistic spiking neuron model for decision making with multiple alternatives. The reduced model, proposed by Wang X-J in (1), presents a computational framework for understanding time integration in perceptual decision-making processes in the brain, particularly in the lateral intraparietal area (LIP). The model explores how recurrent neural networks in the LIP contribute to the accumulation of evidence over time and influence decision-making outcomes.

In this project, our objective is to investigate the parameters of this model and then fit them to existing human behavioral data obtained from a random dot motion (RDM) task. The RDM task involved presenting participants with stimuli consisting of random dot patterns at different coherencies, specifically [1.6, 3.2, 6.4, 12.8, 25.6]%. The behavioral data collected from this task can serve as the basis for parameter estimation and calibration.

To accomplish this, we will employ optimization algorithms to estimate the parameter values within the reduced Wang decision model that best align with the observed behavioral data. By iteratively adjusting the model's parameters, we aim to minimize the discrepancy between the model's predictions and the actual decision-making behavior exhibited by humans.

Once the parameter fitting is complete, we will assess the goodness of fit and evaluate the performance of the Wang decision model in replicating perceptual decision-making. This evaluation will provide insights into the model's ability to capture the time integration mechanisms underlying human decision-making processes in the context of motion perception.

Results

Time Coarse of Different Motion Strengths. Through parameter adjustments within the model, we conducted simulations to examine the firing rates of neurons under two conditions: a random dot motion (RDM) task with coherence levels of (1) 0% and (2) 51.2%. Figure 1 presents a representative time course of firing rates for these two coherence levels. It is evident that increasing the coherence level, denoted as c', intensifies the ramping activity observed in the population of neurons. Consequently, this phenomenon leads to shorter reaction times, which are defined as the duration between stimulus onset and when the firing rate surpasses the predefined threshold. This observation aligns with our expectations, as stronger motion stimuli facilitate a more efficient accumulation of sensory input.

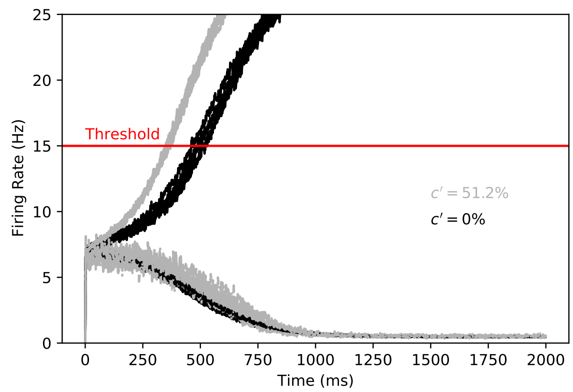


Fig. 1. The time course of the experiment is presented for two different motion strengths: a motion coherence of 0% (represented by black traces) and a motion coherence of 51.2% (represented by light gray traces). Each condition consists of 10 sample trials. The firing rates of the neurons exhibit distinct patterns depending on the direction of the saccades made. The bold traces indicate firing rates that ramp upward, corresponding to the choice of making saccades toward the RF of the neuron. Conversely, the dashed traces indicate firing rates that ramp downward, corresponding to the choice of making saccades away from the RF. Notably, the ramping of firing rates is more pronounced for the higher coherence level, indicating a steeper increase in neural activity with stronger motion signals. To determine the decision time, a prescribed threshold of 15 Hz is fixed. Additionally, to account for non-decision factors, a non-decision latency of around 100 ms can be added to the decision time.

The Impact of Stimulus Strength (μ_0) on Reaction Time. The parameter μ_0 serves as an indicator of stimulus strength. Notably, as the value of μ_0 decreases, neurons require a longer duration to accumulate information from a weaker stimulus, consequently leading to extended reaction times (Figure 2). Moreover, it is worth mentioning that lower values of μ_0 exhibit higher variability in reaction times, as indicated by the standard deviation (SD) observed in the respective figure. The reason behind this, can be attributed to the reduced reliability

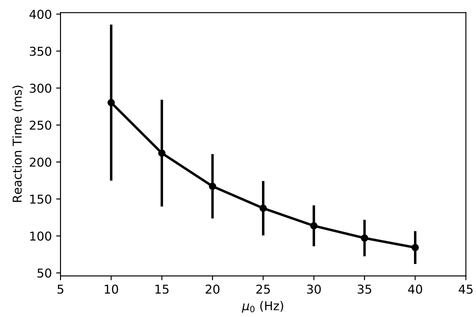
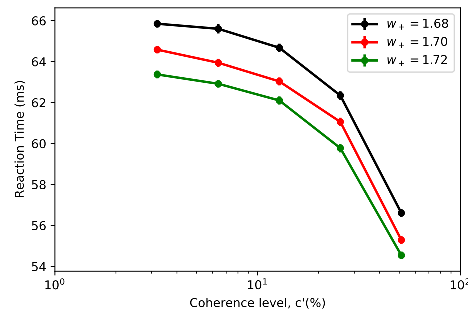
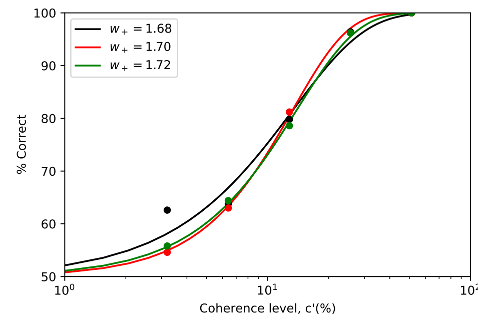


Fig. 2. Reaction time as a function of the stimulus strength (μ_0). Longer reaction time for smaller stimulus strength. Error bars indicate SD.



(a) Reaction time decreases with increasing w_+. Error bars indicate SE.



(b) Accuracy of performance decreases with increasing w_+. Data are fit with a Weibull function.

Fig. 3. Dependence of reaction time and accuracy on the relative strength of recurrent excitation.

of neuronal responses in the face of weaker stimuli. Due to the inherently lower signal-to-noise ratio associated with weaker stimuli, individual neuronal responses may exhibit more substantial variations, resulting in a broader range of reaction times.

The Impact of Relative Strength of Recurrent Excitation (w_+) on Psychometric and Chronometric Curves. The investigation focused on evaluating the impact of the relative strength of recurrent excitation (w_+) on psychometric and chronometric curves. We hypothesized that the effect of w_+ would resemble that of the stimulus strength (μ_0) since both parameters exert direct influence on the two competing neural populations. Consequently, reducing the value of w_+ or μ_0 would prompt the network to exhibit behaviors more similar to the spontaneous state.

Figure 3.a illustrates the consequences of varying w_+ on the psychometric curve at different coherency levels. Notably, as coherency increases, reaction time decreases. However, for lower values of w_+, the psychometric curve demonstrates higher response values. It is important to note that at higher coherency levels, the impact of w_+ becomes less pronounced, resulting in the convergence of different curves associated with various values of w_+. This convergence indicates that the effect of w_+ becomes less discriminative as the coherency level increases and system is strongly attracted to the correct choice.

Figure 3.b depicts the chronometric curves, representing accuracy as a function of the coherency level, for different values of w_+. Surprisingly, there are no significant differences observed among these accuracies. However, it can be speculated that higher values of w_+ might lead to worse performance. This inference arises from the understanding that a small perturbation or noise in the system has the potential to propagate and amplify within the network, potentially resulting in incorrect decision-making.

Fitting Model to Psychometric and Chronometric Curves of the Subject. To fit the model to the psychometric and chronometric curves of the subject, several adjustments were made to the model parameters. Firstly, the psychometric and chronometric variables were extracted from the subject's data. The reaction times were corrected by subtracting 400 ms to account for non-decision time, which includes sensory input latency and motor responses.

The following parameter modifications were implemented to achieve a good fit with the subject's data:

1. μ_0 (stimulus strength): By decreasing μ_0, reaction times were expected to increase, while accuracy levels were anticipated to decrease.

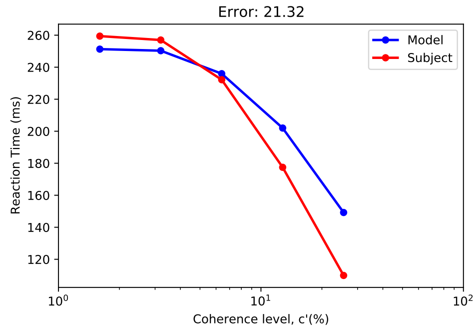
2. Threshold: Decreasing the threshold value within the model was anticipated to expedite the decision-making process, resulting in shorter reaction times. However, this modification was also expected to reduce accuracy levels, as hasty decisions may lead to increased errors.

3. RW (recurrent excitation strength): As previously discussed, decreasing the RW parameter was predicted to elevate reaction times. However, the impact on accuracy was anticipated to be minimal.

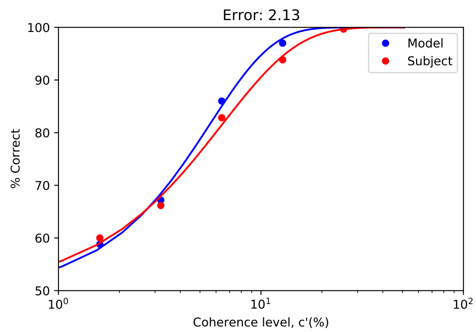
4. RI (recurrent inhibition strength): Increasing the value of RI was expected to slow down the accumulation of information within the neurons, potentially leading to longer reaction times. However, the cautious decision-making associated with higher RI values was expected to yield improved accuracy.

The remaining parameters were maintained at the values specified in the original paper (1), while the aforementioned adjustments were implemented to achieve a favorable fit between the model's predictions and the subject's psychometric and chronometric curves.

Least Square Method for Fitting Parameters to Subject Psychometric and Chronometric Curves.



(a) Chronometric curve of the subject and the fitted model.



(b) Psychometric curve of the subject and the fitted model.

Fig. 4. Chronometric and psychometric curves of the subject alongside with the fitted model. Errors in the title indicates squared root of mean squared error (MSE)

Discussion

In this study, we aimed to investigate different parameters of the reduced Wang decision model and fit the model to human behavioral data obtained from psychometric and chronometric curves. By adjusting the model parameters, we captured key aspects of the subject's decision-making behavior, as reflected in the observed data.

Firstly, by extracting the psychometric and chronometric variables from the subject's data, we obtained the subject's performance in the experimental task. The reaction times were adjusted by subtracting a non-decision time of 400 ms to account for sensory input latency and motor responses.

To achieve a good fit with the subject's data, we modified parameters within the reduced Wang decision model. Decreasing the stimulus strength parameter (μ_0) led to longer reaction times and reduced accuracy, aligning with the subject's performance. Similarly, reducing the threshold parameter expedited decision-making, resulting in shorter reaction times but lower accuracy due to potentially rushed decisions.

Exploring the impact of recurrent excitation strength (RW), we found that decreasing this parameter led to increased reaction times with minimal effects on accuracy. Additionally, increasing the recurrent inhibition strength (RI) within the model led to longer reaction times as neurons required more time to accumulate information and surpass inhibitory influences. However, this cautious decision-making process associated with higher RI values positively impacted accuracy, resulting in more accurate choices.

Overall, by fitting the reduced Wang decision model to the subject's psychometric and chronometric curves, we demonstrated the model's ability to capture important characteristics of human decision-making behavior. It is important to note that the fitted model provided a simplified representation of the complex neural mechanisms underlying decision-making. While the model captured certain aspects of the subject's behavior, there may be additional factors and neural processes that contribute to decision-making that were not explicitly accounted for in the current study.

Materials and Methods

Table 1. Parameter Values - Time Coarse of Different Motion Strengths

μ_0	Threshold	RW	RI	JN11	JN12	JA11	JA12
10	15	1.22	2	0.1708	0.16	0	0

Table 2. Parameter Values - The Impact of Stimulus Strength (μ_0) on Reaction Time

μ_0	Threshold	RW	RI	JN11	JN12	JA11	JA12
10:5:40	15	1	3	0.1	0.039	0	0

Table 3. Parameter Values - The Impact of Relative Strength of Recurrent Excitation (w_+) on Psychometric and Chronometric Curves

μ_0	Thr	RW	RI	JN11	JN12	JA11	JA12
30	35	1.68 1.70 1.72	4	0.156 0.158 0.16	0.0264	9.9×10^{-4}	6.5×10^{-5}

Table 4. Parameter Values - Fitting Model to Psychometric and Chronometric Curves of the Subject

μ_0	Thr	RW	RI	JN11	JN12	JA11	JA12
50	32	0.97	2	0.09	0.0264	9.9×10^{-4}	6.5×10^{-5}

ACKNOWLEDGMENTS. We would like to sincerely acknowledge our supervisor, Dr. Ebrahimpour, for generously granting us additional time to complete this assignment.

References

1. Kong-Fatt Wong and Xiao-Jing Wang. A recurrent network mechanism of time integration in perceptual decisions. *Journal of Neuroscience*, 26(4):1314–1328, 2006.

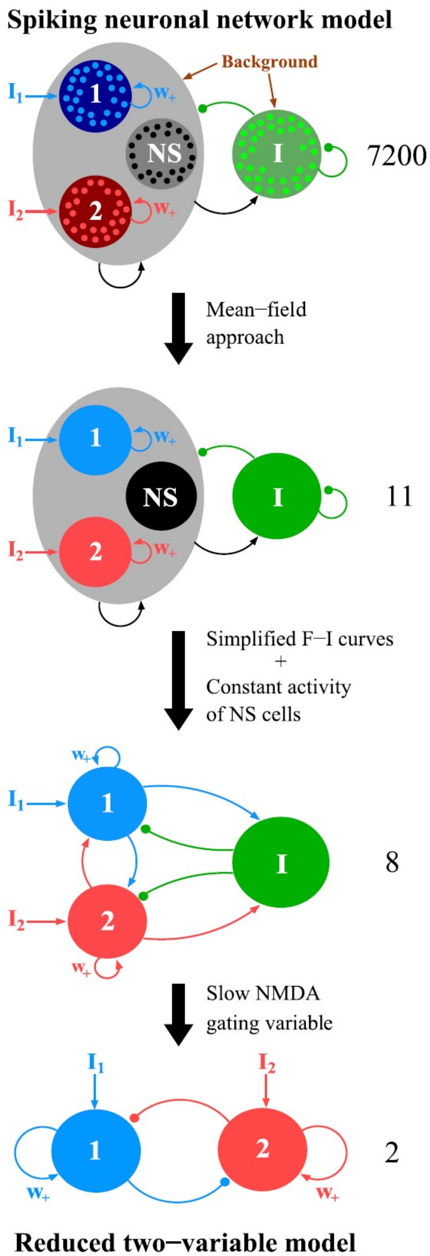


Fig. 5. Illustrates the reduction process of a biophysical neuronal decision-making model. The original model (top) incorporates strong recurrent excitation between neurons with similar stimulus selectivity and effective inhibition through shared inhibition. The nonselective excitatory (NS) and inhibitory (I) pools of cells are denoted by black and green, respectively. Excitatory connections are represented by arrows, inhibitory connections by circles, and inputs from external stimuli to selective neural populations 1 (blue) and 2 (red) are denoted as I1 and I2, respectively. Brown arrows indicate background noisy inputs. Enhanced excitatory connections within each selective neural pool are represented by w+. To simplify the model, a two-step reduction process is employed. Firstly, a mean-field approach reduces the 2000 spiking neurons to four neural units, resulting in a total of 11 dynamical variables. Secondly, the linear input-output relation (F-I curves) of the cells is simplified. This involves 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. Additionally, it is assumed that all fast variables of the system reach steady states earlier than the NMDAR. The final reduced model (bottom) consists of two neural units with self-excitation and effective mutual inhibition. This two-variable model provides a simplified representation of the original biophysical neuronal decision-making model, capturing the essential dynamics of the system in a more manageable form.