A Recurrent Network Mechanism of Time Integration in Perceptual Decisions

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Abstract

In the previous study using two-forced-choice visual motion discrimination, they found the monkey reaction time correlated with the increase of spike activity of the lateral intraparietal cortical neurons. They consider this ramping of neuron activity as evidence of accumulation in time before the monkey makes a decision. Based on this evidence, they developed a decision-making network model ("Wong 2006"). In this paper, first, I use this model to present some biophysical facts. Second I train the model to my behavioral data.

Keywords: reaction time, Accuracy, computational modeling, dynamical systems

1. Introduction

In the past, many psychologists were interested in the decision-making process. They want to find the relation between neural activity and human reaction time or accuracy. They have done some experiments on nonhuman animals and found the firing rate of the neurons in the lateral intraparietal (LIP) cortex correlates with the decision time. In other words, before the subject decided to saccade to the target, LIP neuron activity increased slowly. The monkey response and these neurons' activity were slower when the task was more difficult (in this experiment, the dot motion coherency was lower). So the LIP neuron could be considered an accumulator of uncertain visual information before reaching a specific level of confidence and making perceptual decisions.

This dynamic is similar to the "diffusion model", a popular mathematics model. This model integrates over time the difference between two noisy inputs. They compete with each other until one of them reaches the threshold and the choice is selected. In 2006, Wong presented a simple biological realistic model, which only has two dynamic variables. It is based on the diffusion model and could answer many neurological questions.

2. Spiking Neural Network Model

In the Wang model (2006)1, two thousand spiking neurons are reduced into two general excitatory neural groups, one group is selective for one of choice (e.g. the dominant direction of dots is left), and the other is selective for another decision choice. Both groups have a recurrent excitatory connection by themselves and an inhibitory connection with others. So, when the model accumulates the evidence, the value of one group gradually increases and at the same time, inhibits the opposing group. The value of the success group increase until the decision value reaches the threshold and the decision is made. We can describe the dynamics of these models as follows:

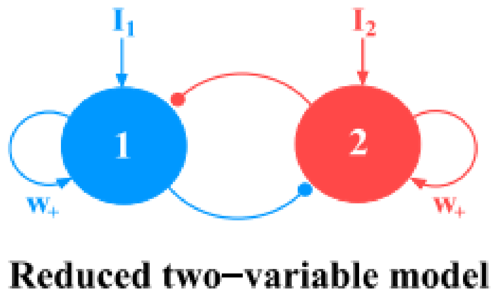

Figure 1: Reduced two variable model.

$$\frac{dS_1}{dt} = -\frac{S_1}{\tau_s} + (1 - S_1)\gamma r_1 \tag{1}$$

$$\frac{dS_2}{dt} = -\frac{S_2}{\tau_s} + (1 - S_2)\gamma r_2 \tag{2}$$

S denote S_{NMDA} ($NMDA$ receptor) and τ_s for τ_{NMDA}. The firing rate r_1 and r_2 are given by:

$$r_1 = \phi(I_{syn,1}) \tag{3}$$

$$r_2 = \phi(I_{syn,1}) \tag{4}$$

$$I_{syn,1} = J_{N,11}S_1 - J_{N,12}S_2 + J_{A,11}r_1 - J_{A,12}r_2 + I_0 + I_1 + I_{noise,1} \tag{5}$$

$$I_{syn,2} = J_{N,22}S_2 - J_{N,21}S_1 + J_{A,22}r_2 - J_{A,21}r_1 + I_0 + I_2 + I_{noise,2} \tag{6}$$

" where I_i represents the visual motion stimulus to the population i and depends on the motion strength." I_{noise}, is a noise term, and I_0 is the external input. "I_0 includes not only direct background input to a selective population but also indirect background inputs from these nonselective cells. 'I_{syn} is the synaptic current. The coefficients JN_{ij} and JA_{ij} are effective coupling constants from neuron j to i mediated by $NMDAR$ and $AMPAR$, respectively."

3. Result

3.1. Part a- Article Result

3.1.1. "Time course with two different motion strengths"

In Figure 2, the firing rate of the winner population g (in the experiment, the neuron whose receptive field (RF) is on the saccadic target) is shown over time for two different coherence levels ($C' = 0nd51.2\%$). For higher coherence, the ramping of the firing rate is faster. It is reasonable because the uncertainty of visual stimulus was lower, and LIP neurons reach the threshold faster. Also, the error rate is lower in higher coherency (the firing rate of the winner neuron always reaches the threshold). In lower coherency, because of the system noise, sometimes the firing rate of the neuron agrees to RF decrease and leads to an incorrect decision.

3.2. Chronometric Function

Figure 3 shows the reaction time over the coherency level (reaction time is defined as the first time a neuron reaches the threshold). The higher coherency, the lower the reaction time. Because the external input (stimulus evidence) is higher and the accumulation of the firing rate is faster. So, the threshold level is gotten in a shorter time.

3.2.1. Effect of the relative strength of recurrent excitation

Figure **??** and 5 show the psychometric and chronometric diagrams. As the strength of the excitatory recurrent increase, the ramping of the diagrams are faster. Also, the reaction time is lower and the accuracy is higher as the strength increase. This value increases the speed of competition between two neuron groups.

3.3. Part b- Fitting the Model

We have behavioral data and want to predict this result by the "Wang" model (fitting the model). I manually change the input variable to find the best fitting based on these rules:

1- By increasing μ_0, the neuron firing rate reached the threshold faster.

2- If the ratio of excitatory to inhibitory rate increases, the slope of the psychometric curve increase.

3- When we have a lower threshold, the response time is faster and RT is lower.

I'm not successful at all (Figure 7). So in the next part, I use the optimization algorithm.

3.4. Part c- Fitting the Model Using Optimization Algorithm

In this part, I use the "leanear_square" Python function, an optimization algorithm base on deviation. You see, the model output fits well with the data.

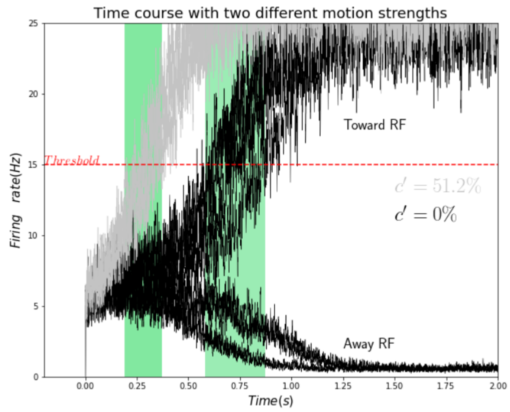

Figure 2: Time course with two different motion strengths. Motion coherence of 0% (black traces) and 51.2% (light gray traces) each with 10 sample trials. The green area shows the time range in which the winner group reached the threshold.

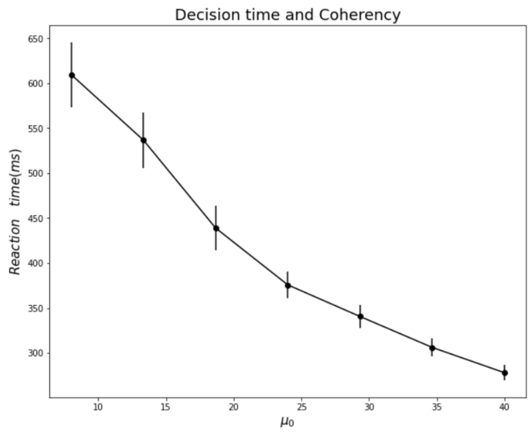

Figure 3: Reaction time over coherency level. The error bar indicate the variance.

4. Summary

The "Wang" model is a simple and powerful decision-making model which could explain some animate behaviors. As we see in the result, it could follow the decision time and accuracy, even for stimuli with low coherency. It could simulate the neural activity during decision-based on the "drift-diffusion" model, which is similar to the Poisson process of the spike times of neurons. We also could solve the fitting problem using an optimization algorithm and get an acceptable error.

References

[1] A recurrent network mechanism of time integration in perceptual decisions,Wong, Kong-Fatt and Wang, Xiao-Jing, Journal of Neuroscience, 2006

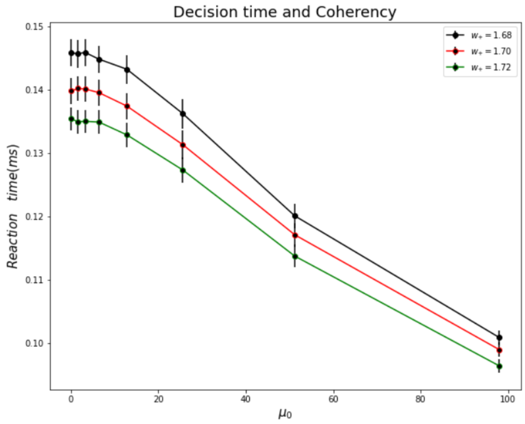

Figure 4: Dependence of integration time on the relative strength of recurrent excitation (reaction time)

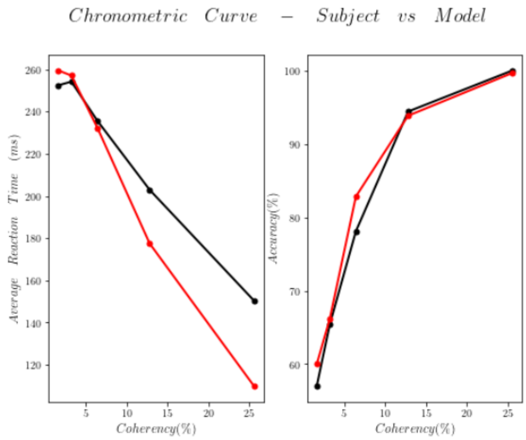

Figure 6: Fitting model on the data. red: RT and Acc the subject. black: RT and ACC the model output. Mean square error (MSE) RT equals 69.96 (ms). MSE accuracy equals 22.52%

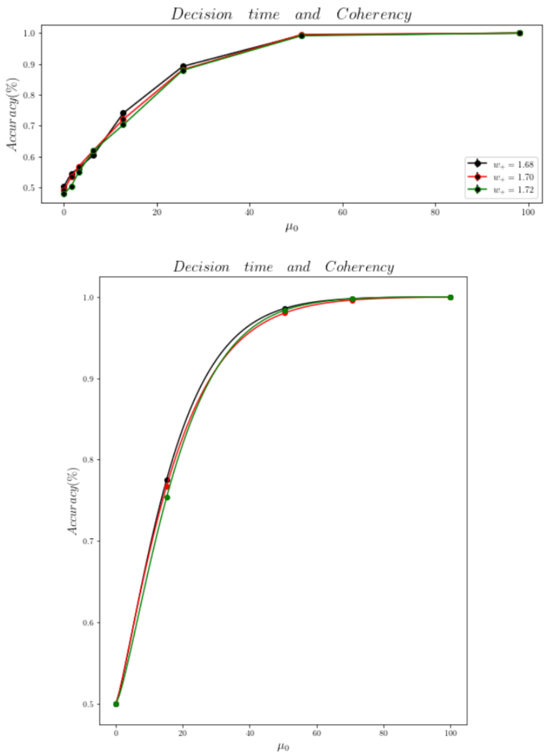

Figure 5: Dependence of integration time on the relative strength of recurrent excitation (accuracy)

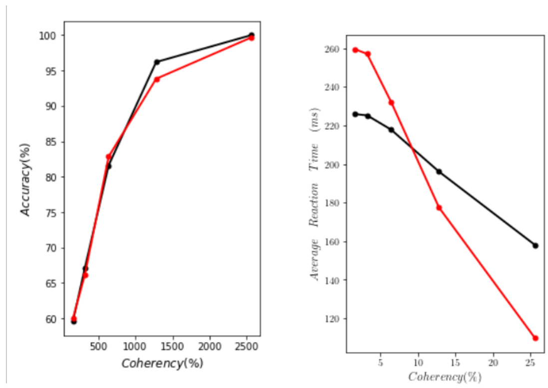

Figure 7: Fitting model on the data using an optimization algorithm. red: RT and Acc the subject. black: RT and ACC the model output. Mean square error (MSE) RT equals 62.44 (ms). MSE accuracy equals 22.00%