Application of RDM, DDM, and Wang Models in Analyzing Reaction Time and Accuracy in Decision-Making Tasks

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Abstract

This study investigates the integration of the Random Dot Motion (RDM) task with the Drift Diffusion Model (DDM) and Wang model to understand decision-making processes. We collected reaction time and accuracy data using the RDM task and employed the DDM and Wang models to fit this data. The results provide insights into the cognitive mechanisms underpinning decision making, with detailed analysis of reaction times and accuracy across different phases of the task.

1. Introduction

Decision-making is a fundamental cognitive process involving the evaluation of sensory information, risk assessment, and selection of appropriate actions. To explore these processes, researchers employ various experimental and computational models. The Random Dot Motion (RDM) task is a popular experimental paradigm used to study perceptual decision-making, wherein subjects are required to determine the direction of motion of randomly moving dots.

This study integrates the RDM task with two computational models: the Drift Diffusion Model (DDM) and the Wang model. Firstly, using RDM task, data is taken from several subjects. The task was deciding if the direction of dots are to the right or left by pushing RightArrow or LeftArrow button. The accuracy and reaction time of all subjects are calculated afterward. In phase two, A DDM model is fit to the reaction time and accuracy of the data. The DDM provides a robust framework for modeling decision-making as a process of evidence accumulation. It characterizes decision-making in terms of parameters such as drift rate, decision boundary, and non-decision time. Lastly, the Wang model is fitted to the data. The Wang model offers a detailed approach to modeling neural mechanisms underlying decision-making by incorporating parameters such as threshold and initial condition parameters (u0).

2. Methodology

2.1. Dataset

Data is collected from two subjects during phase one. The task was to estimate the direction of dots in less than 0.5 seconds. We used four values for the coherency; 3.2, 6.4, 12.8, and 25.6. This task is taken for eight blocks and 200 trials per block for each subject.

2.2. Model Fitting

The collected data were analyzed using the Drift Diffusion Model (DDM) to understand the decision-making process in terms of drift rate, decision boundary, and non-decision time. Subsequently, the Wang model was employed to fit the data, focusing on parameters such as threshold (thr) and initial condition (u0). The fitting process involved minimizing the difference between model predictions and observed data, using optimization techniques to identify the best-fit parameters. I used ”fminsearch”, which is an built-in Matlab function. Also, to get better result I got thr, u0, I0, and nDT as free parameters.

3. Results

3.1. Part 1

After data collection, data should be analyzed. Trials with no responses were omitted. Then after calculating average and standard deviation, the required figures were plotted. (Figure 1, 2)

In the next part, the data is divided to three parts named phases. The first phase consists of two first blocks, the third phase is the last block, and the second phase consists of the rest. After that, the reaction time and accuracy of each phase is visualized. I plotted them both for each coherency and for all of them together.

According to the low allowed response time, the subjects would get drowsy and tired, and that would be the reason of higher reaction time and lower accuracy in phase 3. (Figure 3, 4)

Finally, I did the t-test to find a meaningful observation from the data. The result is as follows:
Accuracy:
T-test between Phase 1 and Phase 2 for Accuracy:
p-value: 0.1241
t-statistic: -2.1210
Degrees of freedom: 3.0000
Confidence interval: [-0.0893, 0.0179]
T-test between Phase 1 and Phase 3 for Accuracy:
p-value: 0.3713

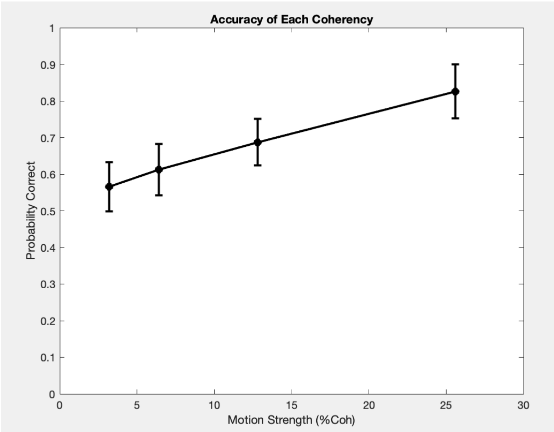

Figure 1: Psychometric Figure

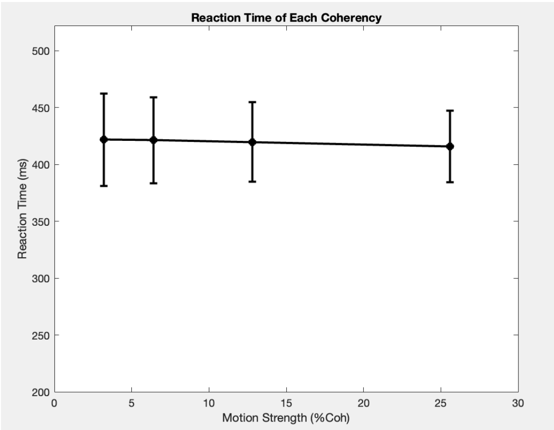

Figure 2: chronometric Figure

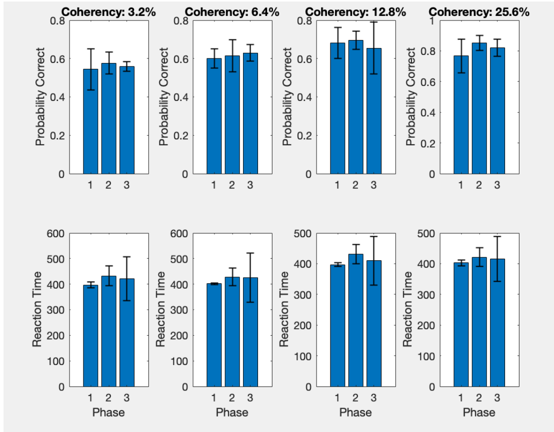

Figure 3: Accuracy and Reaction Time of Each Coherency

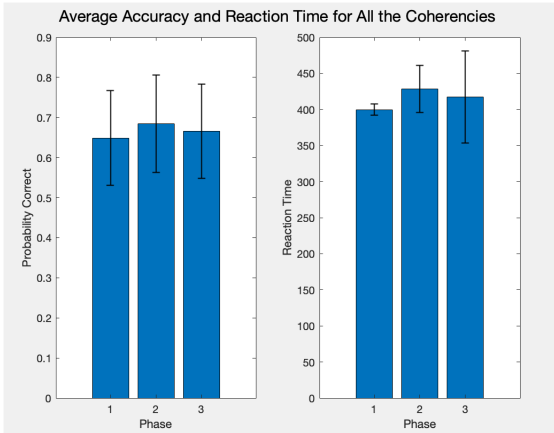

Figure 4: Average Accuracy and Reaction Time

t-statistic: -1.0487
Degrees of freedom: 3.0000
Confidence interval: [-0.0713, 0.0360]
T-test between Phase 2 and Phase 3 for Accuracy:
p-value: 0.2431
t-statistic: 1.4493
Degrees of freedom: 3.0000
Confidence interval: [-0.0216, 0.0577]

Reaction Time:
T-test between Phase 1 and Phase 2:
p-value: 0.0055
t-statistic: -7.2312
Degrees of freedom: 3.0000
Confidence interval: [-40.9955, -15.9387]
T-test between Phase 1 and Phase 3:
p-value: 0.0106
t-statistic: -5.7225
Degrees of freedom: 3.0000
Confidence interval: [-27.7521, -7.9161]
T-test between Phase 2 and Phase 3:
p-value: 0.0762
t-statistic: 2.6627
Degrees of freedom: 3.0000
Confidence interval: [-2.0754, 23.3414]

3.2. Part 2

In this part, we pass the 3 phases that were extracted to fast-dm and get Drift Rate, Decision Boundary, and Non Decision time. (Figure 5,6,7)

3.3. Part 3

In this part, the Wang model is used to estimate the neural mechanisms involved for phase 1 and phase 3. To find the best match, thr, u0, I0, and nDT paramteres are changed. I used fminsearch as the optimization method and its objective function is as follows:

$$Objective\_function = \sum (his(model\_RT) - hist(real\_RT))^2 +$$

$$(mean(model\_RT) - mean(real\_RT))^2 +$$

$$(mean(model\_Acc) - mean(real\_Acc))^2$$

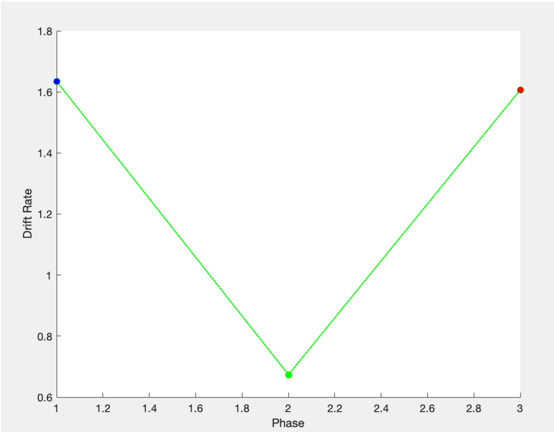

Figure 5: Drift Rate

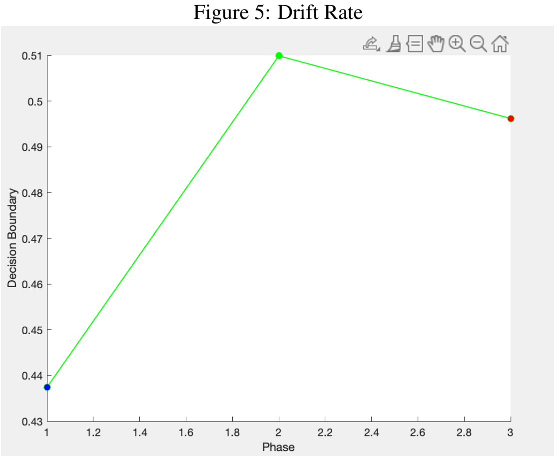

Figure 6: Decision Boundary

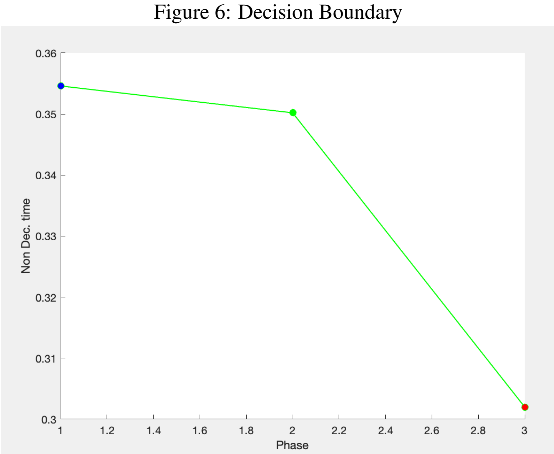

Figure 7: Non Decision Time

4. Conclusion

In this project, our aim was to first get the data and analyze it and secondly fit the model to emulate its behavior. As it is obvious from the figures, some of our results are not as the way we expected. It might be due to the lack of imperfect data, which might be because of exhaustion and tiredness of the subject.

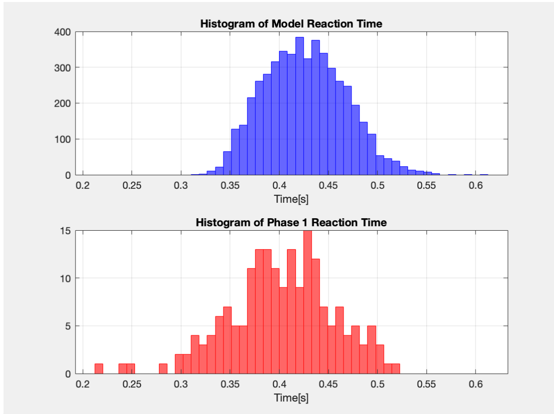

Figure 8: Histogram of Reaction Time of Phase 1

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Fitted parameters for phase_1:
thr: 0.16292
u0: 30.3901
I0: 0.32127
nDT: 0.17355
Model Mean RT: 0.42606
Phase Mean RT: 0.40196
Model Mean Accuracy: 0.8464
Model Mean Accuracy: 0.59788
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Figure 9: Paramteres of Phase 3

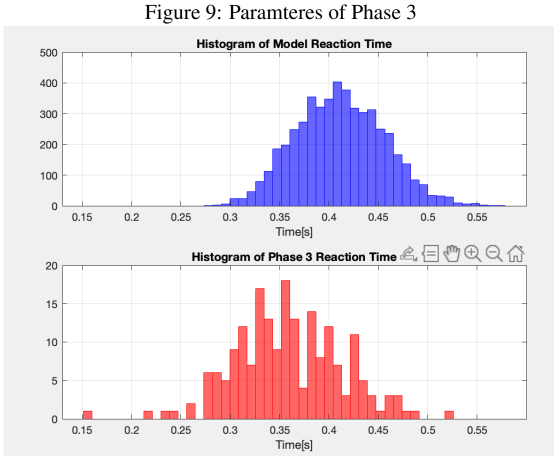

Figure 10: Histogram of Reaction Time of Phase 3

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Fitted parameters for phase_3:
thr: 0.36905
u0: 6.4899
I0: 0.34423
nDT: 0.039502
Model Mean RT: 0.41113
Phase Mean RT: 0.3585
Model Mean Accuracy: 0.632
Model Mean Accuracy: 0.62121
```

Figure 11: Paramteres of Phase 3