Signal Detection Theory, RT and Cue Integration Assignment

Use Matlab and the SDT tutorial to do the following calculations and to answer the questions. Write up a report that explains your solutions, including graphs, and the relevant snips of Matlab code. For each question, please write a brief explanation of what you did, including any equations that you used to do the calculations, and write a brief interpretations of your results. Please submit a single pdf file (not MS Word) that contains everything.

1) Simulate a two-alternative, forced-choice experiment. Each trial consists of one interval with stimulus A or stimulus B. In each 100 ms, the observer collects evidence for whether the stimulus is A or B. The evidence in each 100 ms time step consists of a single number. The expected value of that number is \( +2 \times c \) for an A stimulus, and \( -2 \times c \) for a B stimulus, where \( c \) is the stimulus contrast. However, that number is noisy, perturbed by independent random draws each time step from a standard Gaussian distribution (mean zero, SD = 1).

(a) Simulate this experiment for stimulus durations ranging from 100 ms to 2 s and a contrast of 0.2. Assume A and B are equally likely, payoffs are symmetric and an optimal criterion. Thus, for example, for a 500 ms stimulus there are 5 time steps. And, if the stimulus has contrast 0.2, that means each time step is a random draw from a Gaussian with mean 0.4 and variance 1.0. The observer will optimally combine those bits of evidence by summing the 5 numbers from the 5 time steps. Thus, for an A stimulus, the total evidence is expected to be \( 5 \times 0.4 = 2 \), on average, and \(-2\) for a B stimulus, with the criterion halfway between. Compare your results with theoretical predictions. Repeat this for contrasts ranging from 0.05 to 1 and a fixed duration of 0.2 s.

(b) Change the probability of an A stimulus to 0.75. For a fixed duration of 1 s and contrast of 0.1, simulate performance with the optimal criterion, and then simulate it with the criterion you used in part (a), comparing the performance across the two for 100 trials each. You should be able to compute the optimal criterion. However, you can also determine/estimate that criterion by doing large-scale simulations for a range of criteria (I'd prefer the closed-form computation if you can manage it).

2) With the same setup as in (1), switch to a reaction-time experiment using the accumulated evidence values in a drift-diffusion framework. That is, accumulate the sum across time steps until the sum hits a bound representing a decision to respond “A” (with bound value \( +b \)) and another for response “B” (with value \(-b\)). Use simulations to characterize the reaction-time distributions for correct vs. error trials. Do this for contrasts of 0.1 and 0.5. For each contrast, run simulations for a near decision boundary (relatively small value of \( b \)), a distant decision boundary (large value of \( b \)), and an asymmetric pair of decision boundaries \( (+b \text{ and } -d) \). What happens to the hit and
false-alarm rates (treating stimulus A as “noise” and B as “signal”) with each manipulation of the model?

3) Finally, put this in a cue-integration framework. You now have two sources of evidence for the A/B discrimination. For the first 1 s, evidence source X has contrast 0.1 and evidence source Y has contrast 0.2. After the first 1 s, the contrasts swap.

(a) Simulate a drift-diffusion model that combines these two sources of evidence. In the first model, the two sources are combined with equal weights (i.e., the raw evidence numbers are summed for the two sources, and then accumulated over the duration of the trial until a boundary is hit). This is a sub-optimal model, because it does not take into account the changing contrasts such that Y is more reliable in the first second, and X is more reliable afterward.

(b) For a second model, combine the evidence from sources X and Y with unequal weights that optimally combine the two sources (and thus change after 1 s). Important note: the sources of evidence have, prior to weighting, different means but equal variances. This is analogous to, but subtly different from the optimal cue-integration setup. Nevertheless, there is an optimal set of weights that yields the best signal-to-noise ratio at all time points. First, derive what those weights are. Hint: You can first scale them to have equal means and thus different variances and then weight the resulting numbers using the weights prescribed for optimal cue integration. However, note that you might want the boundaries to reflect the weighting so that RTs are comparable across the two models. Once you have the weights, do the simulation, and compare performance (hits, false alarms, RT) for the fixed and optimal dynamic-weighting schemes.