Final project: using competitive population firing rate models to describe buildup with ambiguous stimuli

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Introduction

For some stimuli in the visual and auditory modalities with ambiguous grouping cues, there is a tendency for the likelihood of perceptual ”splitting” to increase with time. For instance, with ambiguous moving plaids constructed from moving square wave gratings at intermediate speed and angle, observers have consistently reported first experiencing motion coherence, even when steady-state perception is biased towards transparent motion of the individual gratings [1]. Analogously, for ambiguous tone sequences in which observers report alternations between hearing grouped triplet patterns and split streams [2] (see Figure 1), there can be an initial period of buildup over which the probability of stream segregation increases.

Indeed, the process of constructing buildup curves reflects the averaging over many trials of binary timecourses 2. I believe that the observation that the starting state is fixed is sufficient to account for transient increase in probability of split percepts, but that buildup is primarily a consequence of stochastic alternations between two states.

I tested whether perceptual bistability models were capable of producing buildup if the starting state was fixed, and under which dynamical regimes. [6]

Methods

Competition model simulations

Competition model simulations followed the procedures reported previously in [6] for population firing rate model with spike frequency adaptation. Specifically,

$$\begin{cases} \dot{u}_1 &= -u_1 + f(-\beta u_2 - \gamma a_1 + I_1 + n_1) \\ \tau_a \dot{a}_1 &= -a_1 + u_1 \\ \dot{n}_1 &= \frac{-n_1}{\tau_n} + \sigma\sqrt{\frac{2}{\tau_n}}\eta(t) \\ \dot{u}_2 &= -u_2 + f(-\beta u_1 - \gamma a_2 + I_2 + n_2) \\ \tau_a \dot{a}_2 &= -a_2 + u_2 \\ \dot{n}_2 &= \frac{-n_2}{\tau_n} + \sigma\sqrt{\frac{2}{\tau_n}}\eta(t) \end{cases}$$

The variable u_1 corresponding to the short-time averaged firing rate of the population representing the “grouped” perceptual state, and u_2 the firing rate of the population representing the “split” perceptual state. The variables a_1 and a_2 represent the spike-frequency adaptation. Parameter γ controls the strength of the adaptation, and β controls the strength of suppression from the competing population. I_1 and I_2 are the external inputs driving the two populations, and n_1 and n_2 are independent Ornstein-Uhlenback noise generators with mean zero and variance σ, and a timescale of τ_n. The input-output function used was a sigmoid, with $f(x) = 1/(1 + exp((x\theta)/k))$.

The simulation was carried out on a characteristic neuronal timescale, with one unit of time corresponding to 10 msec. The following parameter values are used: $k = 0.1, \theta = 0, \beta = 1$. Time constants given in simulation time units were $\tau_a = 200, \tau_n = 10$. The values of the external inputs to the populations I_1 and I_2, the adaptation gain γ and the noise strength σ were varied as specified in the text, with the value of σ scaled in relation to the integration time step by $1/\sqrt{dt}$ to keep specified variance per unit time. Simulations were implemented in MATLAB using forward Euler integration with a time step of 0.1 (1 msec real time).

For each combination of parameter values, I simulated 500 trials of length 10 s with initial conditions $u_2(0), a_1(0), a_2(0), n_1(0), n_2(0) = 0$ and $u_1(0) = 0.5$; thus, at the beginning of each simulated trial, the first population to become dominant was always that corresonding to the first percept. With the resulting population firing rate timecourses, I obtained dominance durations by finding time points of the zero crossings of the differences of the firing rates. Using the samples of dominance durations obtained for each population (over 1000 durations for each population with each parameter set), I fitted gamma densities using maximum likelihood estimation. Simulated experimental buildup curves were constructed by averaging across trials the binary timecourse $u_2 > u_1$.

Results

Buildup curves look most realistic for noise-driven, not adaptation driven, alternation regimes

See Figure 3. Noise driven switching is necessary for buildup functions that look like those presented in the literature; however, in principle the apparent monotonically increasing likelihood of split percepts over time could also be accomplished by averaging together the timecourses of multiple oscillators with different periods. However, there have been no reports whatsoever of oscillatory buildup functions.

Buildup occurs faster for less ambiguous stimuli

The time it takes to achieve the steady state fractional dominance ratio should depend on both how far the original fractional dominance ratio from the steady state as well as the strength of the biasing input in favor of either of the two states. In 5 we see that the strength of the biasing input is much more important to defining the overall timescale of buildup than the distance between starting and steady states. This effect is in contrast to the effect on mean durations; mean durations for grouped percepts in the ambiguous case was 8.07 s, and for split 7.57 (grand mean = 7.8) whereas for the biased case, the average grouped duration was 1.29 s, the averaged split duration was 18.213, and the grand mean was 9.75. So while switches occurred more frequently in the ambiguous case, the time to half-maximum was also longer.

Discussion

These results support the growing body of research suggesting that accumulation of adaptation is not the primary cause of alternations [7]. An oscillator regime would produce extremely oscillatory buildup functions unless the buildup function reflected the average of many different oscillators with different periods or phases. To my knowledge this is the first time that buildup has been produced through model simulations of this kind, and the most parsimonious explanation for the results we see is that the alternations experienced by observers during these kinds of ambiguous stimuli are driven by noise, not adaptation.

Acknowledgments

References

References

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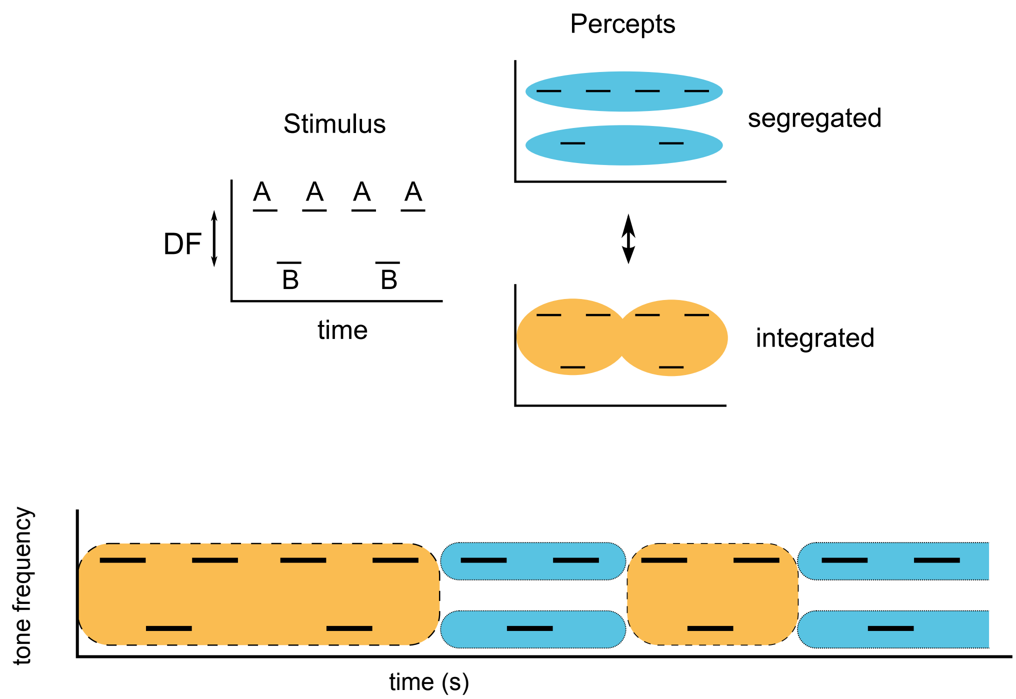

Percepts
Stimulus
segregated
A A A A
DF
B B
time
integrated
tone frequency
time (s)

Figure 1

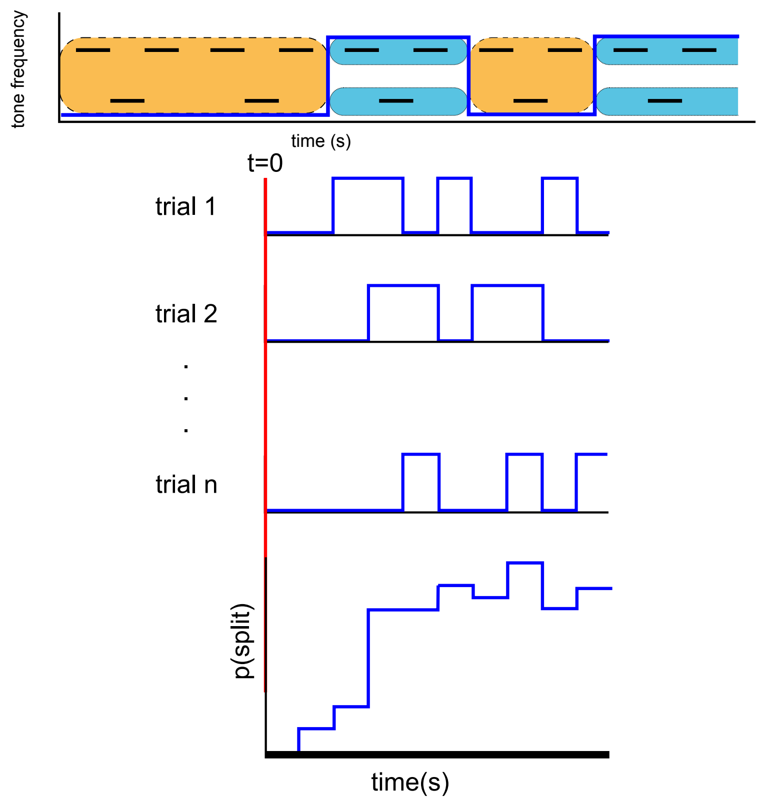

Figure 2

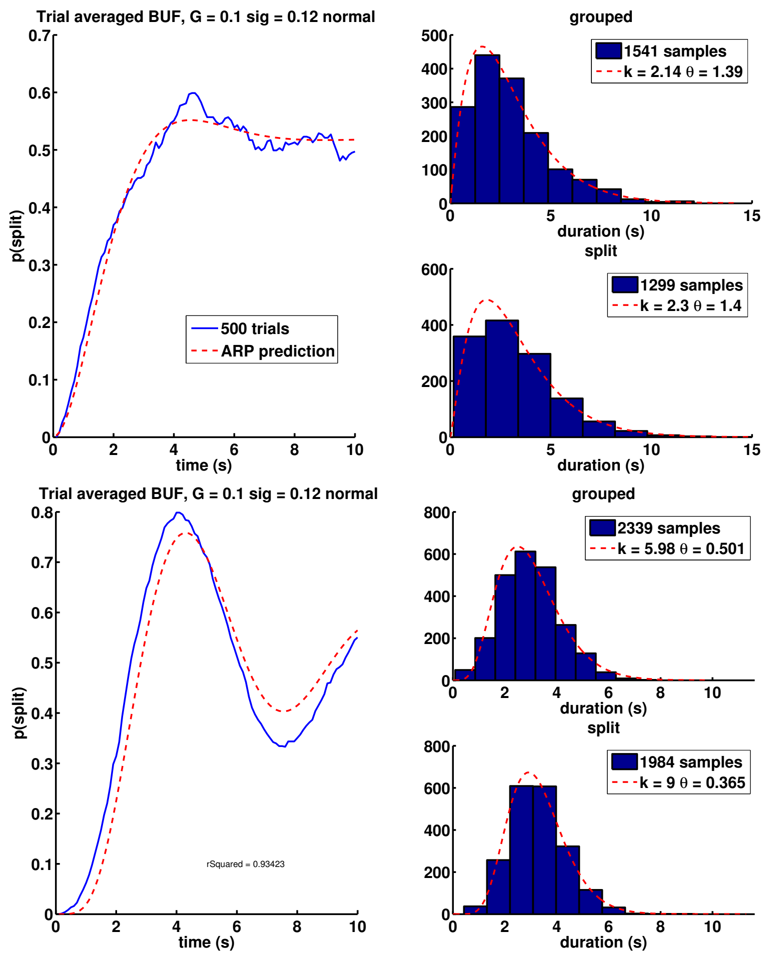

Figure 3. Buildup functions for low-adaptation and high-adaptation, low noise parameter regimes.

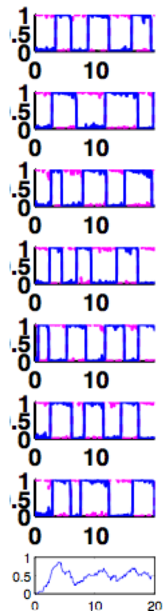

Figure 4. When switches are driven by adaptation, the system behaves as a noisy oscillator around a fixed period. Because of the "clockiness" of the timecourses, the oscillations appear in the average.

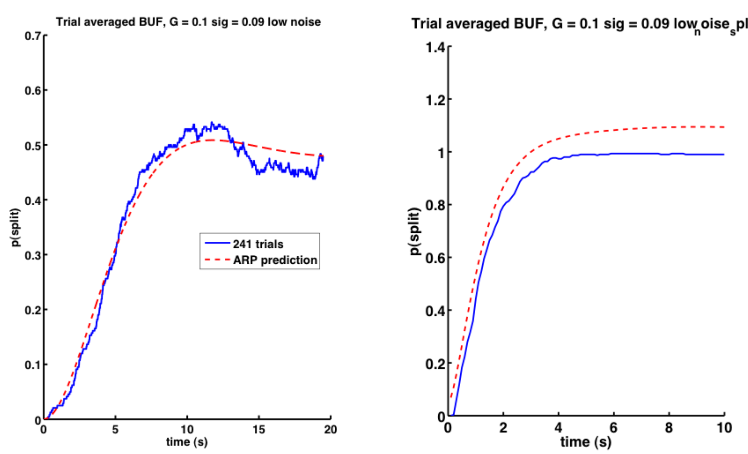

Figure 5. When stimulus is very ambiguous, leading to steady state equal fractional dominance durations, buildup is slow– left, half-maximum is achieved after about 5 s. However when the stimulus is strongly biased, the steady state is achieved in much shorter time (2s), even when this is further from the starting state.