Decision Commitment with Incomplete Evidence

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Abstract

How is commitment achieved in perceptual decisions under incomplete evidence? Standard models relying on bounded accumulation of evidence assume a readout based on the sign of the accumulator at stimulus termination, but this has not been properly validated. We aimed to resolve this by adapting an established rat auditory lateralization task, imposing varied maximum sound durations (SDmax). When SDmax was shorter than typical reaction times, accuracy decreased, but remained surprisingly high even for very brief stimuli (e.g. 15ms). Computational modeling, using an adapted DDM framework incorporating both stimulus-dependent and stimulus-independent decision processes, explored how choices are determined post-offset. Models assuming the aforementioned standard readout failed to capture the data. Instead, behavior was best explained by assuming evidence integration continues after offset (approximated by exponential decay of the neural activity providing the sensory input), but crucially, if the decision bound is not reached during this period, the subsequent choice is random. Overall, this work quantifies decision-making under temporal constraints, indicating that bound-crossing is a fundamental requirement to reliably convert integrated sensory evidence into a specific behavioral choice.

Keywords: perceptual decision-making; evidence accumulation; Drift Diffusion Model; reaction time; computational modeling; decision commitment; incomplete evidence; rats

Introduction

Perceptual decisions are often thought to involve integrating sensory evidence over time into a Decision Variable (DV) until a threshold is met, triggering a response (Ratcliff & McKoon, 2008). This framework, often formalized by the Drift Diffusion Model (DDM), explains behavior well in reaction time (RT) paradigms where subjects control the stimulus duration.

However, sensory information in natural settings is often transient. What mechanisms govern choice when the stimulus terminates before a decision bound is reached? Almost universally, it has been assumed that decision-makers will, in these conditions, choose the option to which the DV is closest when evidence is terminated (Green, Swets, et al., 1966; Ratcliff, 1980). However, the empirical validity of this rule has not been scrutinized against alternatives. We addressed this by experimentally limiting the sound duration (SDmax) in a well-characterized rat auditory lateralization task and using computational modeling to infer the underlying decision commitment rules.

Methods

We reproduced an auditory lateralization task in freely moving rats (Pardo-Vazquez et al., 2019), in which animals (n=6) discriminate Inter-Aural Level Differences -ILDs- (±1 to ±8 dB) at different Average Binaural Levels -ABLs- (20, 40, 60 dB SPL). We collected a larger dataset with more maximum sound durations (15, 30, 60, 120, 240, 480 ms), randomly interleaved with standard RT trials where the sound terminated upon response. RTs are always determined by the animals leaving the central port, regardless of SDmax.

Behavioral data (choices, RTs) were analyzed across conditions. We employed an adapted DDM framework incorporating parallel proactive (anticipatory) and reactive (stimulus-driven) processes that race to trigger a response (Hernández-Navarro, Hermoso-Mendizabal, Duque, De la Rocha, & Hyafil, 2021). Using parameters constrained by fitting the RT trials, we obtained the performance on SDmax trials under different hypotheses about post-stimulus evidence processing (e.g., immediate stop, continued integration with decay) and choice readout rules for sub-threshold evidence states (e.g., based on sign of DV, random choice). Model fits were compared to empirical psychometric and tachometric (accuracy conditioned on RT) functions.

Results

Limiting stimulus duration significantly impacted performance. Accuracy decreased for shorter SDmax values, in a manner dependent on the overall sound intensity – performance dropped more severely for quieter sounds (lower ABLs), reproducing the results of (Pardo-Vazquez et al., 2019) (Fig 1C). Nonetheless, accuracy remained well above chance even for the briefest stimuli (15 ms), suggesting that some form of evidence processing might be taking place post-offset. Our focus was to capture this accuracy profile at the level of psychometrics and tachometric functions (Methods).

Computational modeling tested several plausible mechanisms for decision commitment after stimulus termination (Fig 1B). Models assuming a simple readout of the DV's sign at SDmax plus delays failed to replicate the observed behavior (Fig. 1 D1). The data were best explained by a model incorporating two key features.

First, there is **post-offset integration**: following the sensory delay, the decision variable continues to evolve for an extended window (Fig 1B, 3), driven by a decaying trace of the sensory evidence (approximated as exponential decay). This allows the DV to sometimes reach a bound even after the stimulus ends, explaining the relatively high accuracy. However, this feature alone overestimates accuracy, particularly by missing the decline of the tachometric (Fig. 1 D2).

Thus, we added a second feature, a **random readout rule**: if the decision bound is *not* reached by the end of this post-offset integration period, the model assumes the animal makes a random choice, independent of the final value of the DV. This combination captures well the data (Fig. 1 D3). Crucially, the model parameters fit to just SDmax = 30ms generalize remarkably well to the full set of durations and ABLs (Fig. 1E).

Discussion

This study examines the mechanisms of decision commitment when sensory information is available only briefly. By experimentally limiting sound duration in an auditory lateralization

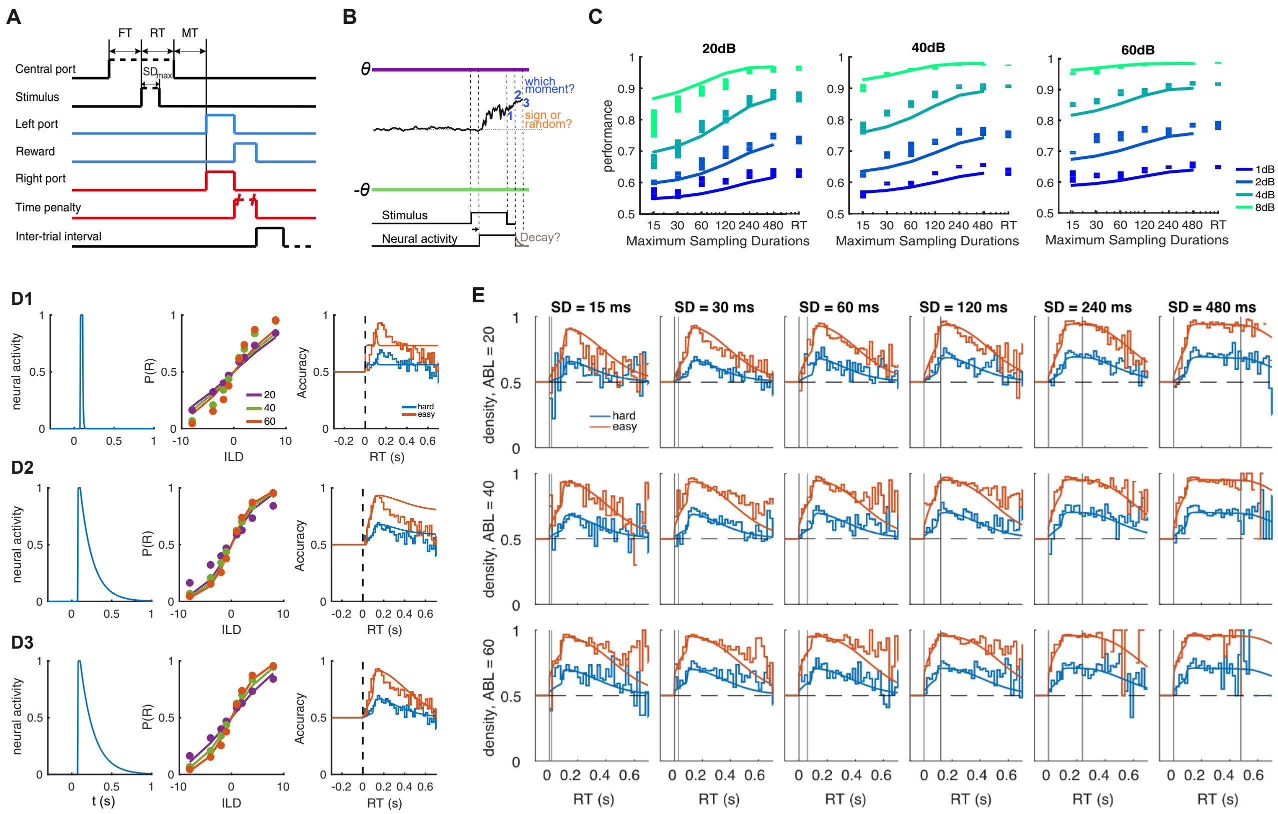

Figure 1: **Task, empirical data, and model fits for short-duration stimuli.** **(A)** Schematic of the 2AFC auditory lateralization task. Rats initiated trials at a center port and reported the side (left/right) with the louder sound at a side port. **(B)** Simple model schematic, highlighting the elements to be explored. **(C)** Empirical accuracy breakdown for short stimuli. Proportion correct versus SDmax for different ILDs (colors) and ABLs (different panels). Solid lines show the model fits as in E. **(D)** Model fits (solid lines) to psychometric data (middle column, markers) and tachometric data (right column, jagged lines), for an example with SDmax = 30ms and ABL = 20 dB SPL. Left column represents the firing rate of sensory neurons.**(D1)** Model with instanteneous decay and sign-based choice readout. **(D2)** Model with exponential decay and sign-based choice readout. **(D3)** Model with exponential decay and random choice readout. **(E)** With the same parameters as in C3, the model generalizes to the tachometric data for all ABLs and SDmax values.

task, we created conditions where decisions often must be made based on incomplete evidence accumulation, and our focus is on how the final choice is determined in these scenarios.

Our findings challenge simple readout models (like SDT or sign-based DDM readout at offset). The relatively high accuracy maintained even for short stimuli, coupled with responses often occurring well after sound offset, points at the involvement of post-offset evidence integration, likely reflecting persistent neural activity in addition to sensory/motor delays (Hartley, Dahmen, King, & Schnupp, 2011; Takahashi, Nakao, & Kaga, 2004).

Crucially, our computational modeling indicates that reaching a decision bound is a prerequisite for evidence to guide choice in this task. When accumulation remains subthreshold, choices appear to default to random, irrespective of the final evidence state. Decision bounds thus emerge not merely as mechanisms controlling the speed-accuracy trade-off, but as essential gates determining whether accumulated evidence translates into directed action. This quantitative framework reveals thus a critical mechanism underlying decision commitment, particularly when choices must be formed from temporally limited information.

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