Acta Psychologica 149 (2014) 157–168

Contents lists available at ScienceDirect

Acta Psychologica

journal homepage: www.elsevier.com/locate/actpsy

Decision processes in temporal discrimination

Fuat Balcı [a,*], Patrick Simen [b]

[a] Department of Psychology, Koç University, Turkey
[b] Department of Neuroscience, Oberlin College, United States

ARTICLE INFO

Article history:
Received 10 January 2013
Received in revised form 13 March 2014
Accepted 18 March 2014
Available online 13 April 2014

PsycINFO classification:
300 Human Experimental Psychology
2340 Cognitive Processes

Keywords:
Choice behavior
Diffusion model
Interval timing
Response time
Temporal bisection

ABSTRACT

The processing dynamics underlying temporal decisions and the response times they generate have received little attention in the study of interval timing. In contrast, models of other simple forms of decision making have been extensively investigated using response times, leading to a substantial disconnect between temporal and non-temporal decision theories. An overarching decision-theoretic framework that encompasses existing, non-temporal decision models may, however, account both for interval timing itself and for time-based decision-making. We sought evidence for this framework in the temporal discrimination performance of humans tested on the temporal bisection task. In this task, participants retrospectively categorized experienced stimulus durations as *short* or *long* based on their perceived similarity to two, remembered reference durations and were rewarded only for correct categorization of these references. Our analysis of choice proportions and response times suggests that a two-stage, sequential diffusion process, parameterized to maximize earned rewards, can account for salient patterns of bisection performance. The first diffusion stage times intervals by accumulating an endogenously noisy clock signal; the second stage makes decisions about the first-stage temporal representation by accumulating first-stage evidence corrupted by endogenous noise. Reward-maximization requires that the second-stage accumulation rate and starting point be based on the state of the first-stage timer at the end of the stimulus duration, and that estimates of non-decision-related delays should decrease as a function of stimulus duration. Results are in accord with these predictions and thus support an extension of the drift–diffusion model of static decision making to the domain of interval timing and temporal decisions.

1. Introduction

In its simplest form, time tracking ability can modulate an agent's expectancy of events that exhibit some level of temporal predictability (e.g., rewards that are delivered on average every 5 s). Frequently, humans and non-human animals must not only anticipate events but must also make explicit judgments about perceived time. For instance, by comparing the currently perceived time to remembered time intervals, an individual can distribute its responses differentially during a trial between two options that predict reward at different delays in order to maximize reward (e.g., Balcı, Freestone, & Gallistel, 2009; Kheifets & Gallistel, 2012).

Simple, non-temporal perceptual decisions have long been modeled according to principles of rational decision making. Signal detection theory (SDT, Green & Swets, 1966), for example, offers an account of choice proportions that change as a function of a payoff scheme. Evidence-accumulation models such as the drift–diffusion model (DDM) have extended SDT to give detailed accounts of response time distributions in such tasks (Ratcliff, 1978, 1981, 1985, 1988, 2002). Traditionally, the stimuli used in these experiments are categorized according to the level of some defining sensory quality, such as intensity (e.g., loudness) or some other feature (e.g., direction of motion). In contrast, equivalent theoretical accounts have not been given for decisions in which stimuli are categorized only according to their duration.

Historically, to account for performance in such scenarios, models of performance in two-choice temporal decision tasks – such as temporal bisection (Church & Deluty, 1977), temporal generalization (Church & Gibbon, 1982) and time-left (Gibbon & Church, 1981) – incorporate some form of "comparator" that bases decisions on differences between duration estimates (see Buhusi & Meck, 2005). These studies, however, have primarily focused on choice proportions, and to a large extent have overlooked response times. Consequently, the dynamics of comparison and the relation of these dynamics to interval timing processes themselves have largely been left unexamined (although see Leon & Shadlen, 2003; Kononowicz & van Rijn, 2011; Ng, Tobin, & Penney, 2011). This disconnect between analytical approaches to temporal and other simple decision-making performance has resulted in a theoretical gap between the areas of interval timing and perceptual decision-making.

We show that an overarching decision-theoretic framework that encompasses existing, non-temporal decision models can nevertheless

* Corresponding author at: Department of Psychology, Koç University, Rumelifeneri Yolu 34450, Sarıyer, Istanbul, Turkey. Tel.: +90 212 338 1138; fax: +90 212 338 1415.
E-mail addresses: fbalci@ku.edu.tr (F. Balcı), psimen@oberlin.edu (P. Simen).

http://dx.doi.org/10.1016/j.actpsy.2014.03.005
0001-6918/

account both for interval timing itself and for time-based decision-making. We previously showed (Simen, Balcı, deSouza, Cohen, & Holmes, 2011a) that a noisy evidence-accumulation process (specifically, a drift–diffusion process) can account for well-known patterns typically observed in simple, timed responding, such as unbiased estimation and timescale invariance of response time distributions, as well as for new, predicted patterns, such as one-trial learning of intervals, and inverse Gaussian response time distributions with skewness equal to three times their coefficient of variation (standard deviation divided by the mean).

We now go beyond simple, timed responding and demonstrate that a drift–diffusion-based account can explain all the critical features of two-alternative forced-choice (2AFC) tasks in a temporal context. Our results favor a unified theoretical view of timing and both temporal and non-temporal decision-making in terms of drift–diffusion mechanisms, parameterized so as to maximize reward rates earned from repeated decisions. We tested the predictions of this unified theory using one of the most common tasks in the psychophysical study of interval timing: the temporal bisection task.

1.1. Temporal bisection task

In this task, participants are initially trained to discriminate a pair of reference durations, signaled by a stimulus such as a tone or light, as either *short* or *long*. Following this pre-training, participants are presented with a random sequence of short or long reference-duration stimuli and intermediate duration stimuli. Participants are asked to categorize these as *short* or *long* based on their similarity to the two reference durations. Correct categorizations of the reference durations are rewarded; categorizations of intermediate durations and incorrect reference categorizations are not rewarded. The observed proportion of *long* choices as a function of stimulus duration defines a psychometric function of time that is typically sigmoidal. The stimulus duration at which a participant exhibits equal proportions of *short* and *long* choices is known as the point of subjective equality (PSE). The steepness of the psychometric function is an index of the participant's level of timing uncertainty.

In this study, we evaluated a process model of decision-making in temporal bisection as a two-stage drift–diffusion process. Before outlining the basics of this model of temporal bisection, we will briefly describe a single-stage drift–diffusion model of two-alternative forced choice as it is typically applied in a non-temporal context. The model we subsequently propose relies heavily on the same drift–diffusion dynamics.

1.2. The drift–diffusion model

Diffusion models have been successfully applied to two-alternative forced choice in several cognitive domains that include but are not limited to memory (e.g., Ratcliff, 1978. 1988), and perceptual (e.g., Starns & Ratcliff, 2010) and economical decision making (e.g., Krajbich, Lu, Camerer, & Rangel, 2012). The drift–diffusion model (DDM) assumes that sensory information is noisy. The model's decision variable equals the difference between the evidence supporting the two hypotheses, integrated over time. As a result, the variable carries out a random walk, just as a stock price varies over time (see Fig. 1A). When it crosses one of two absorbing boundaries, or decision thresholds, the corresponding decision is made. The first threshold-crossing time is identified as the decision time (DT). An additional non-decision latency (T_{er}) is used to capture sensory encoding (e) and motor response (r) delays. The overall response time is therefore RT $=$ DT $+$ T_{er}.

In its simplest form, the DDM is defined by the starting point (z) and threshold (a) parameters, and an equation governing the decision maker's state of preference x for one or the other choice option. This state of preference changes over time until eventually it descends below 0 or rises above a. Each event corresponds to making one of the two possible choices, so we refer to the 0 and a levels respectively as the *lower* and *upper response thresholds*. Technical details of the diffusion model, including the generalized form of it (Ratcliff, 1978) typically seen in the literature, are described further in Supplementary Online Material.

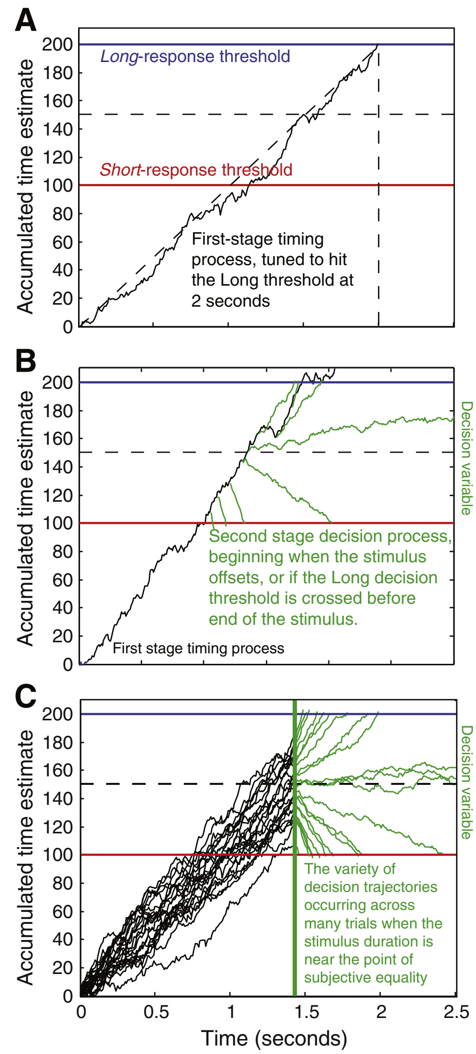

Fig. 1. A) A drift–diffusion process (black) used to track time up to the duration of the long reference duration (when the process intersects the blue threshold). B) A decision process begins when a stimulus duration ends. Seven decision processes (green) are shown for seven different stimulus durations. The starting point of the decision process equals the location of the timer process at the end of the stimulus. Note that the decision process starts at different locations depending on where the first process is at the end of the stimulus duration. Drift is toward the long threshold if the timer location exceeds the level of subjective equality (black dashed line). C) An ensemble of trials with a stimulus duration of 1.4 s. Since this time is near the point of subjective equality, the decision process has a distribution of starting points (centered on black dashed line) and drift values (with mean 0). Note that Fig. 1A only shows the first stage timer process, Fig. 1B shows the trajectory of the second-stage decision process for different stimulus durations (for a given first stage timer trajectory), and Fig. 1C shows the first and second stage trajectories for a given stimulus duration.

In our case, the two hypotheses are *short* vs. *long* (without loss of generality, we can assume that upper threshold crossings produce a *long* response, while lower threshold crossings produce *short* responses). Another key parameter is "v", which represents the average rate of increase in X over time. Biases toward either type of response can be built in by moving the starting point z closer to either a or 0; perfectly unbiased responding occurs when $z = a/2$. We can simulate the DDM's evolution over time with the following simple difference equation, in