**Time Perception Models**

Lorraine G Allan, McMaster University, Hamilton, ON, Canada

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**Abstract**

This article focuses on signal detection and information-processing models for time perception. The pseudologistic model and the scalar timing model are presented as exemplars of these two classes of models. For both models Weber’s law describes the relationship between variability in perceived time and mean perceived time, and a power function with an exponent close to 1.0 describes the relationship between mean perceived time and clock time. The application of the two models to the temporal bisection task is considered.

*Time perception* is a distinct area of study with its own psycho-physical methods designed for assessing the perceived duration of a temporal interval. There is now an extensive database to guide the development of models of time perception. Most timing models are firmly rooted in an *internal clock*. Internal clock models postulate a timing-specific mechanism which produces perceived temporal values that bear orderly relations to real time. This timing-specific mechanism, or internal clock, is an interval timer, rather than a periodic or oscillatory mechanism. A periodic clock, such as the kind responsible for circadian rhythms, is continuously running and self-sustaining. In contrast, interval clocks need to be initiated with a signal. Once started, the system goes to completion, comes to a rest on its own, and must be restarted.

The first psychophysical models for time perception were proposed at about the same time by Creelman (1962) and Treisman (1963). Creelman (1962) introduced the signal-detection approach, which was continued by Allan and Kristofferson (1974). The most sophisticated signal detection model is Killeen et al.’s (1997) *pseudo-logistic model* (PLM). The information processing approach was introduced by Treisman (1963) and continued by many others, including Eisler (1975), Thomas and Cantor (1978), and Zakay and Block (1994). The most developed of the information-processing models is Gibbon et al.’s (1984) *scalar timing* (ST), which has been reformulated as a connectionist model by Church and Broadbent (1991). In direct contrast to information-processing models is Killeen and Fetterman’s (1988) behavioral theory of timing (BeT).

Because signal-detection models and information-processing models have been applied to both human and nonhuman timing data, we shall focus on such models in this article, presenting ST and PLM as exemplars of these two classes of models. Specific versions of ST and PLM have been derived for a variety of timing tasks, such as time-left, temporal generalization, and temporal bisection. We shall examine ST and PLM in their application to temporal bisection.

In the prototypic temporal bisection task (e.g., Allan and Gibbon, 1991), the subject is familiarized with a constant pair of referents, one short (S) and the other long (L). On probe trials, a temporal interval t, S ≤ t ≤ L, is presented, and the subject is required to indicate whether t is more similar to S(RS) or to L(RL). Temporal bisection data are summarized as a psychometric function relating the proportion of long responses, $P(R_L)$, to probe duration t. The *bisection point* ($T_{1/2}$) is the value of t at which $RS$ and $RL$ occur with equal frequency, $P(R_S) = 0.5$. One interpretation of $T_{1/2}$ is that it is the point of subjective equality (PSE), identifying the perceived value of t that is midway between S and L. Empirically, it has been found that the location of $T_{1/2}$ is influenced by the size of the L-to-S ratio (r) and by the spacing of the probes (see Allan, 1998). For $r \leq 2$, $T_{1/2}$ is around the geometric mean (GM) of the S and L referents, but moves toward their arithmetic mean (AM) as r increases. For $r > 2$, $T_{1/2}$ for linearly spaced probes is greater than that for logarithmically spaced probes, with the probe spacing effect becoming negligible for $r \leq 2$.

**Scalar Property**

Both ST and PLM incorporate *Weber’s law* for the duration values used in most psychophysical experiments. According to Weber’s law, for a given clock time $t > 0$, the variability in perceived time ($\sigma_t$) is *scalar* with mean perceived time ($\mu_t$): that is, there is a constant $\gamma > 0$ such that

$$\frac{\sigma_t}{\mu_t} = \gamma \quad [1]$$

Also, for both models, mean perceived time is a power function of clock time with an exponent close to 1.0, i.e.,

$$\mu_t = t \quad [2]$$

and therefore eqn [1] can be rewritten as

$$\frac{\sigma_t}{t} = \gamma \quad [3]$$

The scalar property in eqn [3] results in distributions that superpose when the temporal axis is normalized with respect to the mean of the distribution. This superposition in relative time reflects a rescaling in time, a scale-invariant error distribution for perceived time.

**Scalar Timing**

ST has its origins in scalar expectancy theory (Gibbon, 1977), and made its appearance as a timing model in Gibbon et al. (1984). The model consists of three, interrelated information...
processing stages—clock, memory, and decision—which are associated with timing, storage, and responding, respectively. The clock is responsible for transforming clock time into perceived time. It consists of a pacemaker that emits pulses at some mean rate, a switch that is controlled by a timing signal, and an accumulator that sums the pulses. There are two memory registers for the storage of clock information, working memory and reference memory. Working memory is loaded from the accumulator and serves as an extended buffer for temporal information from the current trial. Reference memory stores critical temporal information from past trials. The comparator determines a response on the basis of a decision rule which involves a comparison of current time stored in working memory with remembered time sampled from reference memory.

According to ST, the decision to respond RS or RL in temporal bisection is made by comparing the similarity of the perceived value of $t$ with memories of the two referents, $S$ and $L$. This comparison is based on a ratio of the similarity of $t$ to $S$ relative to the similarity of $t$ to $L$. If that ratio is less than some fixed value $\beta$, the response is $R_L$. In his mathematical derivation of the bisection function, Gibbon (1981) combined the similarity ratio decision rule with two locations for the scalar variability, perception or memory. In the referent known exactly (RKE) model, he assumed no variability in the perception of the probes. In contrast, in the stimulus known exactly (SKE) model, he assumed no variability in the perception of the probes and placed the scalar variability in the memory for the referents. There are two parameters in these models. The noise parameter $\gamma$ is the coefficient of variation of time. For SKE, $\gamma$ is the scalar variability in the memory representations of the S and L referents; for RKE, $\gamma$ is the scalar variability in the perception of $t$. For both models, $\beta$ is a response bias parameter. It follows from the assumptions of the model that the SKE bisection function is approximately

$$P(R_L) = 1 - \phi \left[ 1 - \beta \left( \frac{t}{\sqrt{SL}} \right)^2 \right]$$

and the RKE function is approximately

$$P(R_L) = 1 - \phi \left[ \frac{\sqrt{SL}}{\beta \gamma^2} - \frac{1}{\gamma} \right]$$

where $\phi$ is the cumulative normal distribution function. For both models, $T_{1/2}$ is proportional to the geometric mean (GM) of the $S$ and $L$ referents:

$$T_{1/2} = \sqrt{SL} = \frac{GM}{\sqrt{\beta}}$$

and for unbiased responding ($\beta = 1$), $T_{1/2}$ is at the GM of the $S$ and $L$ referents:

$$T_{1/2} = \sqrt{SL} = GM$$

For example, with a large $r$ and linear probe spacing, $T_{1/2}$ located at the GM would yield more $R_L$ than $R_S$ responses. To balance the frequency of the two response categories, it would be necessary to set $\beta < 1$, moving $T_{1/2}$ towards the AM. With log probe spacing, however, the two response categories would be equal with $\beta = 1$ and $T_{1/2}$ at the GM.

**Pseudolistic Model**

In addition to deriving the bisection function for the similarity ratio rule, Gibbon (1981) also derived the function for the signal detection likelihood ratio rule. For the likelihood rule, the decision to respond $R_S$ or $R_L$ is based on the odds ratio that the perceived value of $t$ is generated by $S$ or $L$. For this rule, Gibbon (1981) placed the scalar variability in the perception of the probes, resulting in a signal-detection model for temporal bisection. Killeen et al. (1997) simplified the derivation of the bisection function (and the resulting equation) by approximating the normal distribution with the logistic. The pseudolistic bisection function is

$$P(R_L) = \left[ 1 + \exp \left( \frac{C - t}{0.55 + t} \right) \right]^{-1}$$

where $C$ is the signal detection criterion. According to PLM, $T_{1/2}$ is the value of $t$ where the $S$ distribution crosses the $L$ distribution. Killeen et al. (1997) showed that $T_{1/2}$ is proportional to the harmonic mean (HM) of $S$ and $L$; i.e.,

$$T_{1/2} = (1 + k) \frac{2}{S + L} = (1 + k)HM$$

where

$$k = \left[ \frac{\gamma \ln \left( \frac{L}{S} \right)}{2} \right]$$

PLM predicts that the $L$-to-$S$ ratio will affect the location of $T_{1/2}$.

PLM is presented schematically in Figure 1 for $r = 4$ ($L = 8$ and $S = 2$). The spacing of $r$ is linear, $\gamma = 0.15$, and $C$ is located at $(1 + k)HM$. It is clear from Figure 1 that because of the scalar property a percept located at $C = (1 + k)HM$ is more likely to have been generated by $L$ than by $S$. Killeen et al. (1997) suggested that in order to balance the frequency of the two response categories, $C$ would move toward the AM with increasing $r$ rather than being set at $(1 + k)HM$.

**Pseudolistic Model and the BeT**

Killeen et al. (1997) emphasized that PLM is a descriptive rather than a process model in that it resides close to the level of the data and does not postulate particular underlying processes that generate the data. They do describe, however, how in their view PLM dovetails with BeT.

**Other Models**

Allan and Kristofferson (1974: 26) concluded that "There are few quantitative theories of duration discrimination and few
established empirical phenomena to guide theorizing.” Five years later, Allan (1979: 340), referring back to Allan and Kristofferson (1974), stated that “Since that time, there has been a dramatic change. Many articles on the discrimination of brief temporal intervals, and several new quantitative models, have appeared in a period of a few years.” Now in 2000 we have an abundance of quantitative models for time perception. In this short article, I have merely provided the reader with a few gems. To obtain a broader exposure to and appreciation of the current status of quantitative models for time perception, the reader is referred to two special issues of Behavioural Processes in 1998 and 1999 edited by Jennifer Higa.

Bibliography