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Identification and Bisection of Temporal Durations and Tone Frequencies: Common Models for Temporal and Non-Temporal Stimuli

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Abstract

Two experiments examined identification and bisection of tones varying in temporal duration (Experiment 1) or frequency (Experiment 2). Absolute identification of both durations and frequencies was influenced by prior stimuli and by stimulus distribution. Stimulus distribution influenced bisection for both stimulus types consistently, more positively skewed distributions producing lower bisection points. The effect of distribution was greater when the ratio of the largest to smallest stimulus magnitude was greater. A simple mathematical model, Temporal Range Frequency Theory, is applied. It is concluded that (a) similar principles describe identification of temporal durations and other stimulus dimensions, and (b) shifts in temporal bisection point can be understood in terms of psychophysical principles independently developed in non-temporal domains, such as Parducci's (1965, *Psychological Review*) Range Frequency Theory.

Identification and Bisection of Temporal Durations and Tone Frequencies: Common Models for Temporal and Non-Temporal Stimuli

This paper addresses two questions. At a general level, our concern is with whether human identification and discrimination of short temporal durations can be described in terms of the same principles that are known to characterise identification and discrimination of other simple perceptual stimuli (e.g., weights, loudnesses, or line lengths). Is a unified account possible? Recent models of timing have been developed independently from earlier traditions of modeling perceptual identification and discrimination; here in contrast we argue that similar principles may apply in both cases. A second, more specific, issue that we address concerns shifts in the temporal bisection point (the duration that is equally likely to be judged the same as the shortest or longest magnitude in a stimulus set). Several models of timing have proposed accounts of bisection point shifts that are specific to temporal processing; here we argue that a more general account of bisection point shifts can be given in terms of a model developed outside the temporal domain: Range Frequency Theory (RFT; e.g., Parducci, 1965, 1995). The predictions of this claim are explored with a simple mathematical model, which we term Temporal Range Frequency Theory, and tested in two experiments.

Models of timing. Over the past decade, understanding of human timing has been advanced through the use of temporal generalization and temporal bisection tasks. In the temporal generalization task, participants are exposed to a standard stimulus of a fixed duration. They then judge whether or not subsequently presented stimuli are of the same duration as the standard. Here we focus on temporal bisection tasks, a variety of which have been developed for use with human adults and children (Allan, 2002a,b; Allan & Gerhardt, 2001; Allan & Gibbon, 1991; Droit-Volet, Clement, & Fayol, 2003; Droit-Volet & Wearden, 2001, 2002; Gautier & Droit-Volet, 2002; Gibbon, 1981; McCormack, Brown, Maylor, Darby, & Green, 1999; Penney, Gibbon, & Meck, 2000; Rattat & Droit-Volet, 2001; Rodriguez-Girones & Kacelnik, 2001; Wearden, 1991; Wearden & Bray, 2001; Wearden & Ferrara, 1995, 1996; Wearden, Rogers, & Thomas, 1997) based on adaptation of tasks originally used on animals (e.g., Church & DeLuty, 1977; Gibbon, 1981, 1986; Machado & Keen, 2003; Platt & Davis, 1983; Raslear, 1983, 1985; Siegel, 1986; Siegel & Church, 1984). In a typical temporal bisection task, participants initially receive two standard durations, one long and one short. They then judge whether subsequently presented durations are more similar to the long or the short standard. Various versions of such tasks have been employed, allowing manipulation of factors such as the memory demands of the task (e.g., Allan, 2002a; Rodriguez-Girones & Kacelnik, 2001; Wearden & Bray, 2001) or the number of times a given duration is repeated within an experiment (e.g., Allan & Gerhardt, 2001). The stimulus durations that are employed are typically short enough (less than 1 or 2 s) to prevent chronometric counting. These tasks generally produce consistent and orderly data in humans across a wide age range although, as we show below, a complete account of some of the results is lacking.

A variety of models have been developed to account for the results of temporal bisection and generalization tasks. Scalar Expectancy Theory (SET) has been particularly influential in both the human and animal literature, although other perspectives are available (e.g., Block & Zakay, 1997; Dragoi, Staddon, Palmer, & Buhusi, 2003; Killeen & Fetterman, 1988; Killeen & Taylor, 2000; Machado, 1997; Machado & Guilhardi, 2000; Machado & Keen, 1999; McCormack et al., 1999; McCormack, Brown, Maylor, Richardson, & Darby, 2002; Staddon & Higa, 1999). According to SET, timing behavior is based on the output of an internal clock that provides memory representations that can be retrieved and compared with a current temporal interval (e.g., Allan & Gibbon, 1991; Gibbon, Church, & Meck, 1984; Wearden, 1991, 1992, 1995; Wearden & Ferrara, 1995, 1996). A more detailed discussion of SET and its relation to the account we develop here is given in the General Discussion.

Judgment and identification of non-temporal stimuli. A number of modifications to SET have been proposed to account for the detailed pattern of empirical findings. Here we focus on the relation between the temporal bisection and identification tasks that have motivated SET and we introduce more general psychophysical models that have been developed independently to account for identification and discrimination of other perceptual dimensions. First, we note that commonly-used duration judgment tasks are in many respects akin to identification tasks that have been carried out using a number of perceptual dimensions including weight, line-length, and brightness (Berliner & Durlach, 1973; Bower, 1971; Miller, 1956; Murdock, 1960; Pollack, 1952). A typical absolute identification task proceeds as follows. Stimuli that vary along a single dimension (e.g., a series of lines varying in length from short to long) are shown to participants in the first phase of an experiment. Each item in the stimulus set is assigned a number representing its place in the series (e.g., in an eight-stimulus set, the item with the smallest magnitude is labeled “1” and the item with largest magnitude is labeled “8”, although arbitrary non-ordered labels may also be used). In the main part of the experiment, individual items are presented to participants, who must respond with the appropriate number for that item. Magnitude judgment tasks are similar in that responses to presented items must be based on the perceived magnitude of the stimuli, but differ in that a constrained set of stimuli need not be used and feedback is not provided.

It is evident that there are similarities between identification and judgment tasks and the bisection and generalization tasks typically used to investigate timing. In both cases, responses must be made to unidimensionally-varying stimuli based on their position along the dimension. In both absolute identification and temporal generalization, participants must judge whether a presented item is the same or different from an item or items presented earlier. The temporal bisection task is usually described as one in which various test items are judged in terms of their similarity to each of two previously presented items.

The similarities between timing tasks and other widely used identification tasks is of theoretical interest because of the possibility that temporal duration and other dimensions (such as line length or loudness) may be processed in similar ways, and hence that models developed to account for absolute identification performance and magnitude judgments over the past 40 years may be relevant to understanding timing behavior (e.g., McCormack et al., 2002). A wide variety of models of absolute identification have been developed (e.g., Berliner & Durlach, 1973; Lacouture, 1997; Lacouture & Marley, 1991, 1995; Laming, 1984; Luce, Nosofsky, Green, & Smith, 1982; Nosofsky, 1997; Stewart, Brown, & Chater, in press; Treisman, 1985, Treisman & Williams, 1984). Although there are several differences between these models, we emphasise two key points of contrast between models of judgment and identification, on the one hand, and most models of timing on the other. The first of these we refer to as *distribution dependence*. The distribution dependence principle states that responses to a given item will not only depend on the relation between that item and its representation in memory, but will be influenced by the entire distribution of contextual stimuli. For example, the information transmitted in an absolute identification seems to be limited to two to three bits for unidimensional stimuli (Garner, 1953, 1962; Laming, 1984; Miller, 1956; Pollack, 1952). This is equivalent to perfect classification of about five items. Crucially, increasing the separation between adjacent stimuli beyond the point at which pairs of stimuli are perfectly discriminable when presented in isolation does not substantially increase information transmission (Braida & Durlach, 1972; Pollack, 1952), indicating that the identifiability of an item is normally limited not primarily by perceptual factors but instead by the item's location relative to a set of other stimuli. In magnitude estimation tasks, the judged magnitude of a given item is strongly influenced by the skewness of the distribution of other stimulus magnitudes within the set to be judged (e.g., Parducci, 1968, 1995). Some extant results are consistent with some distribution dependence in timing (e.g. Allan, 2002b; Penney, Allan, Meck, & Gibbon, 1998; Wearden & Ferrara, 1995, 1996; Wearden et al., 1997). A key aim of the present paper is to test the prediction that much larger distribution dependence can be seen in temporal judgments and to develop an explicit model.

The second major difference between SET-based approaches and non-temporal models concerns sequential effects. Most models of identification predict that the perception of the identity of a given item will be influenced in consistent ways by the identity of items presented on immediately preceding trials (e.g., Stewart et al., in press; Treisman & Williams, 1984). These sequential effects, such as the assimilation of responses on trial *n* to stimuli on trial *n*-1, are widely observed in the data (e.g., Garner, 1953; Holland & Lockhead, 1968; Long, 1937; Ward & Lockhead, 1970, 1971). Assimilation to previous trials is a general phenomenon that is also observed in judgments of relative intensity (Lockhead & King, 1983), magnitude estimation (e.g., Jesteadt, Luce, & Green, 1977) and matching (Stevens, 1975). Contrast effects are typically observed to trials more than one trial further back in the sequence (e.g., Ward and Lockhead, 1970). Further evidence for the importance of sequential effects in simple perceptual identification is given by the observation that performance is higher when the sequence of presentation is constrained in such a way that the stimulus on each trial is relatively similar to the item on the previous trial (Luce et al., 1982; Nosofsky, 1983).

If the perception and identification of temporal durations is similar to perception and identification of other unidimensionally varying stimuli, strong sequential effects should be observed in absolute identification of durations. One aim of the present paper is to test this prediction. An additional prediction is that the strong serial position effects that are observed in absolute identification of non-temporal stimuli, such that items near the end of the series are more accurately identified (e.g., Braida & Durlach, 1972; Lacouture, 1997; Lacouture & Marley, 1995; Murdock, 1960), will also be observed when temporal durations must be identified (see also Lacouture, Grondin, & Mori, 2001). This prediction is also tested below. We now turn to findings that have been investigated primarily in the timing literature and which have received relatively little attention within the more traditional research on non-temporal stimuli.

Shifts in bisection point. A phenomenon that has received considerable attention in the timing literature has been the location of the bisection point. In temporal bisection tasks, attention is typically given to the length of the duration that is equally likely to be judged as similar to (or identified with) the longest as the shortest duration. More specifically, bisection at the geometric mean (GM) is observed under some experimental conditions, while arithmetic mean (AM) bisection is observed under different experimental conditions. For example, consider a temporal bisection task in which the short standard is 200 ms and the long standard is 800 ms. Assume that participants are exposed to seven experimental durations (200, 300, 400, 500, 600, 700, and 800 ms). For each experimental duration, the overall probability that it will be judged as more similar to the long standard is calculated. Characteristic S-shaped curves of the type seen in Figure 1 are found, such that the probability of responding “long” increases with the duration of the experimental item. The bisection point is calculated (either by curve fitting or simple linear extrapolation) as the point at which this probability is exactly .5. The temporal bisection points typically vary between the GM of the short and long standards (400ms) and the AM (500ms). The location of the bisection point appears to vary systematically with experimental conditions, although clear conclusions are difficult to draw from the existing literature because the AM and GM are typically very close to one another, especially when the ratio between the long and the short standard is small.

More specifically, GM bisection is typically observed in rats (e.g., Church & Deluty, 1977; Gibbon, 1981, 1986), albeit with some exceptions (see Wearden & Ferrara, 1996, for a review). In humans, the location of the bisection point seems to depend on the distribution of the stimuli and on the long:short ratio. Allan and Gibbon (1991) found near-GM bisection when the long:short ratio was small and stimuli were arithmetically spaced (Experiment 1) or logarithmically spaced (Experiment 2). Wearden and Ferrara (1996) suggested that AM bisection is more likely when the long:short ratio is large and also concluded that stimulus distribution is influential only when the ratio is large (see also Allan, 2002b; Penney et al., 1998). Wearden and Ferrara (1995) found that the bisection point moved leftward (i.e., in the direction of the GM) if items were logarithmically rather than linearly spaced, as did Allan (2002b) and Penney et al. (1998), and suggested that time value judgments were context dependent (see also Wearden, Rogers, & Thomas, 1997).

Although the overall pattern of results is far from clear, a possible generalization is that GM bisection is more likely to be obtained with logarithmically spaced stimuli and AM bisection is more likely to be obtained with arithmetically spaced stimuli, with these effects moderated by long:short ratio such that distribution effects are greater when this ratio is large (Allan, 2002b; Penney et al., 1998; Wearden & Ferrara, 1995, 1996). Rather than explore possible exceptions to this generalization (e.g., Wearden, Rogers, Thomas, 1997; Wearden & Ferrara, 1996) in detail, we next consider independent theoretical motivation for the claim prior to experimental testing using more extreme stimulus distributions in order to permit a clearer assessment of the effect of long:short ratio and stimulus distribution on bisection point.

Range Frequency Theory. Is previous research on magnitude estimation relevant to understanding the pattern of results concerning shifts in temporal bisection point outlined above? The application of independently motivated models of judgment to the temporal bisection paradigm might pave the way for a deeper theoretical understanding of changes in bisection point as a function of experimental conditions. Here we argue that just such an account is possible through application of the principles of RFT as developed by Parducci and his colleagues (Parducci, 1965, 1968, 1995).

RFT was designed to account for the subjective magnitudes that participants report for unidimensionally varying stimuli such as weights, line lengths, loudnesses, or tones varying in frequency. A particular focus is on the effects of the distribution of stimuli within the sets to be judged. Earlier accounts of magnitude estimation tasks included Adaptation Level Theory (ALT; Helson, 1964) and Range Theory (Volkmann, 1951). According to ALT, the magnitude judgment for a given item will depend on the distance of that item from some weighted mean of the stimuli to be judged. Range Theory, in contrast, states that the judgment given to a particular item will be determined at least partly by the position occupied by that item in relation to the two endpoints of that range, thus accommodating ALT's failure to account for effects of the variance of a set of stimulus magnitudes on the rating assigned to a particular stimulus magnitude. However, RFT was motivated by the observation that an item's ordinal position within the set to be judged also influences its rating. Consider two distributions of stimulus magnitudes as shown in Figure 2. The mean and endpoints of distributions A and B are identical. Furthermore, the positions of stimuli X and Y with respect to the endpoints of the distribution are identical in each case (being 1/3 and 2/3 up the stimulus range respectively). Therefore, according to both ALT and Range Theory, the magnitude estimations of X and Y will be the same for each distribution. However, as intuition suggests, and Parducci (1968) and others have confirmed, stimulus X will be assigned a lower rating in distribution A than in distribution B, while the reverse will be the case for stimulus Y. In intuitive terms, the observation is that participants 'stretch out' their response scale in relatively crowded regions of stimulus space (see also Krumhansl, 1978). The RFT model (see Parducci, 1995, for a review) incorporates the empirical observations that the rating assigned to a given stimulus is determined both by its position within the range and its ordinal position within the ordered set of stimuli.

This can be formalized as follows (see e.g. Parducci, 1995). Assume an ordered set of n contextual stimuli:

$$\{x_1, x_2, \ldots x_i, \ldots x_n\}$$

Then, if M_i is the subjective psychological magnitude of x_i, it is taken to be given by:

$$M_i = wR_i + (1-w)F_i \tag{1}$$

where R_i is the range value of stimulus i (S_i):

$$R_i = \frac{S_i - x_1}{x_n - x_1} \tag{2}$$

and F_i is the frequency value, or ranked ordinal position of S_i, in the ordered set:

$$F_i = \frac{i-1}{n-1}. \tag{3}$$

where w is a weighting parameter which is often empirically estimated at about .5. In intuitive terms, this amounts to the claim that the subjective magnitude of a given item will be determined not just by the magnitude of that item but by the relation of that item's magnitude to the magnitudes of all the other items in the set to be judged. More specifically, subjective magnitudes will increase relatively quickly as a function of actual stimulus magnitude when stimuli are relatively similar to one another; subjective magnitude will increase more slowly with increasing actual magnitude in less crowded regions of stimulus space.

It seems plausible that such effects may be relevant to the understanding of temporal bisection. If it is assumed that the decision whether to respond "long" or "short" to a given duration is determined at least partly by the subjective magnitude of that duration, RFT would be expected to apply to performance on temporal bisection tasks. This is the hypothesis of Temporal Range Frequency Theory (TRFT). Furthermore, as we now show, TRFT predicts shifts in the bisection point as a function of long:short ratio and stimulus spacing of exactly the type observed in the empirical literature and also makes novel predictions which we test below.

Why does TRFT predict that the bisection point should shift towards the lower end of a stimulus distribution as that distribution becomes more positively skewed? Consider the two illustrative distributions of durations in Figure 3. In both distribution A (positively skewed) and distribution B (negatively skewed), the shortest duration is 200 ms, the longest is 800 ms and the mid-range item (labeled X) is 500 ms. According to the principles of TRFT, the subjective magnitude of X will be higher in the positively skewed distribution than in the negatively skewed distribution (in intuitive terms, TRFT is taking account of the fact that X is the eighth shortest out of the ten durations in distribution A, whereas in distribution B it is the third shortest duration). Stimulus X will therefore be perceived as more similar to the long standard in the positively skewed distribution than it will be in the negatively skewed distribution. This will have the effect of shifting the bisection point to the left. Note that this corresponds exactly to what is often observed in the temporal bisection literature. AM bisection (where the bisection point is shifted to the right compared with GM bisection) is more likely to be found when arithmetically spaced stimuli are used than when logarithmically spaced stimuli are used. Arithmetically spaced stimuli are negatively skewed compared with logarithmically spaced stimuli (analogously to distributions B and A in Figure 3 respectively) and so the empirically observed pattern is consistent with the predictions of TRFT.

We can illustrate the predictions of TRFT more concretely for sets of durations varying in both long:short ratio and in distribution (these are the durations that we use experimentally below). Figure 4 illustrates eight different stimulus distributions. The top four distributions have a small long:short ratio (long = 666 ms; short = 333 ms), while the lower four distributions have a large long:short ratio (long = 900 ms; short = 100 ms). For each ratio there are four different distributions varying in degree of positive skew. The top-most distribution contains negatively skewed stimuli, the second illustrates arithmetically spaced stimuli, the third illustrates logarithmically spaced stimuli, while the fourth illustrates even more positively skewed stimuli. We refer to the first distribution as *antilogarithmic* spacing because the distribution is as negatively skewed relative to arithmetic spacing as a logarithmic distribution is positively skewed. The most positively skewed distribution is dubbed *superlogarithmic* distribution because it is as positively skewed relative to a logarithmic distribution as an arithmetic distribution is negatively skewed.

We applied TRFT to the illustrated distributions, after logarithmically transforming each stimulus value, and assumed a value of .5 for the weighting parameter *w* (as is typically observed empirically). The resulting predicted subjective durations of each stimulus are illustrated for each of the eight distributions in the left-hand column of Figure 5. It can be seen that there are large predicted effects of stimulus distribution on subjective duration, and that these effects are substantially greater for the distributions where the long:short ratio is large. We also derived the predictions of a simple model of temporal bisection (developed in more detail below) according to which the probability of responding "long" to a given item is given by the similarity of the item's subjective magnitude to the subjective magnitude of the long standard relative to the summed similarity of the subjective magnitude of the stimulus to the subjective magnitudes of the short and long standards (i.e., we applied the Luce choice rule). Similarity was assumed to be a negative exponential function of the distance between items' subjective magnitudes. The results can be seen in the right-hand column of Figure 5. The predictions of this TRFT-based model are clear and striking. It can be seen that there is a leftward shift in the bisection point as the stimulus distribution becomes more positively skewed, and that this effect is much greater when the long:short ratio is large. Although the exact form of the curves, and in particular their steepness, depends upon the particular form and parameterization of similarity function chosen, the qualitative effects do not.

Thus, TRFT offers a potential explanation of many of the observed effects of stimulus distribution and long:short ratio on the bisection point obtained in temporal bisection tasks. Furthermore, a clear novel prediction is made: It should be possible to shift the bisection point even further to the left or even further to the right than the GM and AM respectively if sufficiently skewed distributions are chosen. We test these predictions directly in the following experiments.

Experiment 1

The aim of Experiment 1 was to test two hypotheses. The first was that the distribution of durations within a stimulus set, and the ratio of the longest to the shortest duration in the set, will influence the bisection point in a temporal bisection task in ways consistent with the predictions of TRFT. This hypothesis was tested by examining the bisection point for sets of temporal durations that varied systematically in distribution and in long:short ratio. To the extent that the predictions of TRFT for shifts in temporal bisection point are confirmed, the need to postulate duration-specific accounts of shifts in temporal bisection point will be undermined.

The second hypothesis to be tested in Experiment 1 was that identification of durations makes use of the same basic processing mechanisms and decision processes as are used in identification of simple perceptual stimuli varying along other single dimensions (such as weight, line length, or frequency). This hypothesis was tested by examining absolute identification of durations in order to allow investigation of (a) serial position effects in absolute identification, (b) assimilation of responses to immediately preceding trials in absolute identification, and (c) contrast of responses to trials further back in the sequence. If a qualitatively similar pattern of sequential and serial position effects are obtained as have previously been found with other dimensions, the results will go against claims that explanation of identification of temporal durations requires separate models such as those that have recently been developed in the literature.

In both parts of the experiment (absolute identification and temporal bisection) the same eight sets of stimuli were used (see Figure 4). Two long:short ratios (9:1 and 2:1) were crossed with four stimulus distributions (ranging from positively skewed to negatively skewed) in order to permit simultaneous assessment of ratio effects and distribution effects.

Method

Participants. Eighty volunteers from the University of Warwick participated in return for either course credit or a small fee. Ten participants were allocated to each of eight experimental conditions. Task order (absolute identification vs. temporal bisection) was manipulated within-subjects; 40 participants received the absolute identification task first while 40 participants received the temporal bisection task first.

Materials. Eight sets of pure tones varying in duration were constructed to meet the requirements described above. Amplitude was constant throughout. The durations of the tones are given in Table 1, and the distributions are illustrated in Figure 4. Each tone was a constant 261.6 Hz.

Procedure. Tones were presented at a comfortable volume through Sennheiser eH2270 headphones via a Macintosh computer. Responses were recorded via key-presses on a labelled keyboard. For the absolute identification task keys in a horizontal row were labelled 1 through 8; for the bisection task one response key was labelled SHORT and the other was labelled LONG.

The procedure for the absolute identification task was as follows. Participants were told that they would hear some tones and would have to identify them based on their duration. They were told that there was a set of eight tones that formed a series from short to long, with Tone 1 being the shortest in the series and Tone 8 being the longest, and that their task was to judge the number of each test tone that was presented. They were instructed to give a response to every trial even if they were unsure.

Each trial began with a 500-ms pause. A '?' prompt was then displayed in the center of the screen, at the same time as the tone began. The prompt remained until the participant responded. The keys 'F', 'G', 'H', 'J', 'V', 'B', 'N', and 'M' were labeled '1', '2', '3', '4', '5', '6', '7', and '8'. After the participant had responded, and not less than 2000 ms from the stimulus onset, the correct number appeared in the center of the screen for 1000 ms. The screen was then blanked before the next trial. There were 4 blocks of 64 trials. Within the experiment each tone appeared 32 times. A tone (randomly selected without replacement from the 32 * 8 in the distribution condition to which the participant had been assigned) was presented on each trial.

The procedure for the temporal bisection task was as follows. Participants were told that they would hear some tones and would have to make judgments about them based on their duration. Specifically, participants were informed that they must decide whether each tone they heard was more similar to a "long" standard or a "short" standard and respond appropriately. They were instructed to give a response to every trial even if they were unsure.

In the initial exposure phase of the experiment, participants heard the shortest and then the longest standard four times. There was a 2000 ms gap between tone onsets. This initial phase was followed by the main part of the experiment, which consisted of 4 blocks of 64 trials. Each tone appeared 32 times in the experiment. Every trial began with a 500 ms pause. A '?' prompt was then displayed in the center of the screen, at the same time as the tone began. The prompt remained until the participant responded. The keys 'Z' and 'X' were labeled 'SHORT' and 'LONG' respectively. After the participant had responded, and not less than 2000 ms from the stimulus onset, the next trial began. There was no feedback. On each trial, a randomly-selected tone from the 32 * 8 in the distribution condition to which the participant had been assigned was presented.

Results of Absolute Identification Task

As several of the analyses involved investigation of sequence effects, we do not report results from the first ten trials of each block as meaningful sequence effects may not be evident for these stimuli. For each condition overall level of correct performance (with no correction for response bias) is shown in Table 2. Figures 6, 7, and 8 summarise the results of the absolute identification conditions. Figure 6 shows the serial position curves; these were corrected for response bias by dividing the proportion of correct responses for a given item by the proportion of times that response was produced[1]. Figure 7 shows the error on each trial as a function of the item presented on the immediately preceding trial, and Figure 8 shows the effect of both the immediately preceding and earlier trials.

We begin with the data in Figure 6, where the general pattern of results can be summarised as follows. Overall level of performance was greater for more widely-spaced stimuli (large long:short ratio). Clear serial position effects were obtained in all conditions, with an advantage for end-series stimuli. Superimposed on the serial position curves was a tendency for less accurate identification of durations more closely spaced within a range. These effects are very similar to those obtained in absolute identification of stimuli varying along non-temporal dimensions (Brown, Neath, & Chater, 2002), and therefore appear consistent with the suggestion that similar psychological mechanisms may underpin identification of temporal and non-temporal stimuli (see Discussion below). The observations were confirmed by analysis. Analysis of correct responses revealed a main effect of ratio, F(1,64 = 92.09, MSE = 1.86, $p < .0001$, and a main effect of serial position, $F(7,448) = 298.30$, $MSE = 1.95$, $p < .0001$; but no main effect of distribution, $F(3,64) = 0.83$, $MSE = 0.017$, $p = .48$. There was an interaction between ratio and serial position, $F(7,448) = 6.37$, $MSE = 0.04$, $p < .0001$; an interaction between distribution and serial position, $F(21,448) = 41.80$, $MSE = 0.27$, $p < .0001$; and a three-way interaction between ratio, distribution, and serial position, $F(21,448) = 16.90$, $MSE = 0.11$, $p < .0001$. The order variable (whether the absolute identification task or the bisection task was carried out first) did not give rise to a significant main effect or any two-way interactions, but there was a three-way interaction between order, ratio, and condition, $F(3,64) = 3.67$, $MSE = 0.08$, $p = .016$. This interaction was small in magnitude and we do not discuss it further.

The next set of analyses examined sequence effects in the same way as is typically done in the analysis of identification of non-temporal stimuli. It is typically found that errors are systematic. For example, if Stimulus 1 (the shortest duration) is presented on trial n-1, and Stimulus 8 (the longest duration) is presented on trial n, the mean error is normally negative; a mean error of −1.5 would indicate that the mean response to stimulus 8 is 6.5 (i.e., assimilation is observed). We therefore examined the mean error on trial n as a function of stimulus on trial n and stimulus on trial n-1 (Figure 7). Each panel shows these data for a given combination of ratio and distribution, and may be interpreted as follows. Each line represents the mean errors for pairs of adjacent stimuli. To the extent that the lines in a given panel have a non-zero slope, there is an effect of trial n-1 on response n. To the extent that the lines are separated, positive in slope, and cross zero, there is assimilation to the previous trial.

Analyses of variance revealed a main effect of stimulus on trial n, $F(3,192) = 401.66$; $MSE = 123.20$, $p < .001$, and of stimulus on trial n-1, $F(3,192) = 175.38$, $MSE = 50.89$, $p < .0001$ with a significant interaction between them, $F(9,576) = 13.33$, $MSE = 1.522$, $p < .0001$. These effects reflect a tendency for responses on a given trial to be assimilated towards (i.e., correlated with) the stimulus on trial n-1, with this effect being greater as the difference between the stimuli on trial n and on trial n-1 increases. There are therefore clear sequential effects apparent in identification of temporal duration, and these exhibit the same pattern as is typically observed for non-temporal dimensional stimuli. The main effects of trial *n* and of trial *n*-1 interacted in various ways with ratio and with distribution, and various higher-order interactions were evident. However we do not report these interactions in detail as our main purpose is to show that the normal effects of assimilation are evident, and as analysis of simple main effects revealed effects of both trial *n* and of trial *n*-1 for each ratio and for each distribution (for the effects of stimulus on trial *n*: all *F*s > 80, *MSE* = .307; for the effects of stimulus on trial *n*-1: all *F*s > 25; *MSE* = .290; *p* < .0001 in all cases).

The final analyses of sequence effects examined mean error on trial *n* (averaged over different stimuli on trial *n*) as a function of the stimulus on trial *n-k* and of *k*. Data are shown in Figure 8. Overall, as is observed with identification of non-temporal stimuli, there is a clear tendency for assimilation of the response to the stimulus on trial *n*-1, and a weaker tendency for response on trial *n* to contrast with stimuli on trials *n-k* (*k* > =2). The statistical significance of assimilation and contrast effects was assessed through regression analyses, carried out for individual participants, to assess the correlations between response on trial *n* and the stimulus on trial *n-k* (where *k* took values 1 through 5). Note that the sequences were virtually random; there was effectively no correlation between the stimulus on trial *n* and on trial *n-k*. Figure 9 shows the mean regression coefficients for lags 1 through 5. A positive coefficient reflects assimilation (i.e., a positive correlation between response *n* and stimulus *n-k*); a negative coefficient reflects contrast. All coefficients except that for lag = 2 were significantly different from zero [all *t*(79) values > 3.3; *p* < .001 in all cases]. Thus the classic pattern of assimilation to immediately preceding stimuli, and contrast to more distant stimuli, was evident. Analyses of variance on the coefficient values revealed no effect of Ratio or Distribution on the coefficient values at any lag (*p* > .05 in all cases).

Discussion of Absolute Identification results

The aim of the absolute identification analyses was to determine whether absolute identification of temporal durations would show similar effects to absolute identification of stimuli varying unidimensionally along non-temporal dimensions. The results were consistent with the suggestion that similar mechanisms are involved in identification of temporal durations as have been previously investigated for other dimensions. First, clear serial position effects were observed. These have previously been observed for absolute identification of line length (Bower, 1971), area (Eriksen & Hake, 1957), position along a semantic continuum (DeSoto & Bosley, 1962; Pollio & Deitchman, 1964, cited in Bower, 1971), spatial position (Ebenholtz, 1963; Jensen, 1962), brightness (Bower, 1971), temporal duration (Lacouture et al., 2001) and tone frequency (Brown, Neath, & Chater, 2002; Experiment 2 of the present paper). Moreover, the serial position effects were asymmetrical, reflecting lower levels of performance in relatively crowded regions of stimulus space. Similar effects have been found for tone frequency (Brown et al., 2002); we investigate parallels in detail in Experiment 2.

Second, there was clear evidence of assimilation of responses to immediately preceding trials. Such effects have previously been observed in judgments of other dimensions (e.g., Garner, 1953; Holland & Lockhead, 1968; Hu, 1997; Lacouture, 1997; Lockhead, 1984; Long, 1937; Luce et al., 1982; Purks, Callahan, Braida, & Durlach, 1980; Staddon, King, & Lockhead, 1980; Ward & Lockhead, 1970, 1971). Third, there was evidence of contrast of responses to trials further back in the sequence; this result again parallels findings in absolute identification of other dimensions (e.g., Holland & Lockhead, 1968; Lacouture, 1997; Ward & Lockhead, 1970, 1971).

Overall, then, the key effects observed in identification of non-temporal dimensions are also obtained in duration identification, consistent with the general claim that similar models may be applicable in both cases.

Results of temporal bisection task.

Analysis of the temporal bisection data focused on two key questions. The first question was whether the bisection point would shift as a function of the distribution of durations within a set and with the long:short ratio. Such shifts are predicted by TRFT (cf. Figure 5) and have already been observed when just arithmetic and logarithmic stimulus spacings are used (Allan, 2002b; Penney et al., 1998; Wearden & Ferrara, 1995, 1996; Wearden et al., 1997). The second more general question was whether a model of bisection based on TRFT principles would permit a good fit to the observed data.

The overall results are shown in Figure 10. It is evident that the overall pattern of results corresponds qualitatively to the predictions, with a wider separation of the bisection curves for the large-ratio conditions and the predicted shift in bisection points.

In order to provide a more detailed assessment, we first estimated a bisection point for each individual participant. This was done by fitting the equation:

$$p(long \mid D_i) = \frac{1}{1 + e^{-s.(D_i - t)}}$$

to each participant□s data, where D_i is duration i, and estimating, for each participant, the parameters t (bisection point) and s (steepness of the function). The equation did well at fitting individual participant data (median $R^2 = .987$). The resulting mean estimated bisection points are shown in Figure 11a, where there is a clear tendency, as predicted, for the bisection point to become larger in the more positively skewed distributions when the long:short ratio is large. This tendency appears much smaller when the long:short ratio is small, again as predicted by TRFT.

Analyses of variance confirmed these impressions. There was a main effect of ratio, $F(1,64) = 29.42$, $MSE = 114943.59$, $p < .0001$; a main effect of distribution, $F(3,64) = 22.60$, $MSE = 88354.22$, $p < .0001$; and an interaction between ratio and distribution, $F(3,64) = 14.44$, $MSE = 56452.43$, $p < .0001$. Analysis of simple main effects revealed an effect of distribution for large ratio, $F(3,64) = 36.49$, $MSE = 3908.92$, $p < .001$, but no effect of distribution for small ratio, $F(3,64) = .555$, $MSE = 3908.92$, $p = .646$.

Note that in the small ratio conditions the GM and the AM are 471 ms and 500 ms respectively, while in the large ratio condition the GM and AM are 300 ms and 500 ms respectively. Thus when the stimulus distribution is sufficiently extreme, and when the long:short ratio is large, the observed bisection point may either exceed the AM (antilogarithmic distribution) or fall below the GM (superlogarithmic distribution). The observed bisection points for the arithmetic and logarithmic distributions are generally consistent with previous results, being closer to the GM and AM for logarithmically and arithmetically spaced stimuli respectively. We next examined the ability of a TRFT-based model of bisection to account for the complete bisection curves.

Modeling

The aim of the modeling was to determine whether the basic qualitative patterns observed in the temporal bisection data (particularly the shifts in bisection point resulting from changes in stimulus spacing and long:short ratio) could be captured in a simple model that incorporated the basic principles of TRFT. In order to preserve transparency of explanation we therefore aimed to produce a simple model with relatively few parameters rather than a more detailed and perhaps over-parameterized model that might produce a better fit to the data but at the cost of obscuring the relation between model and data.

The model we explored was essentially an exemplar model of identification, similar to those proposed in other (non-temporal) domains. The model makes two core assumptions. First, it is assumed that the subjective magnitude of a given duration is determined according to the principles embodied in TRFT. Second, when the subjective magnitude of a test duration has been calculated, the probability of responding "Long" to that duration is given by the psychological similarity of the test duration to the "Long" standard divided by its summed similarity to the "Long" and the "Short" standard. (This latter assumption is essentially a simple application of the Luce choice model.) Many extant models of temporal bisection assume that each test stimulus is compared to the long and/or short standard; our aim in the modeling was to incorporate TRFT while making as few additional assumptions as possible.

These assumptions were implemented as follows. First, the subjective magnitude M_i of a test duration, S_i, is calculated according to Equation 1 above, with prior logarithmic transformation of the stimulus durations (discussed below). Second, the probability of responding "Long" given a test duration of psychological magnitude M_i is given by:

$$P(Long \mid M_i) = \frac{\eta_{i,L}}{\eta_{i,L} + \eta_{i,S}}$$

where $\eta_{i,j}$ is the psychological similarity between M_i and M_j ; M_L is the psychological magnitude of the "long" duration and M_S is the psychological magnitude of the "short" duration, and the similarity of M_i and M_j is given by:

$$\eta_{i,j} = e^{-c.|M_i - M_j|^a}$$

This similarity-distance model, which is widely used in models of generalization, categorization, and memory (e.g., Nosofsky, 1986; Shepard, 1987), has the effects of reducing the psychological similarity between any two magnitudes as a function of the psychological distance between them. The scaling parameter c governs the rate at which similarity/confusability decreases with distance; in previous work on absolute identification we have found that larger values of c must be associated with larger ratios between the smallest and largest magnitudes within a stimulus set to account for small or absent effects of stimulus range (Brown et al., 2002) and (to anticipate the model fitting procedure described below) the same was true in the present experiment. Finally, the a parameter describes the form of the generalization gradient. When $a = 2$, the similarity-distance function is Gaussian in form. Gaussian similarity-distance functions may provide the best characterisation of human identification data when the stimuli are sufficiently close in psychological space that perceptual confusability of stimuli or noise in perceptual representations may be a significant factor in performance (Ennis, 1988; Nosofsky, 1988; Shepard, 1988). When $a = 1$, the similarity-distance function is exponential in form, and when (as here) magnitudes are assumed to be represented on a logarithmic internal scale this has the consequence that the psychological similarity between any two temporal durations would simply be a function of the ratio of the shorter to the longer if TRFT principles were not applied. More specifically, when $w = 1$, $c = 1$, and $a = 1$, the model reduces to a simple ratio-based similarity model akin to many previous models of temporal bisection. Thus the use of a logarithmic transformation of stimulus durations should not be taken as a strong claim that the psychological magnitudes of temporal durations are logarithmic; instead the formalism allows extension of a ratio-based similarity metric in a straightforward manner. For simplicity and transparency of interpretation, we held a constant at 1.0 in all simulations below; additional unreported simulations found that allowing a to vary led to only small improvements in fit (adding less than 0.5% to the variance accounted for) and did not change the qualitative behavior of the model in any way.

There are thus two free parameters. The w parameter, which specifies the relative weight given to the ordinal position of a test duration in a series in determining its psychological magnitude, was held constant for all spacing and both long:short ratios. The *c* parameter was allowed to vary with ratio but not with distribution; this decision was motivated by the *a priori* theoretical expectation that *c* would be higher when the long:short ratio is larger.

Best-fitting parameter values were obtained, and the resulting model behavior is shown in Figure 10 (lower two panels). The parameter values that gave rise to the observed output were: w = .49 (all conditions); c = 4.5 (large ratio) and 2.8 (small ratio). The overall R^2 obtained was .98.

The bisection points derived from the model's data are shown in Figure 11b. It is evident that the model does well at capturing the key changes in bisection points as a function of changes in ratio and distribution, despite the fact that the parameter fitting procedure did not optimise fits for these points directly.

The best-fit parameter values were generally in accordance with expectations. The value of .49 for the weighting parameter (which determines the relative importance of ordinal position and location with respect to endpoints in the calculation of subjective magnitude) is close to that obtained in other studies involving magnitude estimation for other dimensions (e.g., Parducci, 1995). It was predicted on the basis of previous work with non-temporal stimuli (Brown et al., 2002) that the *c* parameter would be larger when the long:short ratio was large, and this proved to be the case.

Most importantly, the model captures the tendency of bisection points to change as function of stimulus spacing, and for change to be larger when the ratio between the longest and the shortest duration is large. As we noted in the Introduction, this is essentially the pattern that has often been obtained in the previous literature although the empirical effects have not always been clear perhaps because the distributions used in previous experiments (linear and logarithmic) were not so extreme. Why does the model exhibit this behaviour? The crucial feature of the model is the assumption that the principles embodied in TRFT are relevant to determining the subjective magnitude of a given temporal duration. TRFT offers a principled account, one developed independently on the basis of models of data from non-temporal domains, for the effects of distribution. Thus one feature of the current model that sharply distinguishes it from most models of timing is its assumption that durations are not perceived in isolation, or even simply in terms of their relation to the shortest and longest durations in an experimental set. Rather, the distribution of *all* durations within the experiment influences the treatment of any one of them, exactly as predicted by TRFT. Another feature of the current approach is its importation of the terminology and machinery of exemplar theory into models of timing (see also McCormack et al., 2002); potential advantages of this strategy include (a) the possibility of integrating models of timing more closely with models independently developed in other areas, and (b) the ability to make use of the modeling machinery developed and well understood in the context of models of identification, categorization, and recognition.

In other respects the model proposed here is highly similar to previous models. In particular, we note that when a, w, and c all = 1, the similarity of any two durations (e.g., a test duration and the "Long" or the "Short" standard) is simply a function of their ratio.

Experiment 2

Experiment 1 found that many of the classic effects previously obtained from studies of absolute identification of non-temporal stimuli were also obtained when stimuli varying in duration had to be identified. One aim of Experiment 2 is to confirm that the same effects emerge when stimuli varying in frequency must be identified when the experimental conditions correspond exactly to those used in Experiment 1.

The main aim of Experiment 2 is to examine whether the shifts in bisection point found in Experiment 1 for temporal stimuli can also be observed in an analogous "frequency bisection" task. If similar effects are found when frequency rather than duration is the relevant stimulus dimension, further evidence will be consistent with the hypothesis that similar psychological mechanisms are involved in identification of both temporal and non-temporal stimuli.

In Experiment 2, therefore, we replicated the conditions of Experiment 1 as closely as possible, with the single difference that stimuli were tones varying in frequency rather than tones varying in duration.

Method

Participants. Eighty volunteers from the University of Warwick participated in return for either course credit or a small fee. Ten participants were allocated to each of eight experimental conditions. All participants completed both the absolute identification and bisection tasks. Forty participants received the absolute identification task first while 40 participants received the bisection task first.

Materials. Eight sets of eight pure tones, constant in amplitude but varying in frequency, were constructed to have the same distributional properties as the durations used in Experiment 1. The frequencies of the tones are given in Table 3. Each tone lasted 500 ms.

Procedure. Tones were presented through Sennheiser eH2270 headphones at a comfortable volume via a Macintosh computer. Responses were recorded via key-presses on a labeled keyboard. The procedure for the absolute identification task was identical to that used in Experiment 1, with the exception that the eight stimuli were tones varying in frequency and forming a series from low to high, with Tone 1 being the lowest in the series and Tone 8 the highest. Instructions to participants were modified to reflect this change. The frequency bisection task was again identical to that used in Experiment 1, except that the Long and the Short tones were replaced with High and Low tones, and the instructions to participants were modified accordingly.

Results of absolute identification task

An important component of the analyses involved investigation of sequence effects, we do not report results from the first ten trials of each block as meaningful sequence effects may not be evident for these stimuli. Figures 12, 13, and 14 summarize the results of the absolute identification conditions in a format similar to the one that was used for durations, although we report results in less detail as our aim is simply to confirm previous findings. Figure 12 shows the serial position curves (corrected for response bias); Figure 13 shows the error on each trial as a function of the item presented on the immediately preceding trial, and Figure 14 shows the effect of both the immediately preceding and earlier trials. In Figures 13 and 14, data are collapsed over Distribution and high:low ratio.

We begin with the data in Figure 12 (level of correct performance as a function of condition and serial position). The overall pattern was essentially identical to that observed for durations, but performance was somewhat higher overall. Overall level of performance was greater for more widely-spaced stimuli (large long:short ratio); clear serial position effects were obtained in all conditions, with an advantage for end-series stimuli, and there was a tendency for less accurate identification of stimuli more closely spaced within a range.

For each condition, overall level of correct performance (with no correction for response bias) is shown in Table 2. Analysis of correct responses revealed a marginally significant effect of ratio, $F(1,64) = 3.38$, $MSE = .307$, $p = .071$; a main effect of serial position, $F(7,448) = 202.88$, $MSE = 1.87$, $p < .0001$, but no main effect of distribution, $F(3,64) = 2.103$, $MSE = 0.191$, $p = .11$. There was an interaction between ratio and serial position, $F(7,448) = 2.35$, $MSE = 0.022$, $p <. 0229$; an interaction between distribution and serial position, $F(21,448) = 13.94$, $MSE = 0.129$, $p < .0001$; and a three-way interaction between ratio, distribution, and serial position, $F(21,448) = 4.76$, $MSE = 0.044$, $p < .0001$. The order variable did not give rise to a significant main effect or any interactions. This pattern of results is qualitatively the same as that obtained in Experiment 1, except that in the present experiment the effect of ratio was only marginally significant.

We now turn to analysis of sequential effects. The first set of analyses examined error on trial *n* as a function of stimulus on trial *n* and stimulus on trial *n*-1 (Figure 13). The overall mean error on trial *n* as a function of both the stimulus on trial *n* and the stimulus on trial *n*-1 is shown. The data have been collapsed across distribution and ratio as the data otherwise appear somewhat noisy and we are in any case concerned simply to show that the standard findings replicate; the lower panel of Figure 13 shows the equivalent plot for Experiment 1 data for ease of comparison. Note that the current effects are smaller in magnitude than were observed in Experiment 1; there is a change of scale on the figure. The interpretation of the figure is the same as previously: To the extent that the lines have a non-zero slope, there is an effect of trial *n*-1 on response *n*; and to the extent that the lines are separated, positive in slope, and cross zero, there is assimilation to the previous trial.

Analyses of variance revealed a main effect of stimulus on trial n, $F(3,192) = 114.81$; $MSE = 23.2004$, $p < .0001$, and of stimulus on trial *n*-1, $F(3,192) = 55.41$, MSE = 7.31, $p < .0001$, with a significant interaction between them, $F(9,576) = 5.45$, $MSE = 0.477$, $p < .0001$. These effects reflect a tendency for responses on a given trial to be assimilated towards (i.e., correlated with) the stimulus on trial *n*-1, with this effect being greater as the difference between trial *n* and trial *n*-1 increases. There are therefore clear sequential effects in identification of tones varying in frequency, replicating previous results with other stimuli, including the durations used in Experiment 1. The main effects of trial *n* and of trial *n*-1 interacted in various ways with ratio and with distribution, and various higher-order interactions were evident. However we do not report these interactions in detail as our main purpose is to show that the normal effects of assimilation are evident, and as analysis of simple main effects revealed effects of both trial *n* and of trial *n*-1 for each Ratio and for each Distribution [for the effects of stimulus on trial *n*, all Fs > 10.57, $MSE = .201$; for the effects of stimulus on trial *n*-1, all Fs > 21, $MSE = .132$, $p < .001$ in all cases, except that there was no effect of trial *n*-1 for the logarithmically spaced condition, $F(3,192) = .895$, $p = .445$].

Finally, as in the analyses of Experiment 1, we examined how the error on trial *n* varies as a function of stimuli presented on previous trials (up to five back in the sequence). Figure 14 shows the average error on trial *n* (averaged over all possible trial *n* stimuli) as a function of the stimuli presented on trial *n-k* and *k*. As in Figure 13, the figure shows the data averaged over condition as the data otherwise appear somewhat noisy and the primary aim is to examine comparability with equivalent effects seen in duration identification in Experiment 1. The lower panel of Figure 14 shows the equivalent averaged data from Experiment 1. It is evident that a qualitatively similar (albeit less marked) pattern of assimilation and contrast is observed, with the response on trial *n* being assimilated towards the stimulus presented on trial *n*-1 but being negatively correlated (i.e., contrasted with) stimuli presented on trial *n-k* ($k > 1$).

The statistical significance of assimilation and contrast effects was again assessed through regression analyses, carried out for individual participants. Figure 15 shows the mean regression coefficients for lags 1 through to 5. A positive coefficient reflects assimilation (i.e., a positive correlation between response *n* and stimulus *n-k*); a negative coefficient reflects contrast. All coefficients were significantly different from zero except for lag = 2; [all $t(79)$ values > 2.8; $p < .01$ in all cases]. Thus the classic pattern of assimilation to immediately preceding stimuli, and contrast to more distant stimuli, was evident as for temporal durations (Figure 9 above) and consistent with previous research on other dimensions. Analyses of variance on the coefficient values revealed no effect of Ratio or Distribution on the coefficient values at any lag ($p > .1$ in all cases).

Overall, the key effects parallel those observed in absolute identification of duration in Experiment 1. Serial position effects were similar, with an overall tendency for U-shaped serial position curves superimposed on a tendency for stimuli that were relatively closely spaced to be less accurately identified. Sequential effects, although smaller in Experiment 2 than in Experiment 1, followed the same pattern with both assimilation and contrast to previous stimuli.

Results of frequency bisection task

The final analyses focused on the frequency bisection task. The key question of interest was whether shifts in the frequency bisection point as a function of stimulus distribution and the ratio of the extreme stimuli occur in the same way as observed for bisection of temporal duration in Experiment 1.

The results are shown in Figure 16. The top two panels show the frequency bisection data for the large ratio and small ratio conditions respectively; the lower two panels show the fit of the model as described below. We first report conventional statistical analyses. The first step was to estimate each individual participant's bisection point by fitting a sigmoid curve to each individual participant's data as was done for Experiment 1. The median R^2 value for this preliminary curve fitting was .981. The estimated bisection points are shown in Figure 17 (top panel) where it is evident that there was a clear tendency for the bisection point to be smaller for the more negatively skewed distributions. This parallels the effect seen in Experiment 1, and conforms to the predictions of the RFT-derived model described there. Also, as in Experiment 1, the effect of stimulus spacing was much greater when the ratio of the two extreme stimuli (in this case the ratio of the highest to the lowest frequency) was greater.

Analyses of variance confirmed these impressions. There was a main effect of ratio, $F(1,64) = 41.29$, $MSE = 435600$, $p < .001$; a main effect of distribution, $F(3,64) = 63.00$, $MSE = 664772$, $p < .001$; and an interaction between ratio and distribution, $F(3,64) = 37.50$, $MSE = 395697$, $p < .001$. Analysis of simple main effects revealed an effect of distribution for large ratio, $F(3,64) = 98.56$, $MSE = 10552$, $p <. 001$, but no effect of distribution for small ratio, $F(3,64) = .1.76$, $MSE = 10552$, $p = .164$.

It is noteworthy that, as in Experiment 1, the frequency bisection point could, when the skewness of the stimulus distribution was sufficiently extreme, either exceed the arithmetic mean of the highest and lowest stimuli, or fall below the geometric mean. We next examined the ability of the RFT-based model of bisection to account for the results.

Modeling

The purpose of the modeling was to assess the ability of the model of temporal bisection that we developed in the context of Experiment 1 to account for the new frequency bisection results. The fit of the model to the complete bisection curves is shown in the lower two panels of Figure 16 and the bisection points of the model are shown in the lower panel of Figure 17. It is evident that a reasonably good fit was obtained, and that all the key effects were captured by the model. As before, the weighting parameter w was held constant for all conditions; it was estimated at .35. The parameter c was 4.7 (large ratio) and 3.9 (small ratio). The overall R^2 obtained was .99.

Overall, the results of the frequency bisection task, as well as of the absolute identification task described earlier, were consistent with the hypothesis that similar principles may describe identification and bisection of tones varying in duration as govern tones varying in frequency. In particular, the temporal bisection point and the frequency bisection point varied in similar ways as a function of stimulus distribution and the ratio of the extreme stimuli, and the nature of these variations was well predicted by a model based on the principles of RFT.

General Discussion

We began this paper with two key questions, and we address these in turn. The first question concerned the similarity between temporal and other dimensions. More specifically, is the identification and discrimination of short temporal durations similar to the identification and discrimination of other unidimensionally varying stimuli? The evidence that we have presented is consistent with an affirmative answer. In both absolute identification and bisection tasks, the key effects were qualitatively identical for temporal duration and for frequency as well as being consistent with previous results obtained using other dimensions. In absolute identification, similar bowed serial position curves were seen in both cases. Similar sequential effects (assimilation and contrast) were also observed. Finally, temporal bisection and frequency bisection appeared to follow similar principles. In the previous literature, accounts of human timing data have generally been developed independently within the temporal processing research literature. The results we have presented here suggest that it may be fruitful to examine whether older models that have already been developed in the psychophysical literature may be applicable to the domain of timing.

The second question with which we introduced the paper was more specific and concerned the shifts in temporal bisection point that have previously been observed in the literature. As we noted in the introduction the temporal bisection point may fall close to the geometric mean, close to the arithmetic mean, or somewhere in between, with the observed result appearing to depend on factors such as (a) whether humans or animals are tested; (b) whether the stimuli are arithmetically or logarithmically spaced; and (c) whether the longest and shortest stimuli stand in a high or a low ratio to one another. However, as we noted in the introduction, the pattern of data is not entirely consistent, it seemed possible that Range Frequency Theory, a model independently developed in the magnitude estimation literature, might offer some general principles that would enable shifts in bisection point to be understood. More specifically, RFT and TRFT predict (with some auxiliary assumptions) that the bisection point for any unidimensionally varying stimuli, including temporal durations, should vary in predictable ways with the skewness of the distribution of presented stimuli. Two experiments confirmed these predictions for both a temporal bisection task and a frequency bisection task. The results are consistent with the claim that stimulus spacing may be important, particularly when the ratio of the longest to the shortest experimental duration is large (Allan, 2002b; Penney et al., 1998; Wearden & Ferrara, 1995, 1996). More specifically, the results of the bisection task may offer an illustration of how older psychophysical models may be useful in interpreting the more recent temporal processing literature.

How does TRFT, and its account of contextual effects in timing, relate to the dominant model of timing, Scalar Expectancy Theory (SET)? SET is a detailed and widely-applied model, driven by principles such as the scalar property and time-scale invariance. Furthermore, the parameters and components of SET's mathematical specification can be mapped onto a process-level interpretation in terms of mechanisms such as a pulse-generating clock, a comparator, and long-term and working-memory representations of durations. TRFT, in contrast, is a descriptive model of how context influences the subjective judgment of durations. It is therefore more limited in scope than SET, and is neutral as to the underlying neurobiological mechanisms that underpin duration perception. However a sampling-based account of how rank-dependent effects such as those assumed by TRFT may arise in magnitude judgement through ordinal comparison of a target stimulus with samples retrieved from memory is given by Stewart, Chater, and Brown (2005), and similar sampling mechanisms could potentially provide a process-based account of rank-dependent effects in duration perception. Furthermore, the parameters of TRFT can, like those of SET, each be given a psychological interpretation. The scaling parameter *c* governs the rate at which the similarity between two durations decreases as their difference increases and is expected to increase with stimulus range; the *a* parameter governs the form of the similarity-distance function (e.g. exponential, Gaussian, or intermediate) and is expected to increase as stimuli become more perceptually confusable, and the *w* parameter determines the degree to which the ranked position of a stimulus affects its subjective duration. Each of these parameters has been widely studied and interpreted outside the timing literature.

TRFT contrasts with SET and its relatives both the account given of context effects and in basic assumptions such as the scalar property; we deal with each of these in turn. Context effects, although ubiquitous in experiments on perception of non-temporal magnitudes, have not been widely incorporated in SET-based models. Wearden and Ferrara (1995) approached stimulus spacing effects with a model in which participants in a temporal bisection task responded "long" or "short" according to whether a test duration was longer or shorter than the arithmetic mean of a stimulus set, while Wearden and Ferrara (1996) applied Wearden's (1991) modified difference model, according to which participants have a bias to respond "long" which comes into play whenever the difference between the test duration and the "long" standard and the difference between the test duration and the "short" standard are difficult to discriminate. The current account is clearly closer in spirit to the former account than the latter, for comparison of test durations to the arithmetic mean will naturally lead to spacing effects that qualitatively follow those observed here.

The “memory mixing” model of duration bisection (e.g. Penney et al., 1998; see also Penney et al., 2000) could potentially account for context effects of the type emphasized in the present manuscript. The memory mixing model assumes that test durations that are similar to the “short” or “long” standards contaminate the memory trace, particularly when the long:short ratio is large and the standards do not need to be remembered accurately for reasonable performance to result. This mechanism would lead to the “short” standard becoming represented in memory as longer than it is, and this will occur to a greater extent in more positively skewed distributions (the reverse will be the case for the memory of the “long” standard). Penney et al. (1998) show that such an approach may account for the observed differences between logarithmic and arithmetic spacing, and the same account could potentially be applied to the present results.

The account given by TRFT, while not denying that extant accounts could potentially be extended to account for the empirical effects described above, contrasts with previous models of context effects in that it imports a model independently developed and empirically successful outside the duration judgment literature, and explicitly assumes that the same principles apply in both cases.

A fundamental difference between TRFT and SET concerns the assumptions of the scalar nature of timing. The scalar assumption states that the coefficient of variation in timing is close to constant. TRFT has strong Weberian and scale-invariant properties, in that the confusability of two subjective durations will be a function of the ratio of the shorter to the longer if durations are represented on a logarithmic scale and generalisation is exponential. However in temporal bisection tasks the scalar assumption is normally tested by superposition —if two temporal bisection curves superimpose when the probability of responding “long” is plotted as a function of test duration divided by bisection point, scalar timing is said to occur (Allan & Gibbon, 1991). Several previous studies have indeed found good superposition under a wide range of conditions (e.g. Allan, 2002b; Allan & Gerhardt, 2001; Allan & Gibbon, 1991; Penney et al., 1998, 2000; Wearden & Bray, 2001; Wearden & Ferrara, 1996; Wearden et al., 1997) although small departures are sometimes observed (Penney et al., 1998, 2000; Wearden et al., 1997). However TRFT makes the strong prediction that superposition of bisection curves obtained from different stimulus spacing need *not* occur, especially when the long:short ratio is large. TRFT predicts absence of superposition, even if stimulus range is held constant, because the subjective value of a given duration will depend on its context. For example, consider a set of durations ranging from 200 ms to 800 ms. According to TRFT, a duration of (say) 400 ms will be associated with a higher probability of responding "long" if it occurs in a positively skewed distribution than if it occurs in a negatively skewed distribution (range being held constant). Of course the bisection point will also be lower for the positively skewed distribution, and this will cause a tendency towards overlap of the bisection functions for the positively and negatively skewed distributions. However the location of the bisection point need not (except by coincidence) exactly cancel out the effects of stimulus skewing in such a way that superposition is obtained. The degree to which the probability of responding "long" will be elevated in the positively skewed distribution will be determined by its changed ranked position in the stimulus set, whereas the location of the bisection point will be determined by the precise values (i.e., not just the ranked position) of the other stimulus durations in the set. Thus the bisection point and the probability of responding "long" to a given item can vary with some degree of independence, and hence superposition need not occur.

To illustrate, we plotted superposition graphs to illustrate both the predictions of the model and the deviations from superposition obtained in the data. The top two panels of Figure 18 show the lack of superposition predicted by the model for both the large long:short ratio and the small long:short ratio cases. The bisection point for the model fit was used for the normalisation, and model parameters were those previously used to fit the data. It is evident that a clear failure of superposition is predicted for the large ratio stimulus set: The bisection curve for the more positively skewed (superlogarithmic) case is flatter than the curve for the most negatively skewed distribution (antilogarithmic). The superposed curves for the conditions of intermediate skewness (logarithmic and arithmetic), while not shown, exhibit the expected intermediate pattern. A similar failure of superposition is observable in the small ratio set although the effect is much smaller in magnitude.

The lower two panels of Figure 18 show the equivalent normalized bisection curves observed in the data. It is evident that the predict departure from superposition is indeed observed. Thus TRFT differs strongly from SET in predicting a failure of superposition, and the prediction is upheld empirically.

We note that the claim that TRFT principles may be relevant to judgment of temporal durations is a more general one than the specific hypotheses embodied in the model of bisection presented here. For example, a number of authors (e.g., Allen, 2002a, Allen & Gerhardt, 2001; Wearden & Ferrara, 1995) have suggested that participants may perform tasks such as temporal generalization and temporal bisection by comparing test tones to an implicit mean of some kind rather than reference to explicitly stored and remembered exemplars. Such an account could be consistent with TRFT principles, according to which the mean of the subjective magnitudes of positively skewed stimuli will be lower than the mean for negatively skewed stimuli even when the range is held constant (Parducci, 1968). For example, TRFT would predict that observed temporal bisection points will be lower for logarithmically-spaced duration than for arithmetically-spaced durations even if temporal bisection occurs through comparison of test durations to a single criterion such as the psychological mean or mid-point. Further research will be needed to evaluate the potential contribution of TRFT to paradigms outside adult temporal bisection.

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Footnote

1. This correction procedure can lead to distortion of the data when response bias is large and systematic, but is unproblematic when, as here, participants exhibit small and non-systematic preferences for particular responses.

Table 1

Temporal Durations Used in Experiment 1 (ms)

	Large Ratio		
Antilogarithmic	Arithmetic	Logarithmic	Superlogarithmic
100	100	100	100
343	214	137	114
520	329	187	134
649	443	256	162
744	557	351	203
813	672	480	274
863	786	658	420
900	900	900	900
	Small Ratio		
Antilogarithmic	Arithmetic	Logarithmic	Superlogarithmic
333	333	333	333
396	381	368	359
453	428	406	389
505	476	448	424
551	524	495	466
594	571	547	518
632	619	604	583
666	666	666	666

Table 2

Proportion Correct Absolute Identification Performance in Experiments 1 and 2.

	Experiment 1, Large Ratio	Experiment 1, Small Ratio	Experiment 2, Large Ratio	Experiment 2, Small Ratio
Antilogarithmic	.416	.298	.565	.530
Arithmetic	.431	.311	.644	.635
Logarithmic	.401	.292	.631	.561
Superlogarithmic	.398	.297	.635	.581

Table 3

Frequencies Used in Experiment 2.

Large Ratio			
Antilogarithmic	Arithmetic	Logarithmic	Superlogarithmic
200	200	200	200
685	429	274	229
1039	657	375	268
1298	886	513	323
1487	1114	702	406
1625	1343	961	548
1726	1571	1315	840
1800	1800	1800	1800
Small Ratio			
Antilogarithmic	Arithmetic	Logarithmic	Superlogarithmic
666	666	666	666
792	762	736	718
906	857	813	778
1009	952	897	848
1103	1048	991	933
1187	1143	1094	1037
1264	1238	1208	1167
1333	1333	1333	1333

Figure Captions

Figure 1. Temporal bisection curves illustrating geometric mean bisection and arithmetic mean bisection.

Figure 2. Two distributions of stimulus magnitudes to illustrate predictions of Range Frequency Theory.

Figure 3. Positively skewed (A) and negatively skewed (B) distributions of temporal durations.

Figure 4. The eight distributions of temporal durations used in Experiment 1. See text for details.

Figure 5. Predicted subjective magnitudes of temporal durations (left panels) and predicted temporal bisection curves (right panels) for stimulus distributions with large long:short ratios (top panels) or small long:short ratios (lower panels).

Figure 6. Serial position curves obtained from absolute identification of stimulus durations (Experiment 1).

Figure 7. Effects of stimulus on trial *n-1* on mean error on trial *n* for absolute identification of temporal durations (Experiment 1).

Figure 8. Contrast and assimilation effects observed in the absolute identification of temporal duration (Experiment 1).

Figure 9. Regression coefficients observed in analysis of sequence effects in identification of temporal durations (Experiment 1).

Figure 10. Observed temporal bisection curves (upper panels) and fit of the model to the data (lower panels). See text for details.

Figure 11. Observed (Figure 11a) and predicted (Figure 11b) temporal bisection points as a function of stimulus distribution and long:short ratio.

Figure 12. Serial position curves obtained from absolute identification of tone frequencies (Experiment 2).

Figure 13. Summary of effects of stimulus on trial n-1 on mean error on trial n for absolute identification of tone frequencies (Experiment 2; Figure 13a) and stimulus durations (Experiment 1; Figure 13b). Note that axes differ.

Figure 14. Contrast and assimilation effects observed in absolute identification of tone frequencies (Experiment 2; Figure 14a) and stimulus durations (Experiment 1; Figure 14b).

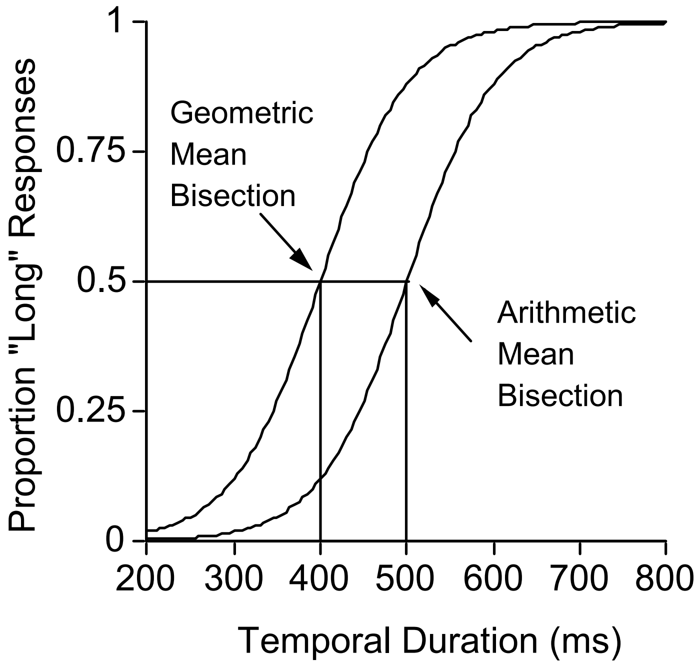
Figure 15. Regression coefficients observed in analysis of sequence effects in identification of tone frequencies (Experiment 2).

Figure 16. Observed frequency bisection curves (upper panels) and fit of the model to the data (lower panels). See text for details.

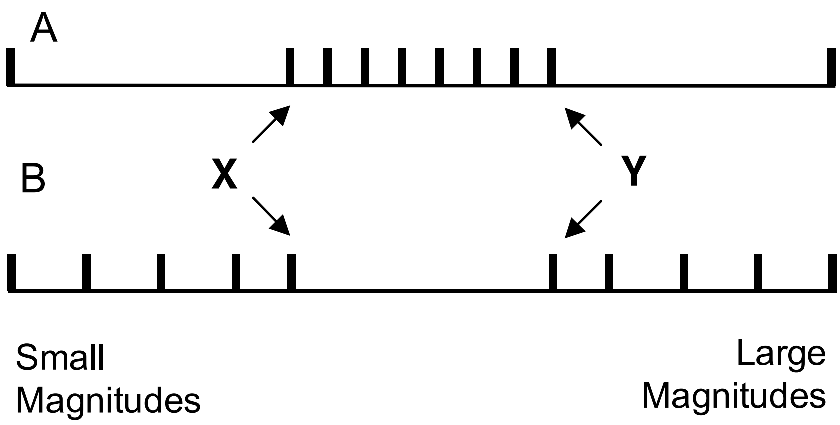
Figure 17. Observed (Figure 17a) and predicted (Figure 17b) frequency bisection points as a function of stimulus distribution and high:low ratio.

Figure 18. Predicted (upper two panels) and observed (lower two panels) bisection superposition graphs as a function of stimulus distribution and long:short ratio.

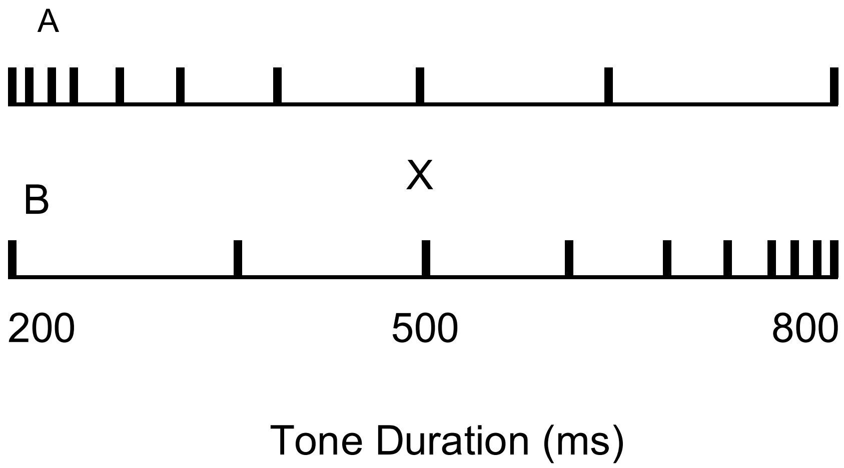
(Figure 1)


Proportion "Long" Responses
1
0.75
0.5
0.25
0
Geometric
Mean
Bisection
Arithmetic
Mean
Bisection
200
300
400
500
600
700
800
Temporal Duration (ms)

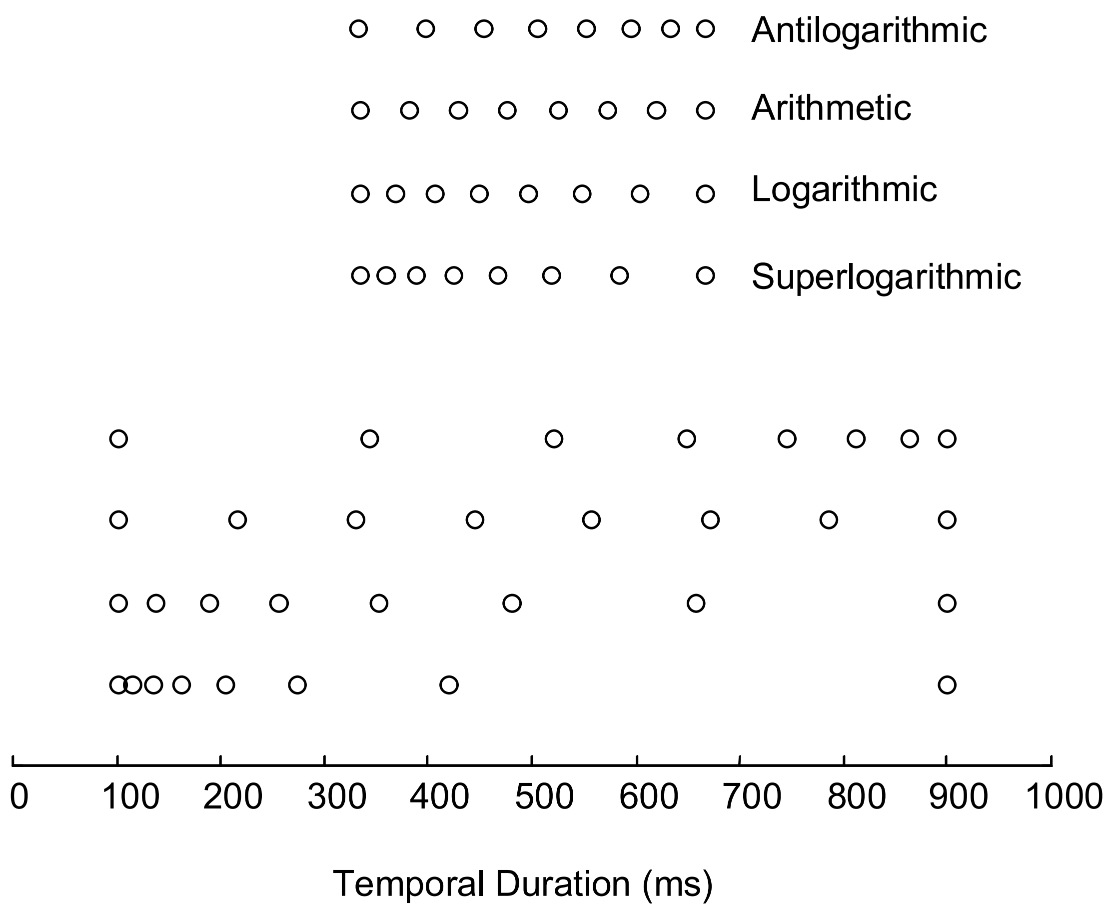
(Figure 2)



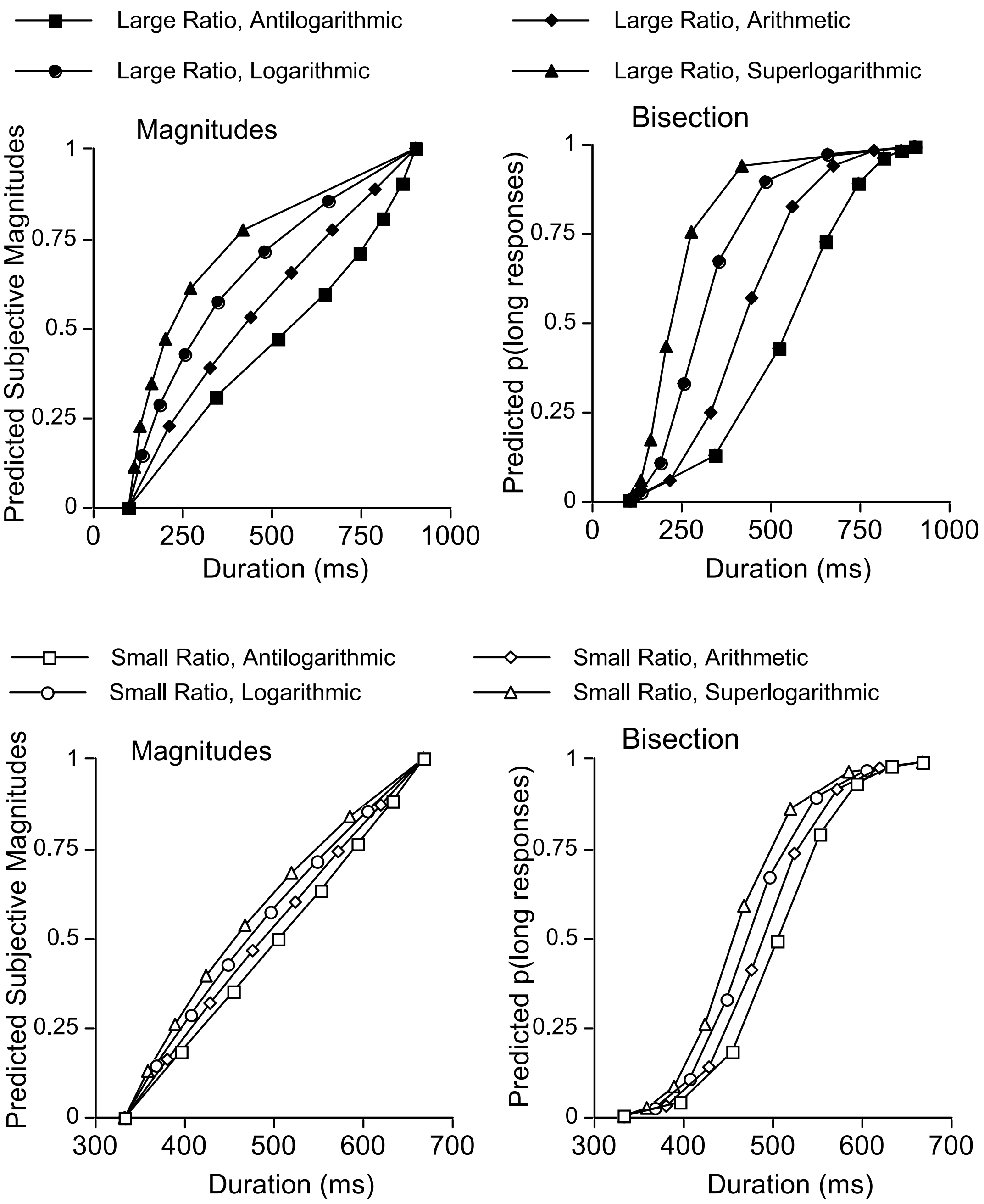
(Figure 3)



(Figure 4)

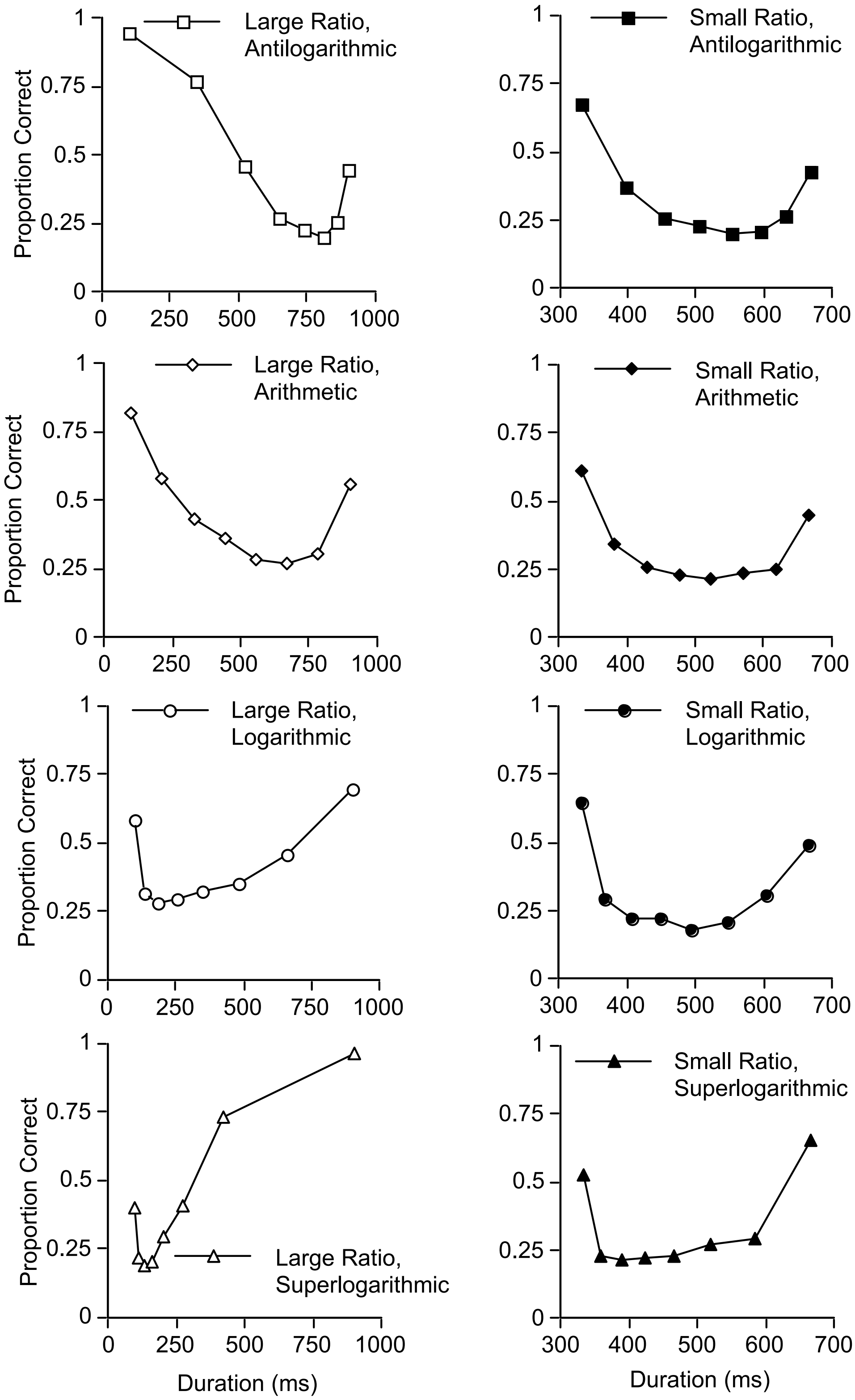

Antilogarithmic
Arithmetic
Logarithmic
Superlogarithmic
0
100
200
300
400
500
600
700
800
900
1000
Temporal Duration (ms)

(Figure 5)



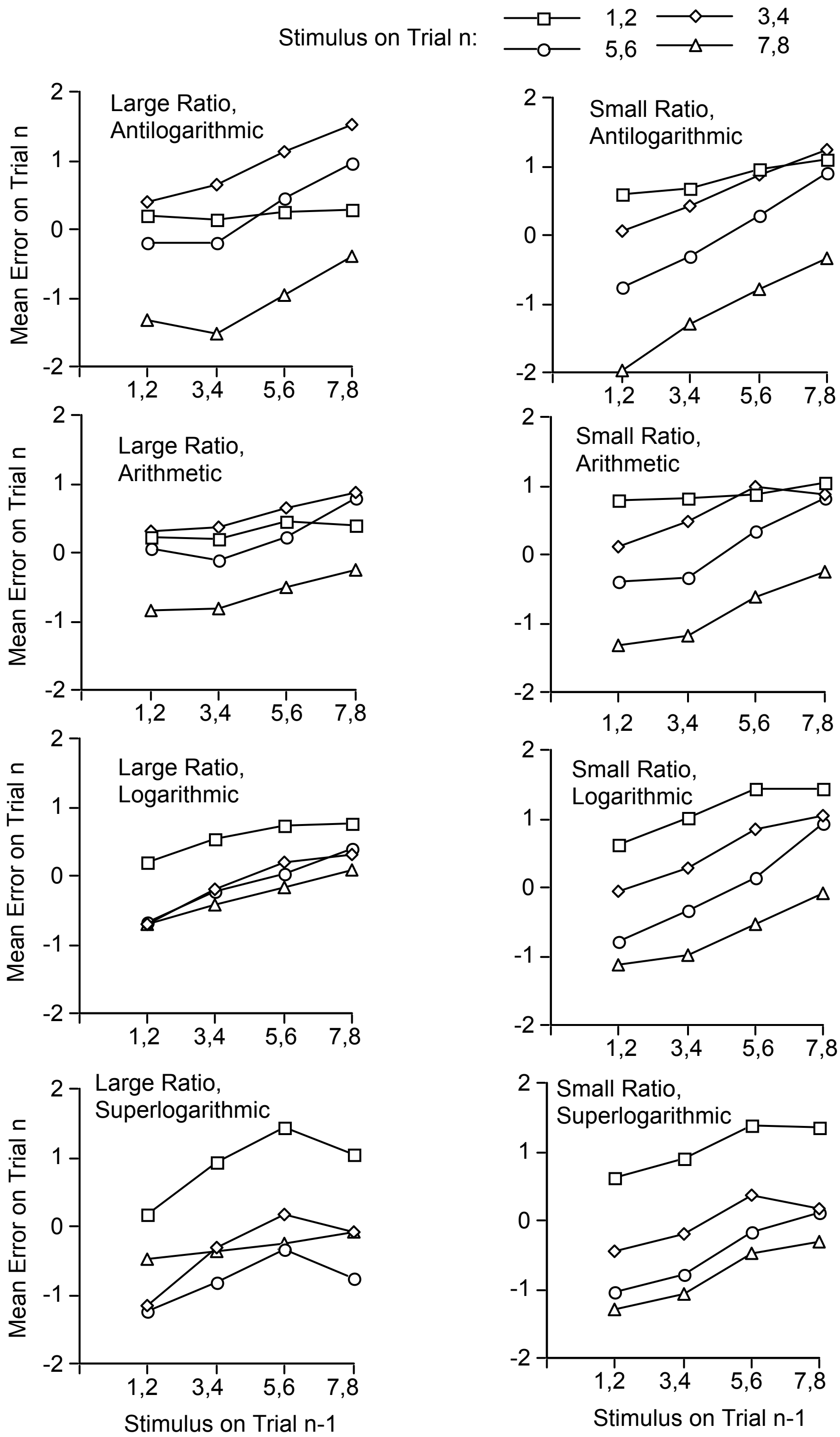
Large Ratio, Antilogarithmic
Large Ratio, Arithmetic
Large Ratio, Logarithmic
Large Ratio, Superlogarithmic
Magnitudes
Predicted Subjective Magnitudes
Duration (ms)
Bisection
Predicted p(long responses)
Duration (ms)
Small Ratio, Antilogarithmic
Small Ratio, Arithmetic
Small Ratio, Logarithmic
Small Ratio, Superlogarithmic
Magnitudes
Predicted Subjective Magnitudes
Duration (ms)
Bisection
Predicted p(long responses)
Duration (ms)

(Figure 6)

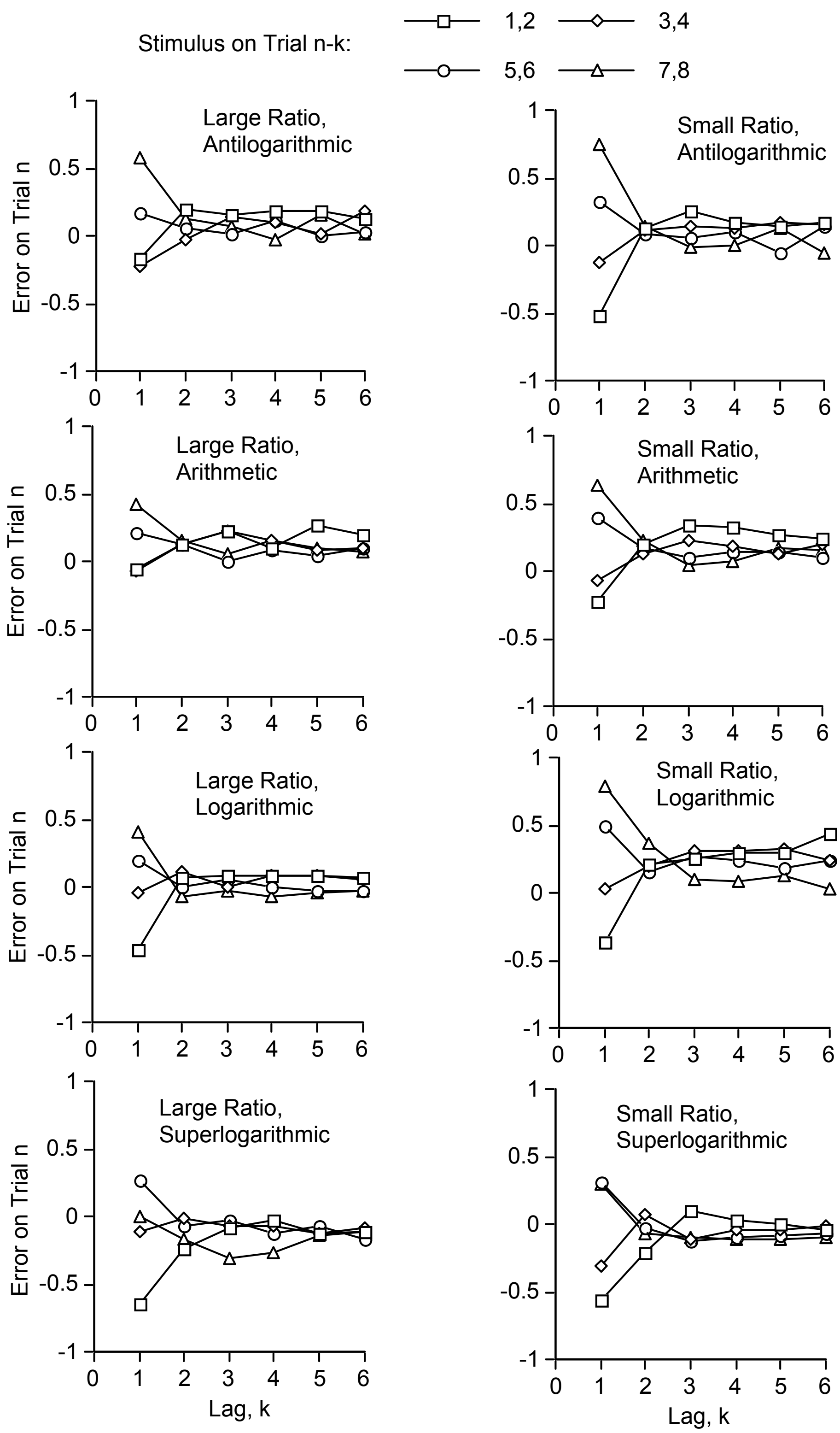


Large Ratio, Antilogarithmic
Small Ratio, Antilogarithmic
Large Ratio, Arithmetic
Small Ratio, Arithmetic
Large Ratio, Logarithmic
Small Ratio, Logarithmic
Large Ratio, Superlogarithmic
Small Ratio, Superlogarithmic
Proportion Correct
0
0.25
0.5
0.75
1
0
250
500
750
1000
300
400
500
600
700
Duration (ms)

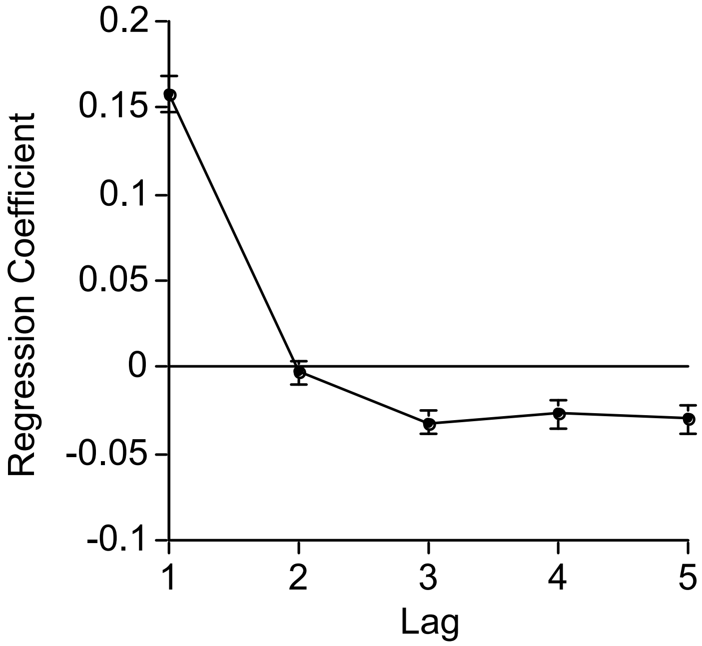
(Figure 7)


Stimulus on Trial n:
1,2
3,4
5,6
7,8
Large Ratio, Antilogarithmic
Small Ratio, Antilogarithmic
Large Ratio, Arithmetic
Small Ratio, Arithmetic
Large Ratio, Logarithmic
Small Ratio, Logarithmic
Large Ratio, Superlogarithmic
Small Ratio, Superlogarithmic
Mean Error on Trial n
Stimulus on Trial n-1
2
1
0
-1
-2
1,2
3,4
5,6
7,8

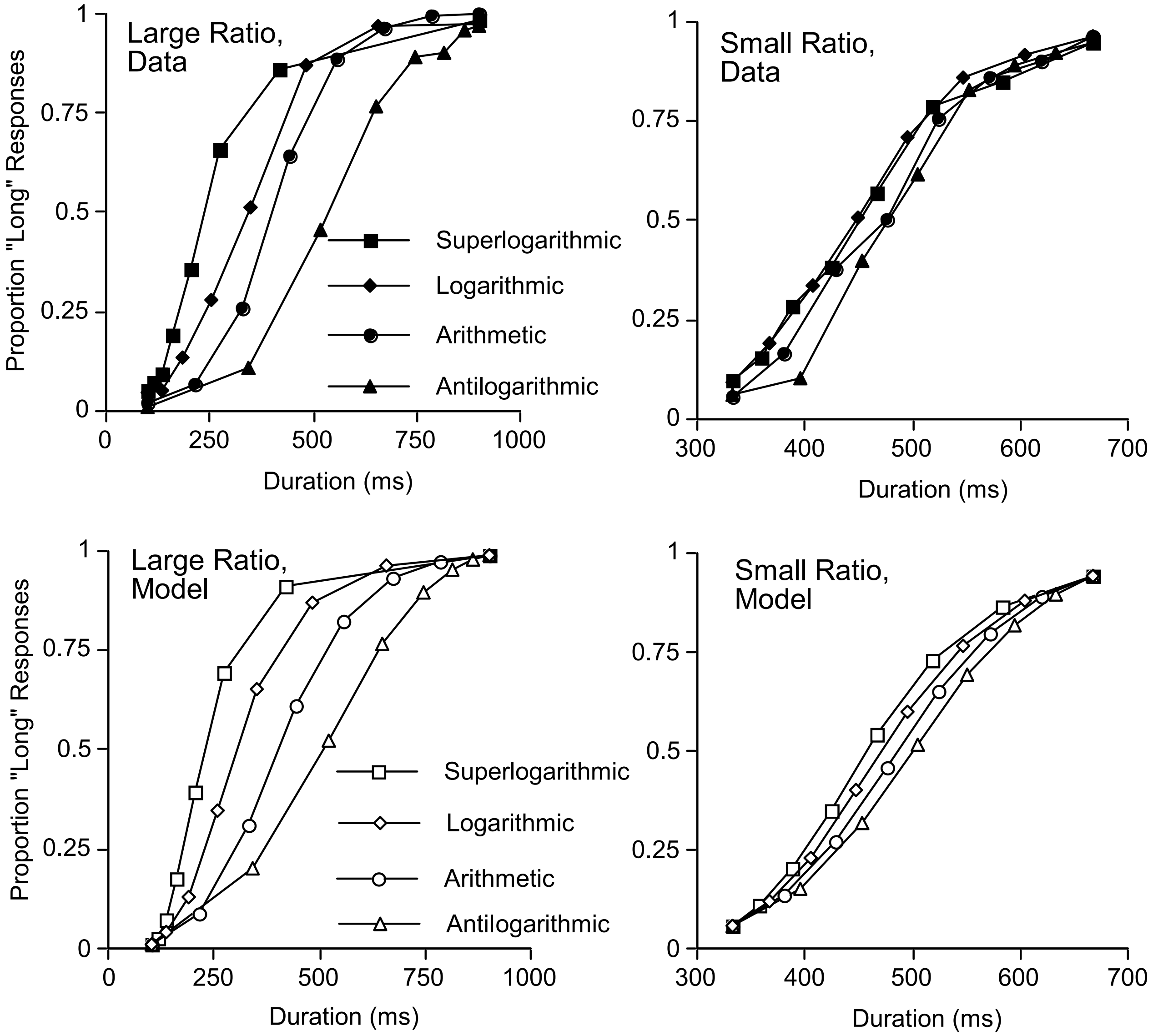
(Figure 8)


Stimulus on Trial n-k:
1,2
3,4
5,6
7,8
Large Ratio, Antilogarithmic
Small Ratio, Antilogarithmic
Large Ratio, Arithmetic
Small Ratio, Arithmetic
Large Ratio, Logarithmic
Small Ratio, Logarithmic
Large Ratio, Superlogarithmic
Small Ratio, Superlogarithmic
Error on Trial n
Lag, k

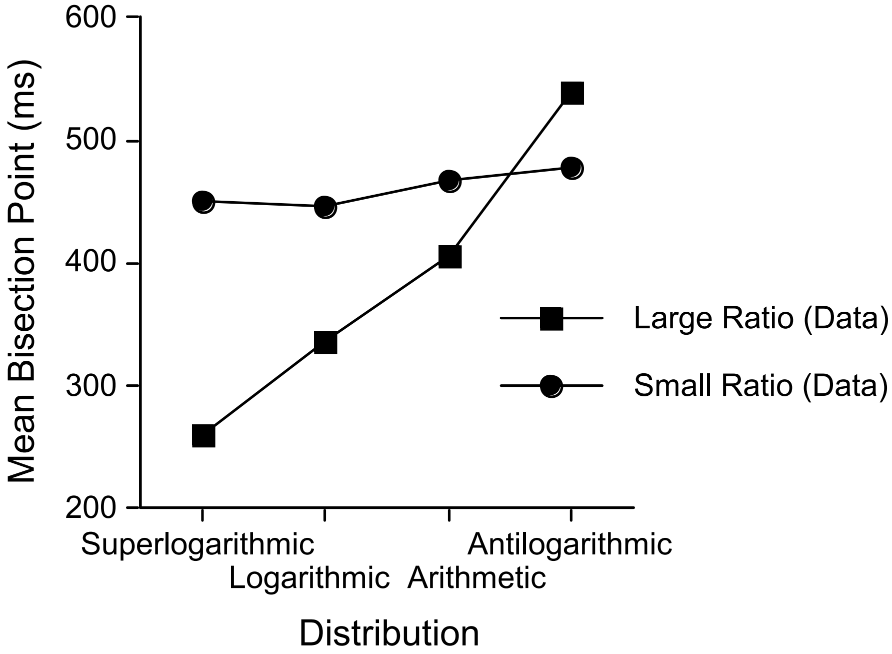
(Figure 9)



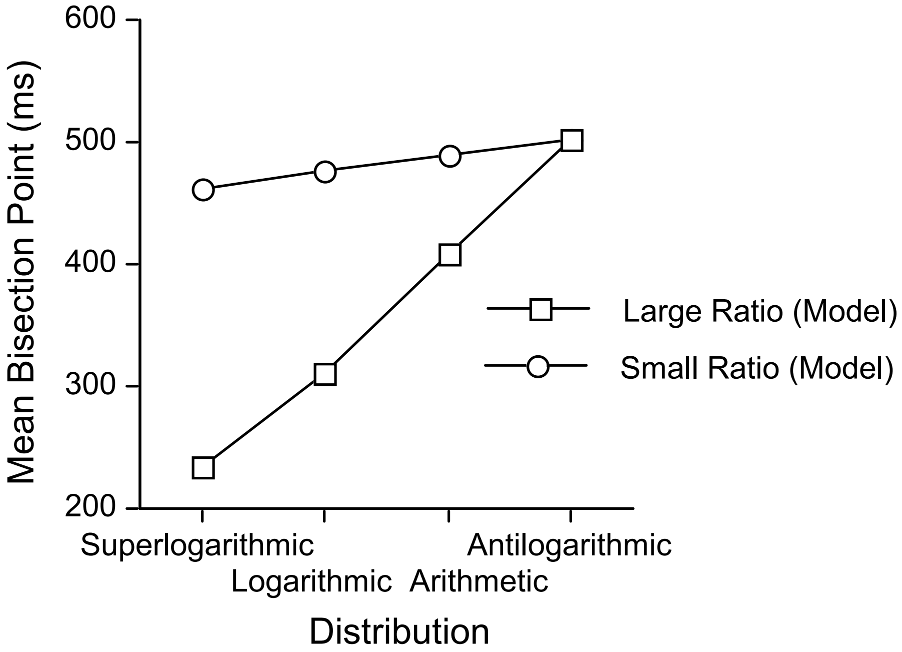
(Figure 10)


Large Ratio, Data
Small Ratio, Data
Large Ratio, Model
Small Ratio, Model
Proportion "Long" Responses
Duration (ms)
Superlogarithmic
Logarithmic
Arithmetic
Antilogarithmic
0
0.25
0.5
0.75
1
0
250
500
750
1000
300
400
500
600
700

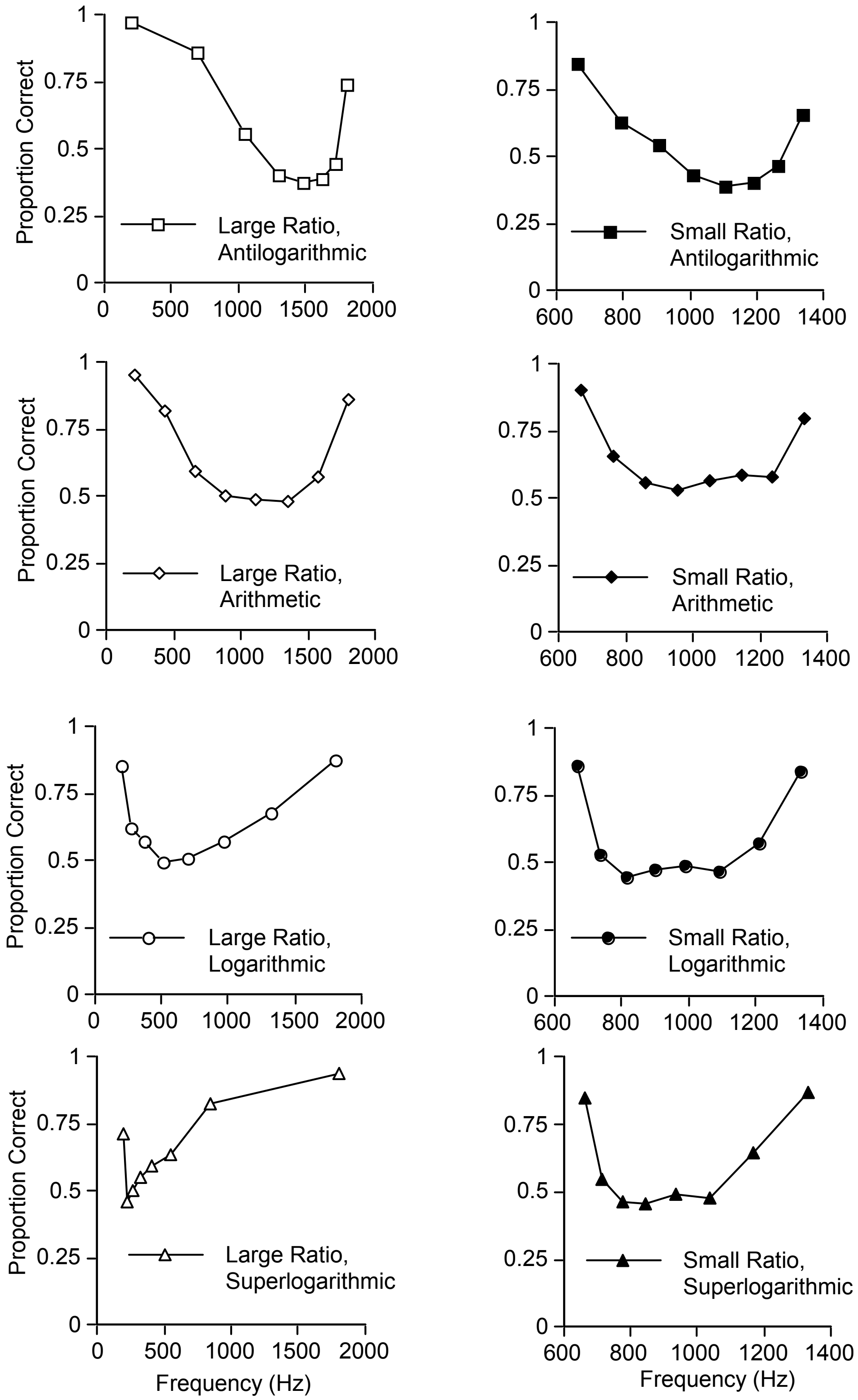
(Figure 11a)



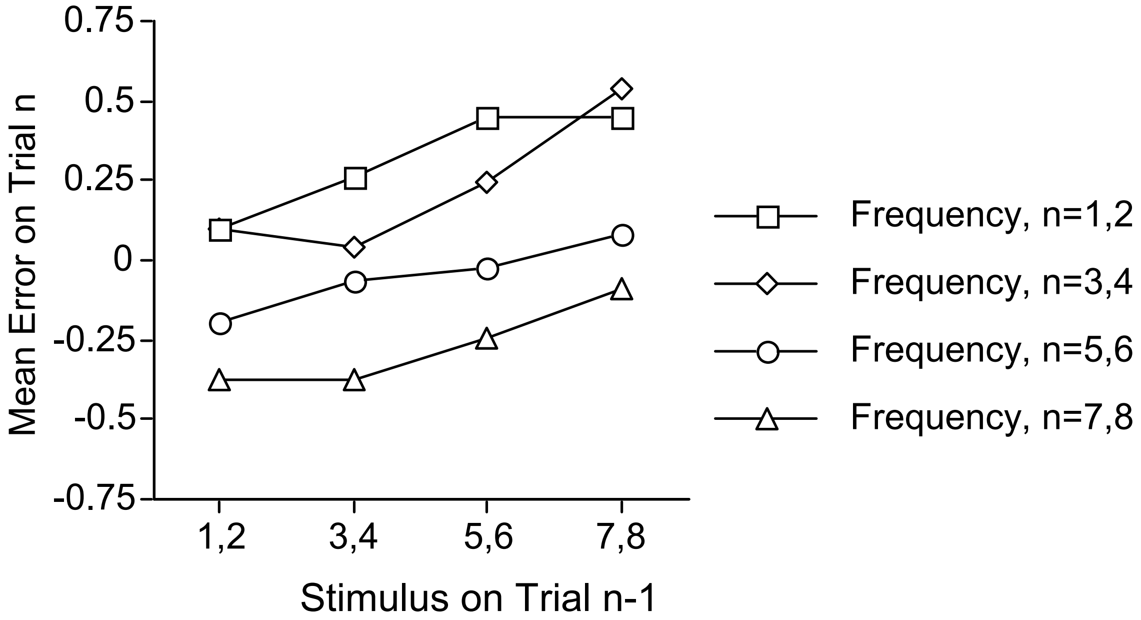
(Figure 11b)



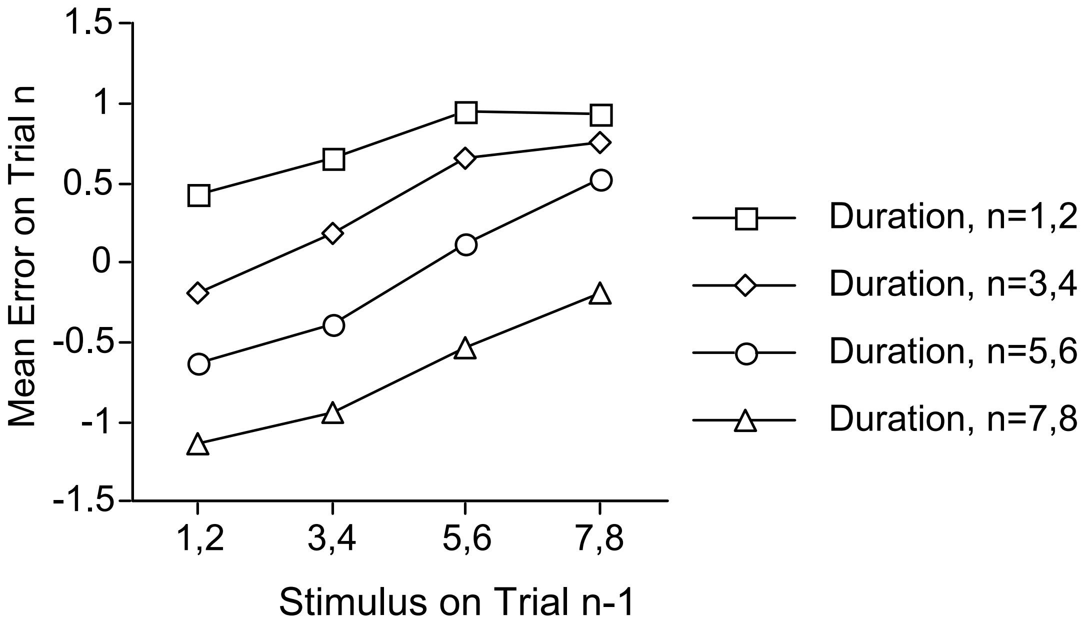
(Figure 12)


Proportion Correct
Large Ratio, Antilogarithmic
Small Ratio, Antilogarithmic
Large Ratio, Arithmetic
Small Ratio, Arithmetic
Large Ratio, Logarithmic
Small Ratio, Logarithmic
Large Ratio, Superlogarithmic
Small Ratio, Superlogarithmic
Frequency (Hz)

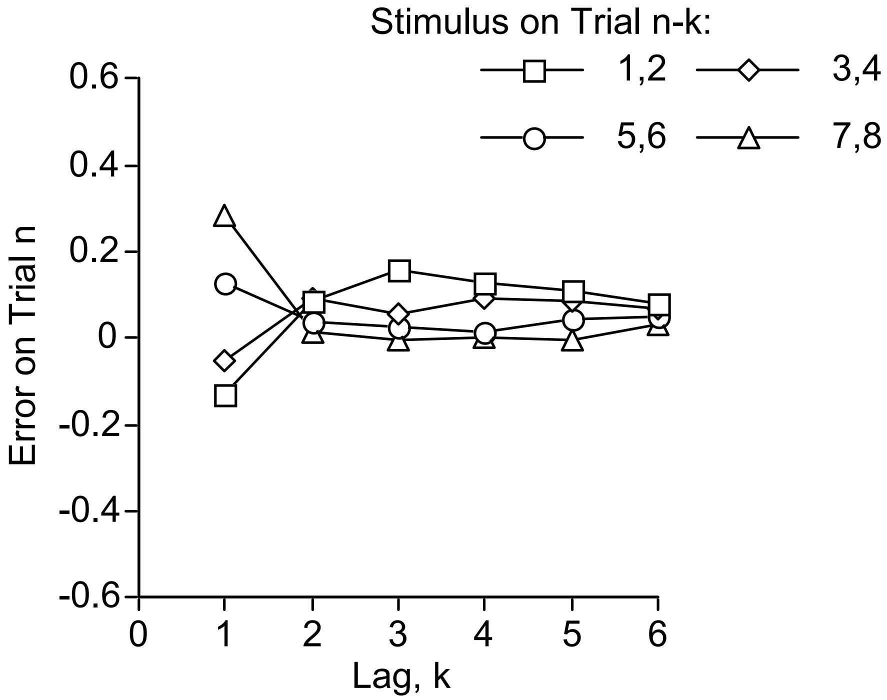
(Figure 13a)



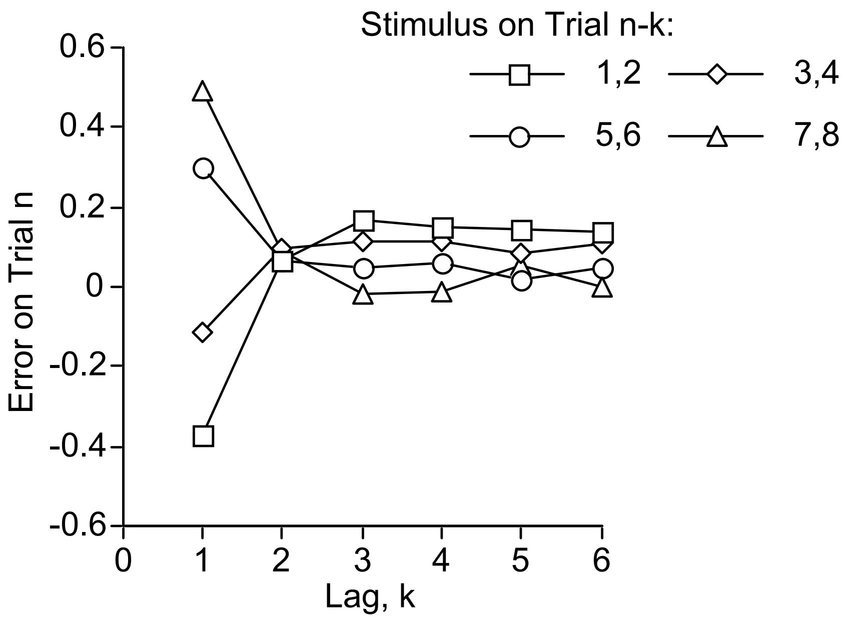
(Figure 13b)



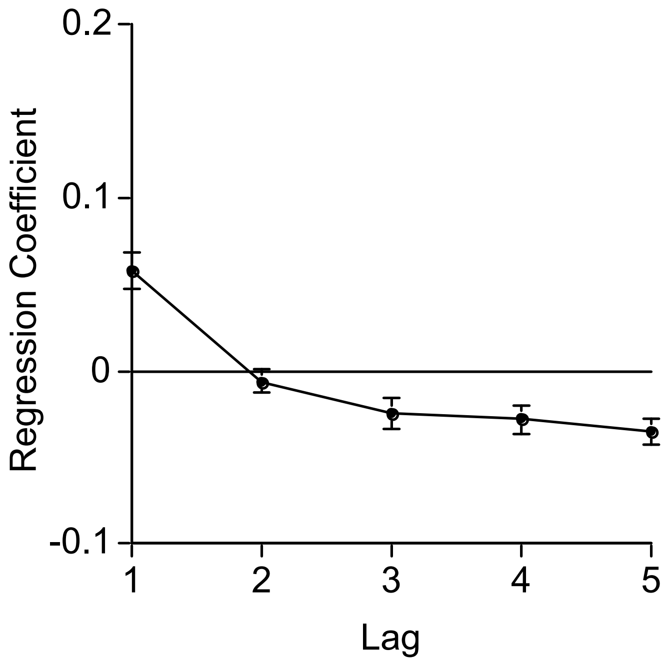
(Figure 14a)



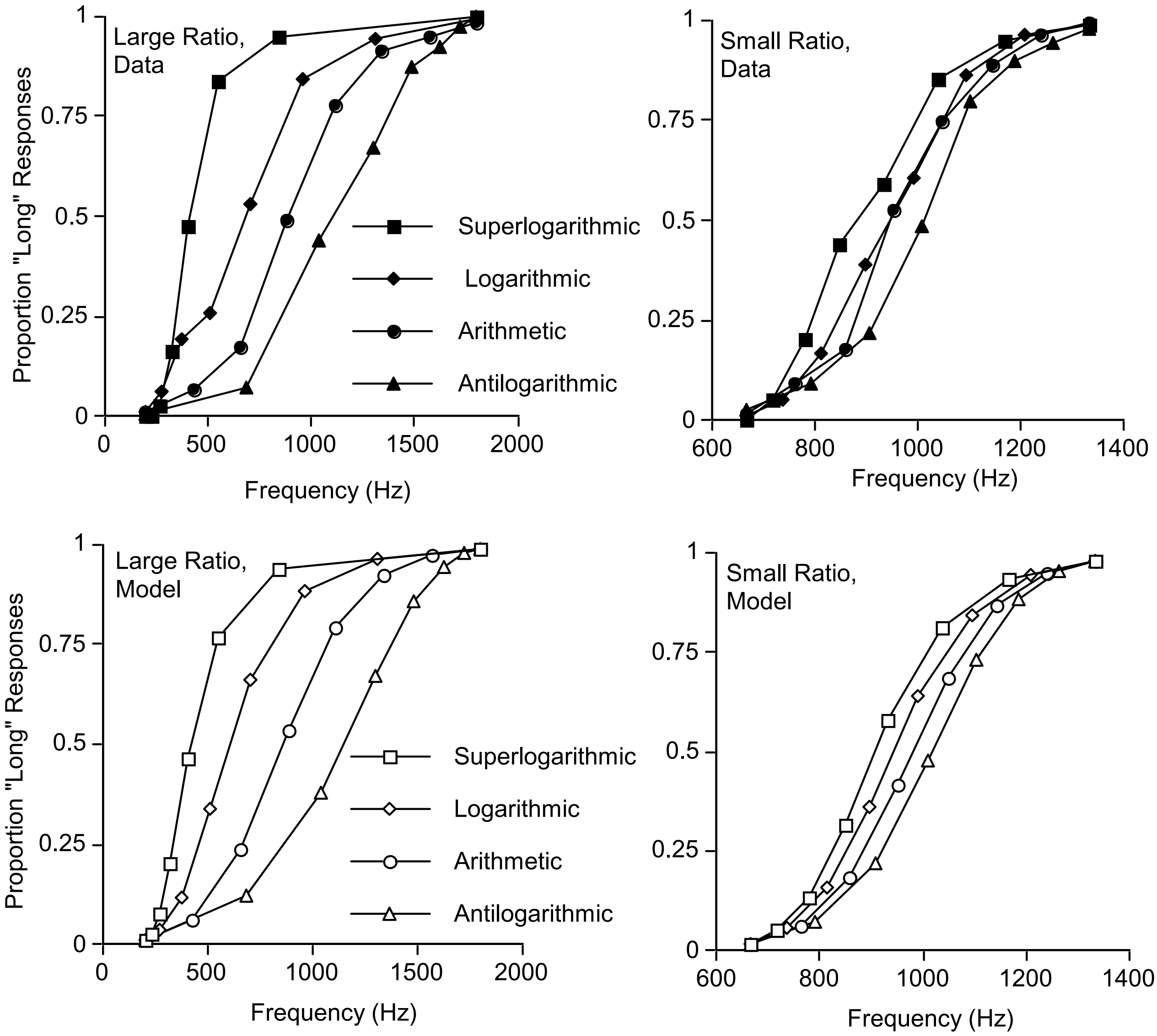
(Figure 14b)



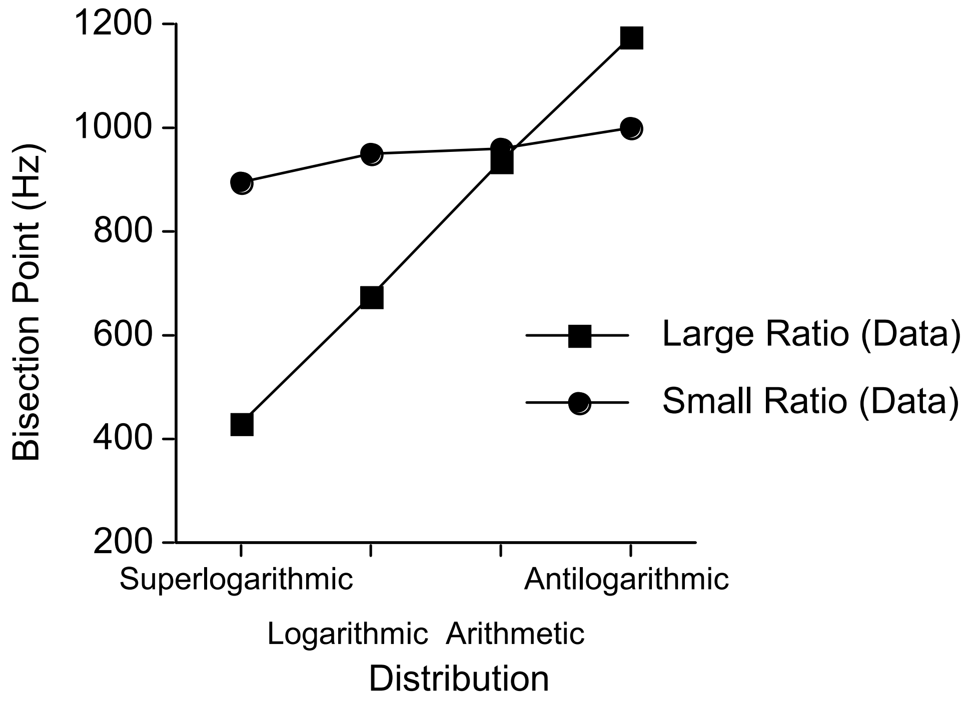
(Figure 15)



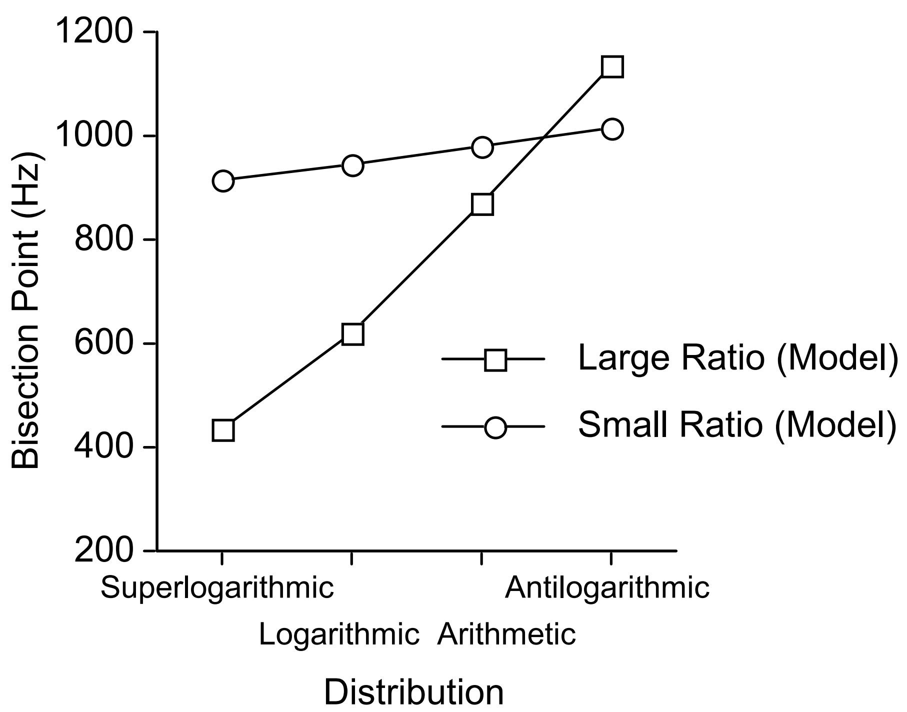
(Figure 16)


Large Ratio,
Data
Superlogarithmic
Logarithmic
Arithmetic
Antilogarithmic
Proportion "Long" Responses
Frequency (Hz)
Small Ratio,
Data
Large Ratio,
Model
Small Ratio,
Model
0
0.25
0.5
0.75
1
0
500
1000
1500
2000
600
800
1000
1200
1400

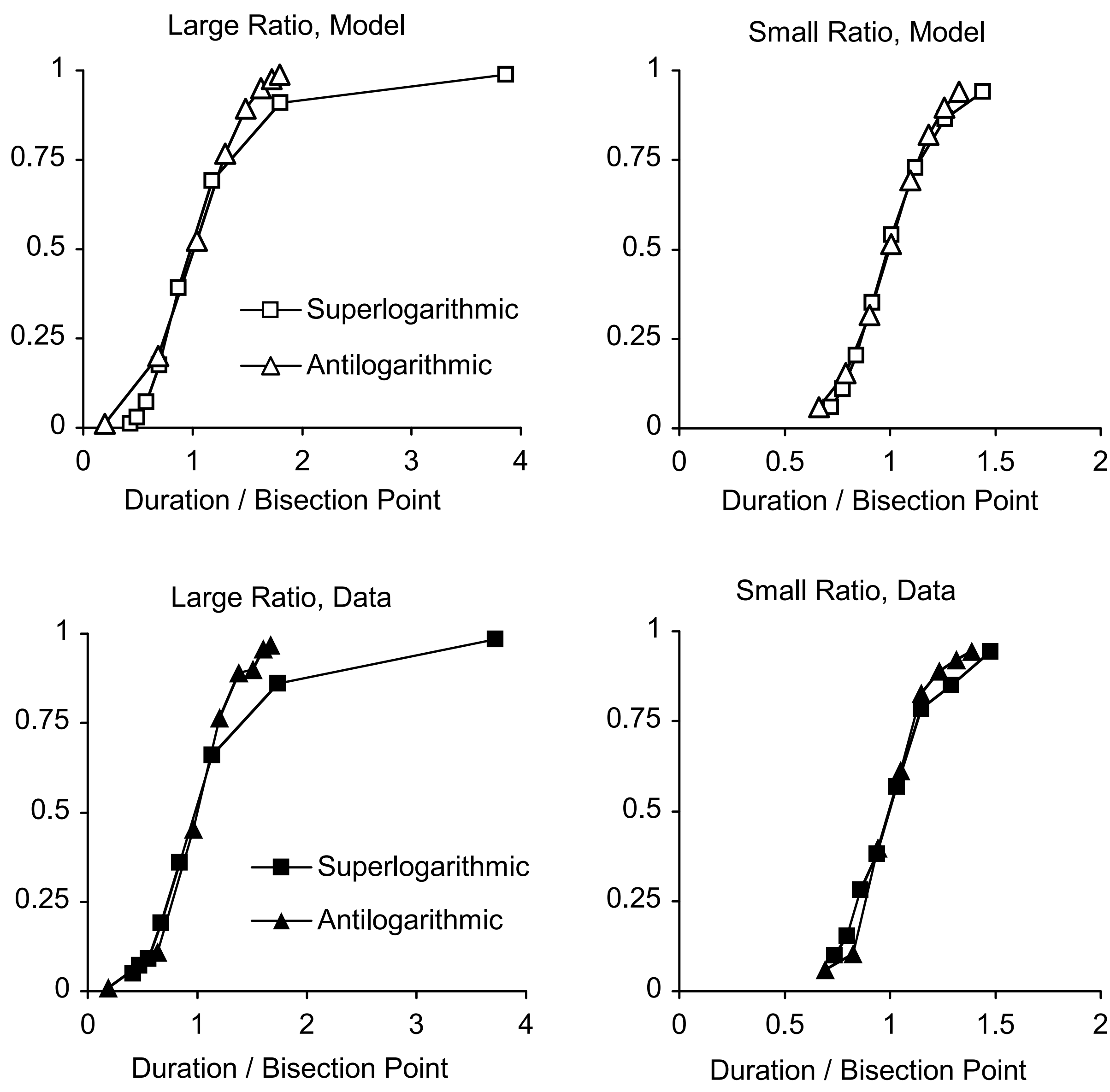
(Figure 17a)



(Figure 17b)



(Figure 18)


Large Ratio, Model
Small Ratio, Model
Superlogarithmic
Antilogarithmic
Duration / Bisection Point
Duration / Bisection Point
Large Ratio, Data
Small Ratio, Data
Superlogarithmic
Antilogarithmic
Duration / Bisection Point
Duration / Bisection Point