1 Attention, Stimulus Range, and Identification of Loudness

R. Duncan Luce

Robert M. Nosofsky
Harvard University

ABSTRACT

Techniques aimed at manipulating both sensitivity and response bias in absolute identification of loudness are explored in order to illuminate features of two Thurstonian-based models: the range theory of Braida and Durlach and the attention-band theory of Green and Luce. Evidence is first offered that signal range affects both the sensory and the criterion variance in the Braida-Durlach model. We then turn to studies of more local changes in sensitivity and response bias by means of experimental manipulations in which overall range is held constant.

One-trial sequential analyses strongly support the idea of shifting category boundaries, although we lack a simple rule to characterize the nature of these shifts as a function of experimental design. Changes in d′ as a function of the relation of the present to the previous signal are, at best, minor. These one-trial sequential analyses do not support the subsidiary hypothesis of the Green-Luce theory that attention tracks the previous signal on a trial-by-trial basis.

A number of additional studies, all using some form of prolonged signal clustering, do however generate substantial local changes in sensitivity. This phenomenon can be interpreted as evidence of an attention mechanism that is somewhat sluggish in tracking signals. The experiments are of three types: probability clustering in which nonuniform distributions of trial independent schedules are used; intensity clustering into narrow (e.g., 10 dB) intensity bands but with outlier signals to maintain the range; and clustering that arises because of sequential dependencies within the signal presentation schedule. All methods provide evidence of substantial changes in d′ when a signal is part of a cluster as compared to when it is not. Several alternative accounts of these phenomena are explored and rejected.

INTRODUCTION

The ability of subjects to resolve signals in unidimensional absolute identification tasks is affected greatly by the experimental context in which the signals are embedded. For example, two auditory signals separated by 5 dB are rarely confused in a two-alternative loudness absolute identification (AI) task. Yet, the same two signals are badly confused when embedded in a multi-signal AI task. This phenomenon and various related ones became widely recognized after G. A. Miller's classic 1956 paper "The magical number 7, plus or minus two: Some limits on our capacity for processing information." Although a great deal has been learned since then, the limit on identification performance remains a paradox in psychophysical research. In this chapter we review and contrast two Thurstonian-based models which have been proposed in an attempt to provide explanations—the range theory of Braida and Durlach (Braida & Durlach, 1972; Durlach & Braida, 1969) and the attention-band theory of Green and Luce (Luce & Green, 1978; Luce, Green, & Weber, 1976). We follow this with a more thorough investigation of the two theories, reviewing a series of experiments that attempt to distinguish between them.

It is not immediately obvious that the phenomenon of limited capacity in absolute identification has anything to do with the theme of this book, preparatory states. We suspect it does for two reasons. First, at least the attention-band theory is very much in the spirit of preparation for signal presentations. Second, and perhaps more persuasive, some of the experiments demonstrate that certain patterns of signal presentation can lead to large changes in sensitivity. To be specific, it appears that a subject is appreciably better prepared for a signal provided several of the immediately preceding signals were similar to it than when they were quite different from it.

1. TWO THEORIES OF UNIDIMENSIONAL ABSOLUTE IDENTIFICATION PERFORMANCE

1.1. Range Theory

If one holds fixed the number of equally spaced signals while increasing the range that they occupy, identification performance does not improve nearly as much as the traditional Thurstonian model predicts (Pollack, 1952). This observation led Durlach and Braida (1969) to hypothesize a direct relation between stimulus range and the variance of the decision variables that determine performance. In particular, they assumed that the decision variance consists of two components: sensation noise and criterial noise.[1] They further assumed that a

[1]To be more precise, Braida and Durlach actually speak of "memory" noise rather than "criterial" noise, although they have provided evidence of shifting category boundaries in their research. Presumably, the locations of the category boundaries are influenced by a subject's memory for past signal presentations, and so we conceptualize all memory noise as being located in the criteria. Other factors may also affect criterial noise, such as systematic changes in response bias, and so forth.

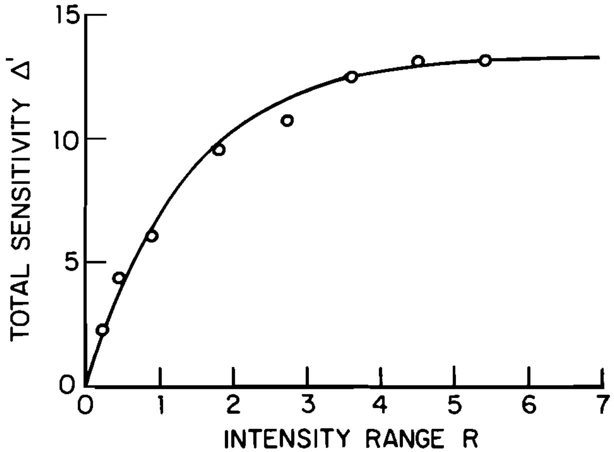

Fig. 1.1. Total sensitivity vs. intensity range R (=dB/10) for loudness absolute identification along with the predictions of the Braida-Durlach model. Assuming N signals, then total sensitivity (Δ') is defined as $\Delta' = \sum_{i=1}^{N-1} d'_{i,i+1}$. This is Fig. 4d of Braida and Durlach (1972).

subject could operate in one of two response modes: the sensory trace mode, in which the subject tries actively to maintain the traces of past stimulus presentations (as in a discrimination task), and the context-coding mode, in which the subject attempts to compare the representation of a given stimulus to the general context of other stimulus presentations in the experiment. Durlach and Braida assumed that only the context-coding mode is used in standard AI tasks and, furthermore, that noise in this mode varies directly with the range of the stimulus set being used, with larger ranges leading to more noise. On the other hand, they assumed sensation noise to be independent of the experimental context.

As reported by Braida and Durlach (1972), the theory did quite well in describing the results of various AI experiments. Excellent fits of the model to data were obtained in a series of experiments in which the number of equally spaced stimuli was held fixed and the overall range varied. These data are reproduced in Fig. 1.1. Additional experiments supplied converging evidence that the range of the stimulus set might indeed be the crucial factor. For example, Braida and Durlach (1972) found that given a fixed stimulus range, overall sensitivity was relatively unaffected by the number of signals to be identified and that the distribution of the signals within the range was also relatively unimportant.[2]

[2]Gravetter and Lockhead (1973) have provided convincing evidence that the distribution of signal intensities within the range can markedly affect sensitivity. They have argued that criterial variance is directly related to *criterial* range, not stimulus range. We review this and related research in section 4.

One shortcoming of the range theory is its inability to explain easily the dependence of sensitivity on the particular locations of the stimuli within the range—identification performance is appreciably better at the edges than in the middle of the range. This observation led Berliner and Durlach (1973) to suggest that the subject forms perceptual anchors at the extremes of the stimulus range, and that as the distance of the signal presentations from the anchors increases, judgmental variability increases. (Note that as stimulus range is increased, distance from the perceptual anchors to each equally spaced signal necessarily increases.)

In more recent research, further support has been obtained for the hypothesis that the variance of the decision variables in AI is a function solely of the range of the stimulus set being used. Lippmann, Braida, and Durlach (1976) found that sensitivity in identifying particular signals was independent of payoffs; Purks, Callahan, Braida, and Durlach (1980) found that sensitivity was independent of the preceding signal presented; and Chase, Bugnacki, Braida, and Durlach (1983) found that manipulating the a priori probability of signal presentations did not affect sensitivity. We discuss each of these results in more detail later.

1.2. Attention-Band Theory

Whereas the range theory stresses criterial and judgmental limitations in AI, the theory of Luce et al. (1976) stresses attentional limitations that affect sensory noise. In brief, the attention-band theory posits the existence of a mechanism of selective attention in the intensity dimension, about 10–20 dB wide, which roves over the relevant intensity range in a given AI experiment. Signal presentations falling within the band are assumed to result in less variable Thurstonian representations than when the presentation of the same signal falls outside the band.[3] The basic idea, then, is that as one increases the range over which signals are to be identified, the probability of a signal presentation falling inside the band is diminished and so sensation noise increases.

Two subsidiary hypotheses were also proposed regarding factors that controlled the location of the band along the intensity continuum. First, it was hypothesized that the band tends to locate itself at the extremes of the intensity range being used in an experiment, thereby accounting for the resolution edge

[3]One way that this could come about is for the representation to arise as an average of neural activity occurring on a sample of statistically independent neural fibers. The attention band corresponds to using a larger sample, estimated to be about an order of magnitude greater than the samples outside the band, and so the standard deviation of the representations differ by a factor of roughly three. Such a mechanism greatly reduces the number of fibers that the CNS must monitor at any one time without sacrificing the ability to monitor a limited region in far more detail. The exact width of the band, or whether it varies systematically over the range, while interesting questions, are not crucial to the qualitative predictions we shall evaluate.

effect. Second, it was hypothesized that the band tends to track the last signal presented. These hypotheses are described only as tendencies, because as strict rules they are inconsistent. Furthermore, as we shall see later, the second of these subsidiary hypotheses is wrong as stated, although perhaps not in general spirit.

Luce et al. (1976) were able to account quantitatively for the AI data of Braida and Durlach (1972) using a specific version of the attention-band model. They also conducted their own set of AI experiments in which the number of signals was held fixed and the range was varied. The data obtained in these experiments are presented in Fig. 1.2. As can be seen, both the Braida-Durlach range theory and the Green-Luce attention-band theory are about equally satisfactory at this level of analysis.

1.3. The Theories Contrasted

The range and attention-band theories may be contrasted in three ways. First, although both explain the range effect in AI in terms of increasing variance in the decision variables that determine performance, they conceptualize this increase as resulting from different underlying components. The range theory stresses

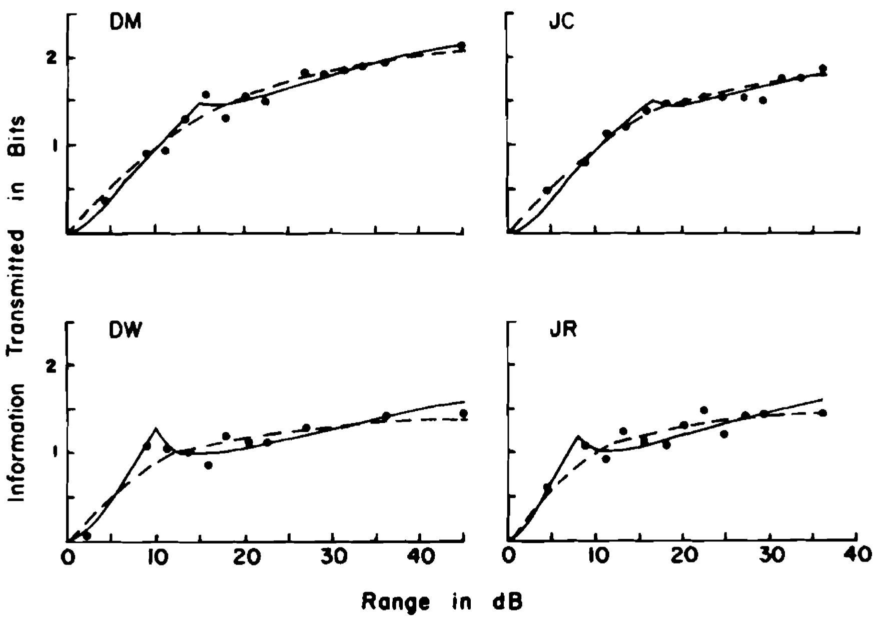

FIG. 1.2. Information transmitted as a function of range for four observers together with theoretical predictions of the attention-band model (solid line) and the Braida-Durlach model (dashed line). This is Fig. 5 (modified) of Luce et al. (1976).

criterial limitations in AI; in particular, it posits that criterial noise increases as the range of the stimulus set is increased. The attention-band theory stresses attentional limitations; in particular, it predicts increasing sensory noise as the range of the stimulus set is increased. In section 2 we report the results of an experiment designed to examine this issue.

Second, the range and the attention-band theories differ in how they conceptualize the role of stimulus range in determining the variance of the decision variables. For the range theory, increased variance in the decision variable is a direct consequence of increasing the range. For the attention-band theory, on the other hand, range plays only an indirect role in determining the decision-variable variance. In particular, that theory leaves open the possibility that even with stimulus range held constant, overall sensitivity may vary depending on the extent to which the attention band is in the correct location for monitoring signal presentations. This idea serves as the guiding theme of sections 3 and 4 of this chapter, in which we report the results of various experimental manipulations designed to control the location of the attention band within the intensity range.

Third, from the point of view of this volume, these two theories offer quite different interpretations of the AI range phenomenon as a manifestation of the subject's preparation. The range theory says that the subject is less able to partition accurately the range of possible representations when that range is large than when it is small. Preparation according to this view has to do with developing response categories, and that process automatically becomes poorer the larger the range. The attention theory postulates a form of preparation that, when correctly located, results in an improved perception of the signal. One of the issues on which the experiments described in sections 3 and 4 will shed light are the experimental conditions that appear to control the location of the attention band. This is an important direction since only as we learn how either to control or to measure the location of the band will it prove possible to gain detailed information about its nature.

2. SENSORY AND CRITERIAL NOISE IN ABSOLUTE IDENTIFICATION

The theory that the response variance inherent in AI is the result of two underlying factors—sensory noise and criterial noise—has been advanced by Wickelgren (1968), Durlach and Braida (1969), Gravetter and Lockhead (1973), and others. In this section we adopt this theoretical framework and ask the question, Are the range effects in AI the result of increasing sensory noise, criterial noise, or both? As stated previously, the range theory of Braida-Durlach states that criterial noise changes, whereas the attention-band theory views sensory noise as changing.

Nosofsky (1983a) ran the following experiment in an attempt to resolve this question. Subjects were run in one of two conditions—a narrow range condition in which signals were located at 65,67,69, and 71 dB; and a wide-range condition in which signals were located at 53,67,69, and 83 dB. Note that the two center signals were the same across conditions. On each trial of the experiment, subjects received four distinct observations of the same randomly selected signal. After each observation they were instructed to judge which signal had been presented, with full knowledge that the same signal was being presented throughout the trial. They were asked to employ all information that accrued during the course of a trial when making each decision. After the fourth and final response, feedback was provided regarding the signal that had actually been presented throughout the trial.

The intuition underlying this experiment was as follows. On the one hand, as subjects listened to repeated samples of the same signal, they were gaining more information regarding its true intensity.[4] On the other hand, listening to the same signal repeatedly should not improve a subject's memory for past signal presentations. In other words, in terms of the two-factor Thurstonian framework, multiple signal observations should serve to reduce sensory noise, not criterial noise.

The idea outlined above can be formalized in a simple mathematical model. Assume that the internal representations for the two center signals are distributed as Gaussian random variables with means μ_2 and μ_3 that are independent of the range and number of observations and with the same variance which is a function of both range (R) and number of observations (N), $\sigma_s^2(R,N)$. The criterion partitioning these internal representations into response classes is assumed to be a Gaussian distributed random variable with variance that depends only on range, $\sigma_c^2(R)$, and is independent of the sensory variances. Given these assumptions, then the sensitivity measure, d', for the center signals, is expressed as a function of both R and N as follows:

$$d'_{2,3}(R,N) = \frac{\mu_3 - \mu_2}{\sqrt{\sigma_s^2\,(R,N) + \sigma_c^2\,(R)}}.$$

As a simple working hypothesis, Nosofsky assumed that multiple observations served to reduce sensory variance by means of an averaging process, as is true of the information integration model studied in signal detection theory

[4]It is important to realize that the effect of repeating a signal several times is not the same as giving a continuous signal of the same total duration. In addition, the length of the interobservation interval may be important. Nosofsky (1983a) has argued that longer interobservation intervals may yield more nearly independent representations. Note that in the current experiment the interobservation interval is lengthened by subjects' responses.

(Green & Swets, 1973). That is, the final internal representation was assumed to be the average of N independent and identically distributed normal random variables. Given this assumption, then we have

$$\sigma_s^2(R,N) = \sigma_s^2(R)/N.$$

Furthermore, since the unit of measurement is arbitrary, we may simply set $\mu_3 - \mu_2 = 1$, and rewrite the above equation as

$$\left[\frac{1}{d'_{2,3}(R,N)}\right]^2 = \frac{\sigma_s^2\,(R)}{N} + \sigma_c^2\,(R).$$

The hypothesis, then, is that as one plots $(1/d')^2$ as a function of $1/N$, it should be linear with slope $\sigma_s^2(R)$ and with y-intercept $\sigma_c^2(R)$.

Eight subjects were run in the narrow-range condition and eight subjects were run in the wide-range condition which we described earlier. The data averaged over subjects are presented in Fig. 1.3. It is evident that the hypothesis of a linear relationship between $(1/d')^2$ and $1/N$ is supported. Furthermore, given that the assumptions of the model are correct, one may conclude that both sensory noise and criterial noise increased with range.

A second experiment was also run which was very similar to the one summarized above, the main difference being that subjects made a response only after all the observations on a given trial had been completed. The number of observations on a trial was varied randomly within blocks from one to four. There was a 2-second interval separating each stimulus observation. In general, the results were again consistent with the predictions of the stimulus integration model proposed above, and led to the same conclusion.

In summary, these results give a preliminary indication that increasing the range in an AI task may lead to increasing both sensory noise and criterial noise. This finding means that the original versions of both the attention-band theory and the range theory give incomplete explanations of performance in absolute identification, although features of each theory may nonetheless be correct.

The guiding theme of the investigations we report in sections 3 and 4 is the notion that if a selective attention mechanism in the intensity dimension does exist, it should certainly monitor relevant regions of the stimulus range. This notion underlies the hypothesis that the attention band tends to track signal presentations. In section 3 we test this hypothesis by examining sequential effects in a standard absolute identification experiment. In section 4 we examine performance in various experiments in which stimulus range is held constant, but in which local aspects of the stimulus presentation structure are manipulated. In particular, we look at the effects of manipulating a priori presentation probabilities, the distribution of signals within the range, and sequential dependencies in signal presentations.

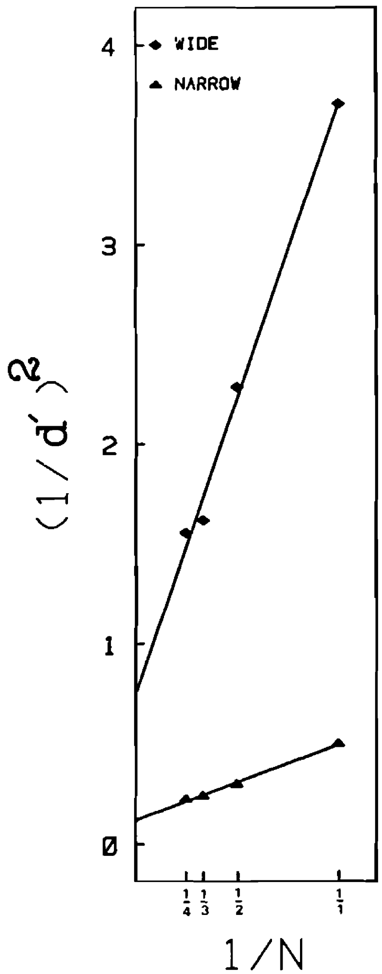

FIG. 1.3. Plots of the averaged $(1/d'_{2,3})^2$ values as a function of $1/N$ for both the narrow- and wide-range conditions. This is Fig. 2 of Nosofsky (1983a).

3. ONE-TRIAL SEQUENTIAL DEPENDENCIES

3.1. d′ as a Function of Signal Separation on Successive Trials

Purks et al. (1980) ran a 15-signal, auditory intensity, absolute identification experiment and decomposed the data into d' and criterion effects. Their conclusion was that d' is not affected by the preceding signal. Luce, Nosofsky, Green, and Smith (1982) carried out essentially the same experiment, using 11 signals, to serve as a baseline for some of the experiments reported in section 4. They computed d′ for each signal pair as a function of the signal presented on the

preceding trial. The preceding signal, S_j, was defined to be "near" to signal pair (S_i, S_{i+1}) when j was equal to either i or $i+1$; it was defined to be "far" when $\min[|j-i|, |j-(i+1)|] \geq 2$. We see in Fig. 1.4 a small but consistent increase in d′ when the preceding signal is near; however, the increase is on the average only about 10% which is really very small compared to some effects to come shortly.

In summary, the results of Purks et al. (1980) and Luce et al. (1982) lead us to conclude that any changes in d′ as a function of previous signal are, at best, minor. This result does not support the hypothesis of an attention band that tracks the previous signal on a trial-by-trial basis.

3.2. Criterion Location as a Function of Signal Separation on Successive Trials

Purks et al. also concluded that systematic sequential effects arise as a result of changes in the criteria locations. In particular, all of the category boundaries move away from the signal on the preceding trial. M. Treisman (1983; Treisman & Williams, 1983) has been pursuing a mathematical model based upon these ideas and has applied it with success to magnitude estimation data, offering a

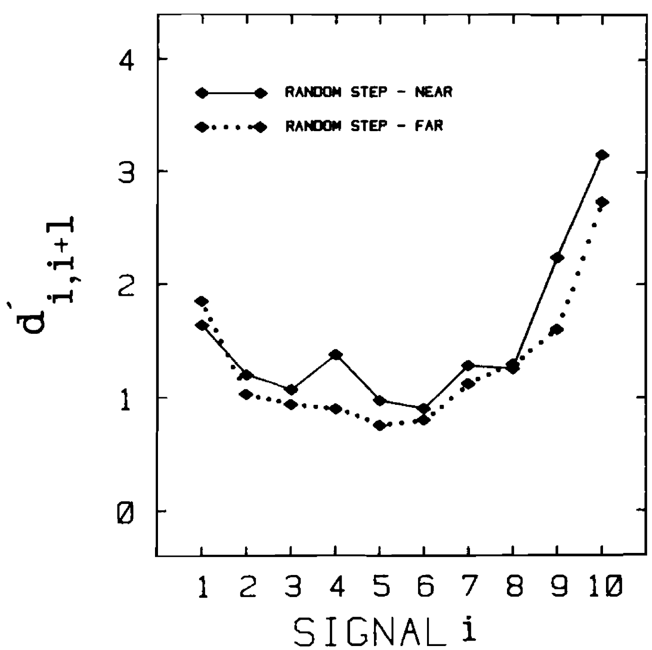

FIG. 1.4. Plots of $d'_{i,i+1}$ for each signal pair as a function of whether the previous signal is near or far. This is Fig. 3 (modified) of Luce et al. (1982).

parsimonious account of response correlations and variance effects described by, for example, Green, Luce, and Duncan (1977).

Luce et al. (1982) opted to study the sequential effects by using an alternative method of analysis that is free of some of the model-specific assumptions made when estimating d′ and criterion location. They estimated the probability of making two types of error—namely, saying the signal was just above or just below the one presented—as a function of the signal on the preceding trial. These are the probabilities:

$$P\left[R^{(n)}_{i+1} \middle| S^{(n)}_i, S^{(n-1)}_j\right] \text{ and } P\left[R^{(n)}_{i-1} \middle| S^{(n)}_i, S^{(n-1)}_j\right],$$

where $S^{(n)}_i$ denotes the presentation of signal i on trial n. If the hypothesis were correct that the attention band closely tracks the previous signal, then these data should have the form shown in Fig. 1.5. By contrast, if the criterion dispersion found by Purks et al. is operating, the data should have the form shown in Fig. 1.6. The data, averaged over signals 3 to 9 and over subjects, are shown in Fig. 1.7, and they clearly support the idea that each criterion shifts away from the

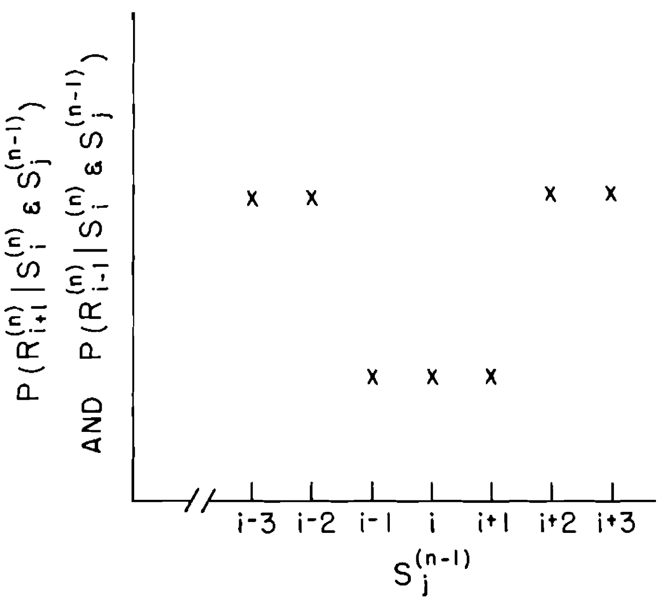

FIG. 1.5. Schematic prediction of the sequential one-step response errors for the attention-band model. This is Fig. 4 of Luce et al. (1982).

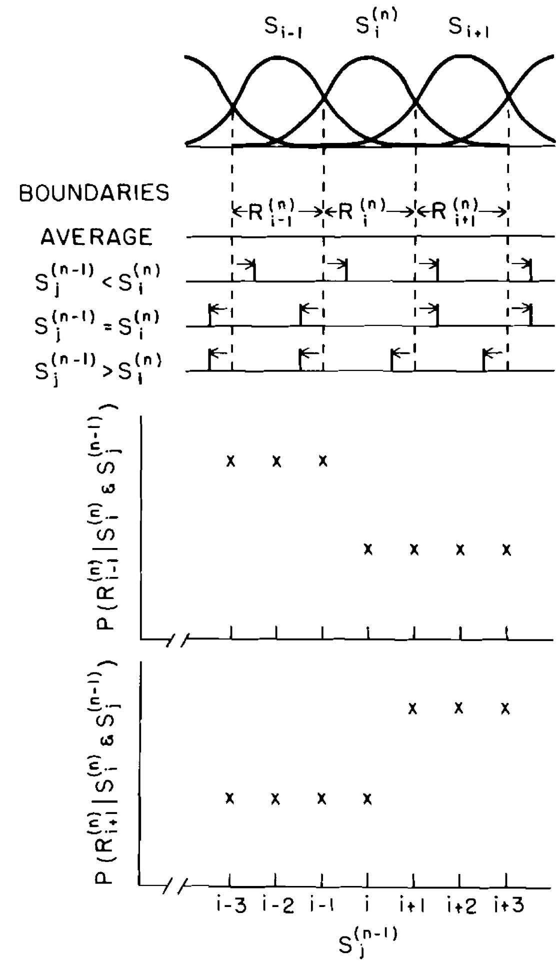

FIG. 1.6. Top panel: Schematic illustration of the shifting category boundary finding of Purks et al. (1980). Category boundaries are pushed away from the last signal presented. Bottom panels: predictions of the sequential one-step response errors under the rule for shifting caregory boundaries shown above. This is Fig. 5 of Luce et al. (1982).

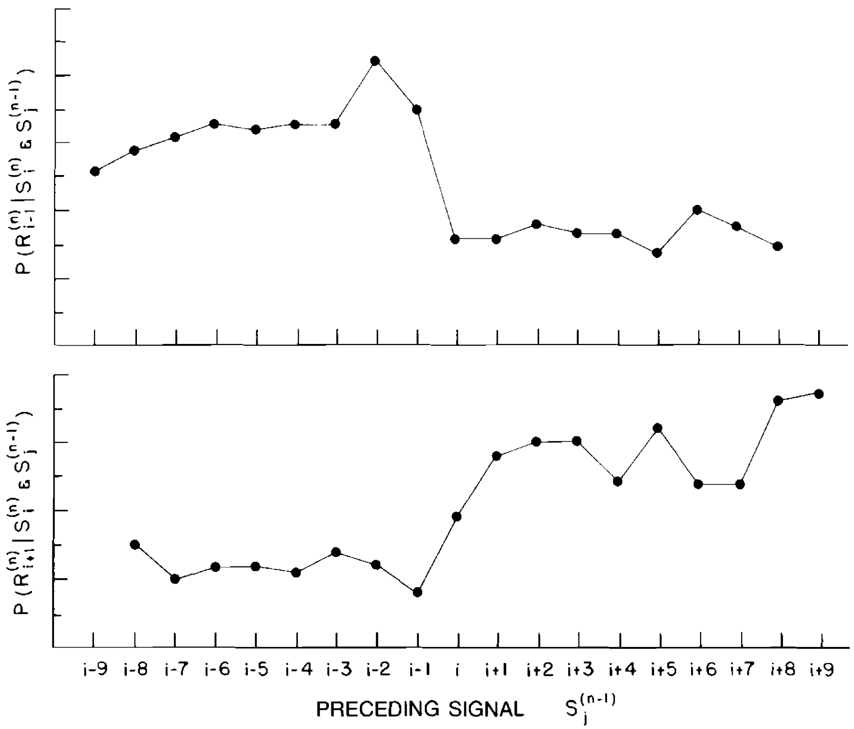

FIG. 1.7. Results of the sequential one-step response error analysis. The data are in accord with the shifting category boundary idea and are inconsistent with the assumption of the attention band centering on the previous signal. This is Fig. 6 of Luce et al. (1982).

previous signal.[5] Moreover, the data suggest that the amount of the shift is approximately the same no matter the size of the separation on successive signals. This seems somewhat remarkable, especially since we know that the end signals are identified with a high degree of accuracy: It implies either that the boundaries "crunch up" at the edge, or that the means of the signal representations are further spaced at the edge than in the middle of the range. The latter possibility is, in fact, what Kornbrot (1980) concluded from a reanalysis of data of Braida and Durlach.

[5]The rule that each criterion shifts away from the previous signal is not valid in some experimental designs. For example, in section 4.4 we discuss a study in which on each trial one of three adjacent signals is presented, but the three are far from the preceding signal. In that case, the data are consistent with the idea that the boundaries shift away from the middle possible signal, not away from the preceding one.

4. EVIDENCE THAT ATTENTION CAN BE FOCUSED BY SIGNAL CLUSTERING

The results of the preceding section seem to point to criterion shifts as the major locus of sequential effects in subjects' responses, with only slight signs of change in sensitivity. Although such data do not rule out the idea of an attention mechanism operating in absolute identification, they make exceedingly clear that if such a mechanism exists it does not rapidly track changes in signal location. The purpose of this section is to summarize three types of studies that give some support to the hypothesis of an attention band that tracks stimulus activity in a somewhat leisurely fashion.

If the focusing of attention is slower than the typical rate of signal presentations, then procedures that reduce the tendency for signals to lie outside the band should result in improved sensitivity. We refer to methods that do this, however achieved, as some form of clustering. The most extreme version of clustering is, of course, the narrow range, absolute identification design in which all of the signals lie in a sufficiently narrow range to be entirely encompassed by the attention mechanism. Indeed, it was the better sensitivity of the narrow as compared to wide range designs that led to the two hypotheses discussed in section 1. Our goal, however, is to see what happens when the overall range of the signals is large but, nevertheless, with most changes sufficiently gradual that a sluggish mechanism can stay with them.

4.1. Probability Clustering

Perhaps the most obvious way to make some signals more salient than others and to increase the tendency for changes not to be great from trial to trial is to use a nonuniform distribution of presentations. Chase et al. (1983) did this with 13 auditory signals equally spaced in dB from 42 to 90 dB SPL. Their conditions were uniform; the middle intensity presented with probability 1/3 and all others with probability 1/18; and the two extreme signals each presented with probability 1/5 and the remainder with probability 3/55. They found shifts in response criteria, but no changes in d'.

We were surprised at this result if for no other reason than the fact that with sufficiently extreme distributions, for example, 0 probability signals outside a narrow region, d' is seriously affected. So Nosofsky (1983b) was led to run several procedures somewhat more extreme than those of Chase et al. He used 11 signals equally spaced from 40 to 90 dB SPL, and ran four conditions. Condition *U* was a standard AI condition with a uniform distribution of signal presentations. In Condition M the a priori probability of each of signals 5 and 6 was 1/4; the remaining signals were equally likely. Condition P had the same presentation schedule as Condition M, but subjects were required only to categorize signals as "5 or less" or "6 or more." And finally, a two-alternative AI of just signals 5 and 6 was run. The order of running was: Conditions U and M on alternating days, followed by Condition P, and then 2-alternative AI.

The d' results are shown in Fig. 1.8, where the categorization data are separated by the first 1400 trials on Day 1 and the second 1100 trials on day 2. Condition M has a small, but significant, effect on d'. Performance in Condition P is the same as in Condition M on Day 1, but performance improves by Day 2. And subjects are near perfect in identifying signals 5 and 6 in the two-alternative AI condition. It is quite clear that something important happens when we go from identification to categorization instructions. A possible explanation is that subjects learned to focus attention in the region of signals 5 and 6. Gravetter and Lockhead (1973) obtained a similar result in their experiment described below, and they suggested that the Thurstonian variability depends upon criterial range, not stimulus range.

4.2. Intensity Clustering

Another way to cluster the signals, without necessarily affecting the uniform distribution of presentations over the several signals, is to vary their separation. The narrow range absolute identification design is one example of such clustering, but it has the disadvantage that the range is affected by the clustering. Gravetter and Lockhead (1973) employed designs in which the range was held

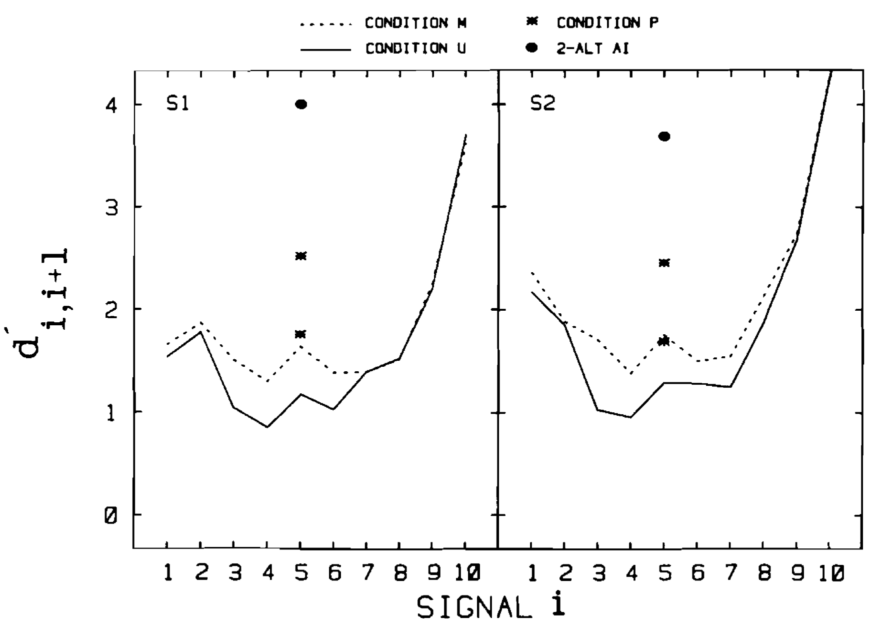

FIG. 1.8. Values of $d'_{i,i+1}$ for Conditions U, M and P, and 2-alternative AI. This is Fig. 3 of Nosofsky (1983b).

fixed and there was a small cluster of signals in the middle with outliers defining the range. They found, among other things, that the effective range was much reduced when the outliers were isolated single signals as compared with the case where discrimination between pairs of outliers was required.

Luce and Green (1978) introduced a variant on the Gravetter and Lockhead design in which a cluster of 8 intensity levels spanning a 10 dB band was accompanied by two intensity outliers. There were three conditions: the cluster at low intensity and the outliers 20 and 40 dB above it; the cluster at mid-intensity and the outliers 20 dB above and below it; and the cluster at a high intensity with the outliers 20 and 40 dB below it. Each signal that is an outlier in two of the conditions is in the cluster of the third. They argued that if attention exists it is to the signal, not just to its intensity, and so the impact of attention should be seen in the subject's ability to discriminate frequency as well as intensity. So they ran a two-frequency, absolute identification design with a uniform distribution of presentation of intensities in each of the three conditions. Note that if the location of the attention band is controlled either by rational considerations or by a tendency to track signal activity, then it should be found centered at the cluster. If so, the fact should be evidenced by poorer performance at the intensity outliers than within the cluster. The data, shown in Fig. 1.9, exhibit an effect in this general direction, but with some exceptions, particularly at the extreme outliers.

4.3. Simultaneous Intensity and Sequential Clustering

Nosofsky (1983b) ran a design involving two intensity clusters of seven equally spaced signals each, one located between 42.75 and 47.25 dB and the other between 72.75 and 77.25 dB. Experimental runs were organized into 10 trials on one cluster alternating with 10 on the other. A trial consisted of a random selection of one of the middle five signals in the cluster being used followed by the signal either just above it or just below it. The subject responded whether the second signal was louder or softer than the first. The data, presented as percentage correct are shown in Fig. 1.10, where we see an improvement in performance over the first 3 to 5 trials of each sequence of 10 trials devoted to a cluster. This is what should occur with a sluggish attention mechanism.

4.4. Sequential Clustering

Each of the above designs destroys a feature of the standard absolute identification design: equal spacing in dB, uniform distribution of presentations, or constant range. One way to maintain all of these features and, at the same time, to create a degree of clustering is to introduce sequential dependencies in the presentation schedule. For example, in what Luce et al. (1982) called the small-step(3) procedure, if i is the signal on trial n-1, then the signal on trial n is either i-1, i, or i+1 each with probability 1/3 except when i is an end signal in which

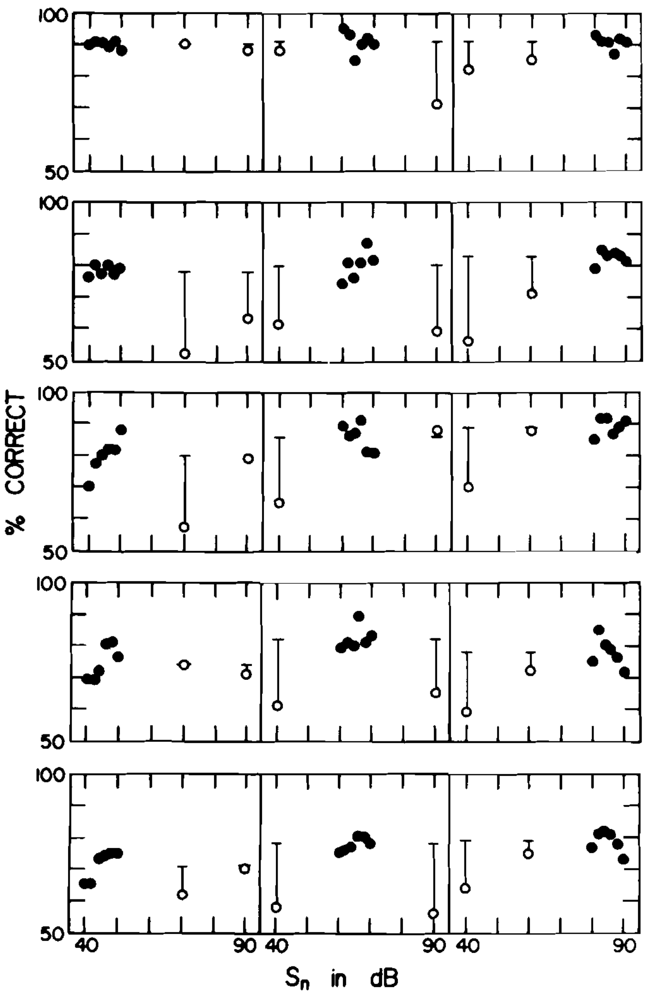

FIG. 1.9. Percent correct frequency identifications as a function of signal intensity for each of the three conditions. The panels, left to right, represent the different positions of the clusters; the rows are for the observers. The vertical line to each outlier intensity shows the drop from the mean percent correct for the cluster. This is Fig. 6 of Luce & Green (1978).

case it is assigned probability 2/3. They also ran a small-step(5) procedure in which the presentations were selected at random from among i-2, i-1, i, i+1, and i+2 (except for the two end cases), and a large-step procedure in which each presentation was one of three adjacent signals quite far from the previous one.

Several aspects of these sequentially constrained AI experiments should be made clear. First, the Markov chains that generated each presentation schedule

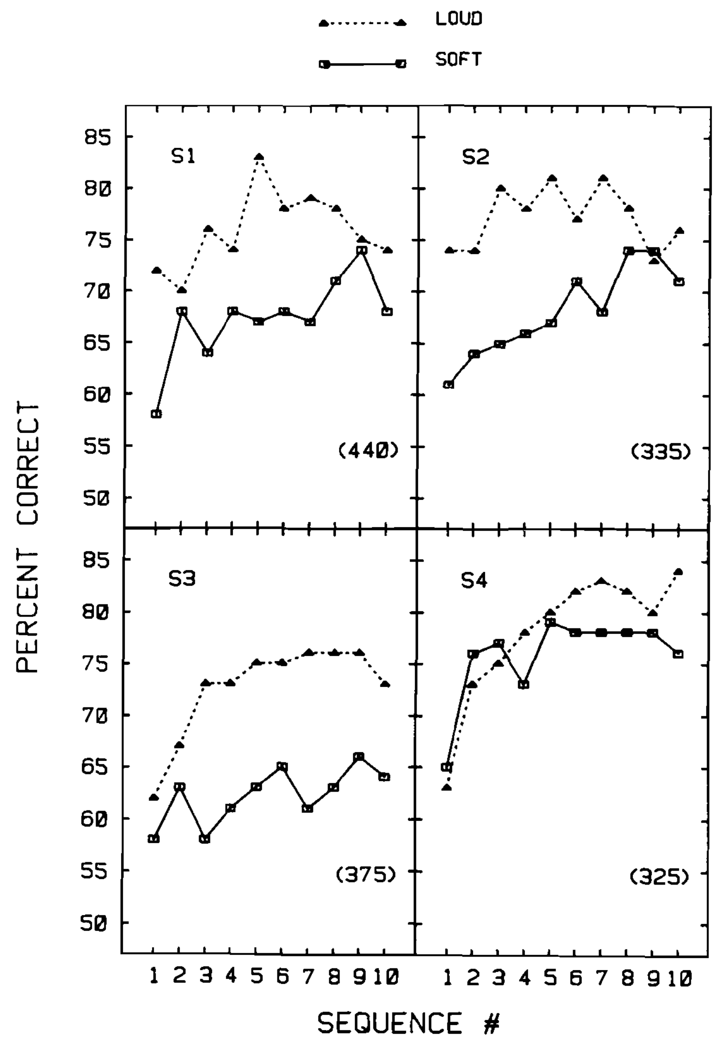

FIG. 1.10. Percent correct as a function of trial sequence number in the sequentially constrained, roving-level discrimination experiment. Values in parentheses are the number of observations upon which each data point is based. This is Fig. 4 of Nosofsky (1983b).

all lead, asymptotically, to a uniform distribution of signal presentations. Second, the sequential constraints in these conditions also resulted in certain response constraints: The subjects knew that only a limited set of responses was possible on any given trial. (In the large-step experiment, they were explicitly informed on each trial as to the possible responses.) As a result, a specialized method of analysis had to be devised to compute d' that controlled for these response constraints. A review of the method of analysis would go beyond the scope of the present chapter; the interested reader is referred to Luce et al. (1982).

The plots of d' for these three procedures plus the ordinary random procedure are shown in Fig. 1.11. There is a pronounced effect of the procedures: the value of d' for the small-step (3) procedure is roughly 1 added to the corresponding value of d' for the random one. This is consistent with the idea of differential attention slowly tracking the signal.

Several alternative hypotheses spring to mind. One is that the information load is greatly reduced in the small-step (3) condition, since there are only 3 response alternatives rather than 11. This is one reason that we ran the large-step design with, again, only three response alternatives. Since, except for the extreme signals, d' performance was uniformly poorer than that found in the purely random presentation, response predictability does not account for the results.

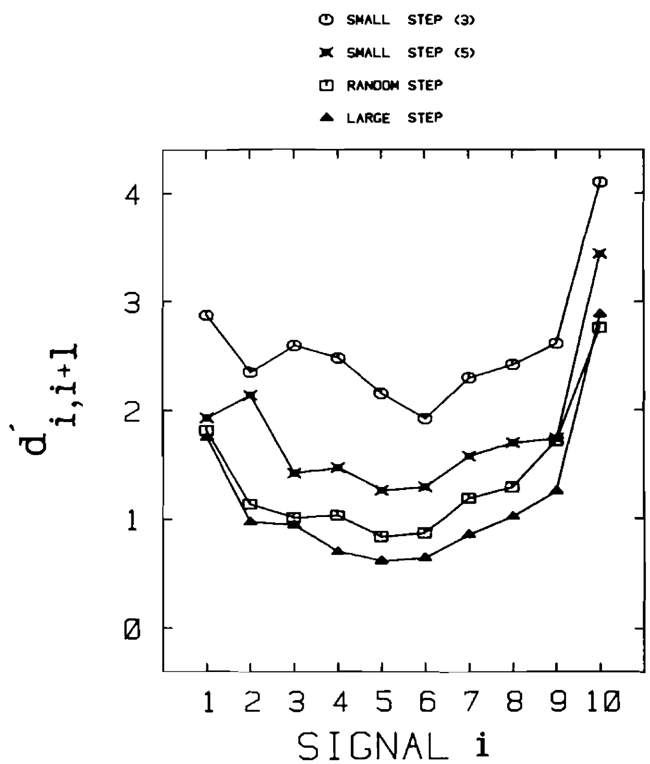

FIG. 1.11. Values of $d'_{i,i+1}$ for each signal pair in the small-step(3), small-step(5), random-step and large-step conditions. This is Fig. 1 of Luce et al. (1982).

A much more serious challenge is the possibility that the subject can shift his or her mode of responding from absolute identification to discrimination: It is sufficient for the subject to decide on each presentation whether the signal presented is above, below, or equal to the preceding one. And it seems plausible that discrimination is easier than identification. To test this, Nosofsky (1983b) ran an ordinary random presentation design with two different response instructions: the ordinary absolute identification ones and discrimination ones in which the subject simply recorded whether the signal was louder, equal to, or softer than the preceding signal. He also ran the small-step(3) design. From the random-step AI and discrimination conditions he selected those trials meeting the small-step(3) constraints, that is, those trials in which the previous signal was "near" as defined in section 3.1, and computed d'. He also computed d' for those trials in which the previous signal was "far" as defined in section 3.1. The results, shown in Fig. 1.12 make clear that the discrimination instructions ac-

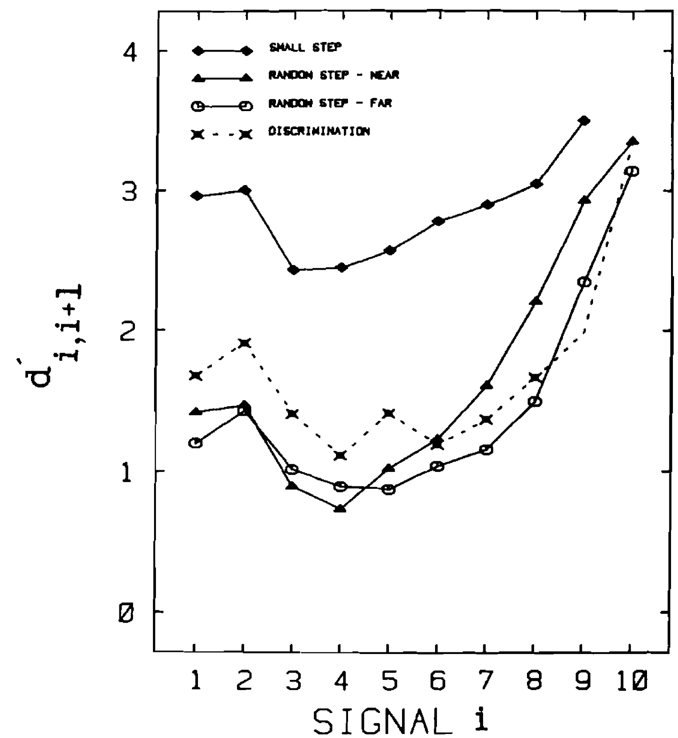

FIG. 1.12. Values of $d'_{i,i+1}$ for each signal pair in the small-step(3) condition, the random-step AI and discrimination conditions when the previous signal is near, and the random-step AI condition when the previous signal is far. Subjects never made an error on stimulus 11 in the small-step(3) condition and so an estimate of $d'_{10,11}$ was unavailable. This is Fig. 1 of Nosofsky (1983b).

count for only a small fraction of the effect found in the small-step(3) procedure. It cannot be the primary account of those results.

A third hypothesis is that subjects carry out a comparison between the current signal and the most recent past signal that was close to it. This is a hypothesis of local comparison of the relevant memory trace. To explore this, Luce et al. (1982) ran a sequential design in which the signal on trial n was "near" to the signal on trial n-k and "far" from the ones on the intervening trials, n-1, ..., n-k+1. This was run using lags of k=1,2,3, and 4, where lag 1 is simply the small-step (3) procedure. The data, Fig. 1.13, suggest that whatever memory effect exists it is complete in one trial. However, a complication exists in the procedure. Because of the nature of the sequential constraints, the signal presentation became, on average, more predictable the larger the value of k. Such an increase in predictability could, conceivably, counteract a decay in memory. To see if this seems to be a serious possibility we analyzed the random data, isolating those trials that fulfilled the conditions for each lag. But since these trials were embedded in the purely random design, there was in fact no change in predictability. The data showed no sign of memory decay beyond one trial, and so we doubt that predictability has masked a deeper memory effect.

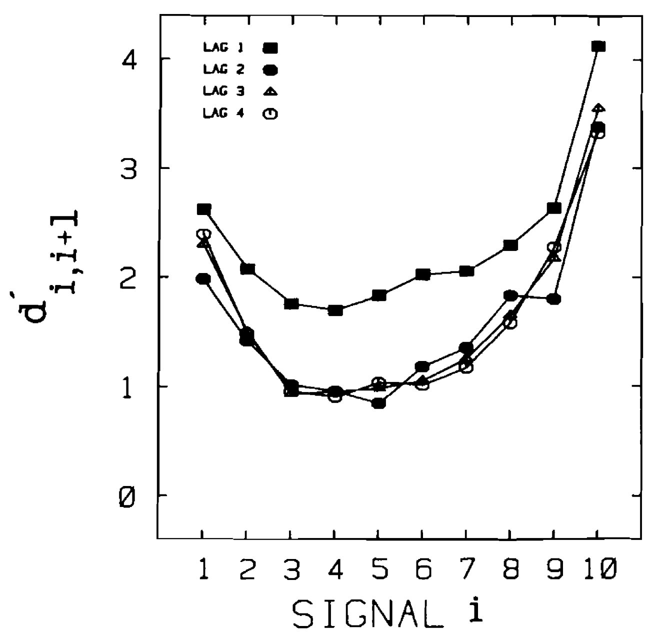

FIG. 1.13. Values of $d'_{i,i+1}$ for each signal pair in the sequentially constrained lag-k experiment. This is Fig. 8 of Luce et al. (1982).

5. SUMMARY AND CONCLUSIONS

Two Thurstonian theories, designed to account for the adverse effect of increased signal range on absolute identification, were contrasted and tested. The range theory of Braida and Durlach partitions the variance underlying the d' performance measure into a sensory term, which is assumed to be unaffected by signal range, and a criterial term, which is affected by it. The attention-band theory of Green and Luce assumes that the signal representation arises from a distribution with either a small or a large variance depending upon whether or not it happens to fall within the band. It attributes the effect of range to changes in the probability that signals fall in the band. In addition, they suggested that the band location is affected by two tendencies: to be at the ends of the signal range, which accounts for edge effects in the data, and to track the previous signal, which accounts for sequential effects. They placed no emphasis on criterion effects.

Examination of data from a number of experiments leads to several conclusions about these theories. An analysis in terms of the Braida-Durlach framework of a multiple-observation AI experiment showed range to affect both sensory and criterion variance. This suggests that both theories are incorrect, the one for assuming range does not affect the sensory component and the other for assuming that it does not affect the criterion component. Detailed sequential analyses make clear that the major component of the one-trial sequential effects is systematic shifts in response criteria, not changes in sensitivity as had been postulated in the original version of the attention-band model. The band does not track signals on a trial-by-trial basis. Nonetheless, a number of experiments all based upon some form of clustering of signals to attract attention make clear that sizable changes in sensitivity can be produced. It appears that attention is drawn in a somewhat sluggish fashion to the region where "the action is," but it is not drawn there in a single trial. Among these studies were ones in which the range, spacing, and distribution of signals were the same as in the usual random design, and the clustering was effected by means of sequential dependencies in the presentation schedule. Pronounced changes in d' were in accord with the attention idea, but inconsistent with the range theory since range was not changed.

REFERENCES

Berliner, J. E., & Durlach, N. I. Intensity perception. IV. Resolution in roving-level discrimination. *Journal of the Acoustical Society of America*, 1973, *53*, 1270–1287.

Braida, L. D., & Durlach, N. I. Intensity perception. II. Resolution in one-interval paradigms. *Journal of the Acoustical Society of America*, 1972, *51*, 483–502.

Chase, S., Bugnacki, P., Braida, L. D., & Durlach, N. I. Intensity perception. XII. Effect of presentation probability on absolute identification. *Journal of the Acoustical Society of America*, 1983, *73*, 279–284.

Durlach, N. I., & Braida, L. D. Intensity perception. I. Preliminary theory of intensity resolution. *Journal of the Acoustical Society of America*, 1969, *46*, 372–383.

Gravetter, F., & Lockhead, G. R. Criterial range as a frame of reference for stimulus judgment. *Psychological Review*, 1973, *80*, 203–216.

Green, D. M., Luce, R. D., & Duncan, J. E. Variability and sequential effects in magnitude production and estimation of auditory intensity. *Perception and Psychophysics*, 1977, *22*, 450–456.

Green, D. M., & Swets, J. A. *Signal detection theory and psychophysics*. New York: Wiley, 1973.

Kornbrot, D. Attention bands: Some implications for categorical judgment. *British Journal of Mathematical and Statistical Psychology*, 1980, *33*, 1–16.

Lippmann, R. P., Braida, L. D., & Durlach, N. I. Intensity perception. V. Effect of payoff matrix on absolute identification. *Journal of the Acoustical Society of America*, 1976, *59*, 129–134.

Luce, R. D., & Green, D. M. Two tests of a neural attention hypothesis for auditory psychophysics. *Perception & Psychophysics*, 1978, *23*, 363–371.

Luce, R. D., Green, D. M., & Weber, D. L. Attention bands in absolute identification. *Perception & Psychophysics*, 1976, *20*, 49–54.

Luce, R. D., Nosofsky, R. M., Green, D. M., & Smith, A. F. The bow and sequential effects in absolute identification. *Perception & Psychophysics*, 1982, *32*, 397–408.

Miller, G. A. The magical number seven, plus or minus two: Some limits on our capacity for processing information. *Psychological Review*, 1956, *63*, 81–97.

Nosofsky, R. M. Information integration and the identification of stimulus noise and criterial noise in absolute judgment. *Journal of Experimental Psychology: Human Perception and Performance*, 1983, *9*, 299–309. (a)

Nosofsky, R. M. Shifts of attention in the identification and discrimination of intensity. *Perception & Psychophsics*, 1983, *33*, 103–112. (b)

Pollack, I. The information of elementary auditory displays I. *Journal of the Acoustical Society of America*, 1952, *24*, 745–749.

Purks, S. R., Callahan, D. J., Braida, L. D., & Durlach, N. I. Intensity perception. X. Effect of preceding stimulus on identification performance. *Journal of the Acoustical Society of America*, 1980, *67*, 634–637.

Treisman, M. A theory of criterion setting II. An alternative to the attention band hypothesis in magnitude estimation. Manuscript in preparation, 1983.

Treisman, M., & Williams, T. C. A theory of criterion setting I. Sequential dependencies. Manuscript in preparation, 1983.

Wickelgren, W. A. Unidimensional strength theory and component analysis of noise in absolute and comparative judgments. *Journal of Mathematical Psychology*, 1968, *5*, 102–122.