Psychological Review
1988, Vol. 95, No. 2, 238–255

0033-295X/88/$00.75

Continuous Versus Discrete Information Processing: Modeling Accumulation of Partial Information

Roger Ratcliff
Northwestern University

David Meyer and colleagues have recently developed a new technique for examining the time course of information processing. The technique is a variant of the response signal procedure: On some trials subjects are presented with a signal that requires them to respond, whereas on other trials they respond normally. These two types of trials are randomly intermixed so subjects are unable to anticipate which kind of trial is to be presented next. For data analysis, it is assumed that on the signal trials observed reaction times are a probability mixture of regular responses and guesses based on partial information. The accuracy of guesses based on partial information can be determined by using the data from the regular trials and a simple race model to remove the contribution of fast-finishing regular trials from signal trial data. This analysis shows that the accuracy of guesses is relatively low and is either approximately constant or grows slowly over the time course of retrieval. Meyer and colleagues have argued that this pattern of results rules out most continuous models of information processing. But the analyses presented in this article show that this pattern is consistent with several stochastic reaction time models: the simple random walk, the runs, and the continuous diffusion models. The diffusion model is assessed with data from a new experiment using the study–test recognition memory procedure. Fitting the diffusion model to the data from regular trials fixes all parameters of the model except one (the signal encoding and decision parameter). With this one free parameter, the model predicts the observed guessing accuracy. In summary, results obtained from Meyer et al.'s (1988) new technique give important qualitative support to some stochastic models and impressive quantitative support to the continuous diffusion model.

The distinction between discrete and continuous models of information processing is central to theory in cognitive psychology. Models based on discrete processing are quite different from models based on continuous processing, and the kinds of data used to support the two different classes of models have different characteristics. However, the problem of discriminating between the classes of models is difficult because it is often possible for a model of one class to mimic the properties of the other class. Currently, the scope of continuous models seems larger because continuous models are able to account for more aspects of the data from reaction time experiments than are discrete models (e.g., the relation between accuracy and reaction time, the shape of reaction time distributions, and response signal data).

The issue of continuous versus discrete processing arose previously in the domain of learning theory, where the question was, Does learning proceed in an all-or-none fashion ("now you have it, now you don't") or continuously? Crowder (1976, pp. 264–273) provided a summary of this issue and concludes that rather than a binary distinction, the question should concern the conditions under which learning is all-or-none or continuous. With respect to information processing in cognitive psychology (and in particular, reaction time models), exemplars of both discrete and continuous models have been developed, yet there are few tests to discriminate the two kinds of models like the tests that were used in learning theory.

Meyer and Irwin (1981) and Meyer, Irwin, Osman, and Kounios (1988) have developed a new technique for investigating the time course of the accumulation of partial information over time, and this technique may help to discriminate between continuous and discrete models. The method is one in which subjects are presented with two types of test trials *randomly intermixed.* One type allows the subject to respond normally in his or her own time (regular trials), and the other type forces the subject to respond when a signal is presented at one of a number of experimenter-determined times (signal trials). The logic of the method is simple: It is assumed that on signal trials, the subject's responses are a probability mixture of fast regular responses based on complete information and guesses based on whatever partial information is available to the subject. A race model (e.g., Ollman & Billington, 1972) is used to extract the accuracy of the guesses from the signal trials (using the regular

This research was supported by Grant BNS 8510361 from the National Science Foundation and Grant HD 18812 from the National Institute of Child Health and Human Development.

I would like to thank David Meyer and John Kounios for useful discussions and information about the experimental method; Bill Hockley, John Kounios, Ben Murdock, Ed Shoben, Jim Townsend, and two anonymous reviewers for comments on the manuscript; and especially Gail McKoon and Dave Meyer for extremely detailed and valuable comments and suggestions.

Correspondence concerning this article should be addressed to Roger Ratcliff, Department of Psychology, Northwestern University, Evanston, Illinois 60208.

trial data to factor out the contribution of fast-finishing regular processes), and these are the results of principle interest. The accuracy of guesses is obtained at several signal lags to show the amount of partial information available as a function of time.

Meyer and Irwin (1981) provided predictions from both continuous and discrete models of information processing and compared these predictions to their data, concluding that the data supported discrete models. They argued that continuous models, such as the diffusion (random walk; Ratcliff, 1978) and cascade (McClelland, 1979) models, predict that accuracy of guesses will grow continuously over time, whereas discrete models (e.g., Sternberg, 1966) predict that accuracy will grow as a single step or series of discrete steps. Meyer and Irwin used a double-word lexical decision task (if two letter strings are both words or both nonwords, respond "yes", otherwise respond "no") and showed that the accuracy of guesses rose to a plateau at a lower level than that of regular responses (e.g., *d'*s of 0.8 vs. 2.5, respectively). They used this step function as evidence against continuous models[1] and evidence for a two-stage discrete model.

In this article, it is shown that some continuous models are qualitatively consistent with Meyer and Irwin's (1981) data. In their updated presentation of the method and theoretical interpretation, Meyer et al. (1988) examined the results presented in this article (in later sections below) and agreed that only certain classes of continuous models are ruled out qualitatively. However, they still argued that the detailed patterns of data are inconsistent with continuous models that otherwise account for a large range of reaction time and accuracy data. In this article I show that the data *are* quantitatively consistent with the continuous random walk (the diffusion model) and that the diffusion model accounts for the data without any change in the structure of the model. The same model that accounts for the behavior of mean reaction time, the shape of reaction time distributions, and accuracy as a function of various experimental variables across a range of paradigms also accounts for the behavior of guessing accuracy as a function of time. In addition, I examine several other sequential sampling models (the simple random walk, the runs model, and the counter or recruitment model) and present their predictions for guessing accuracy as a function of time.

In the experiments reported so far in the literature using the new response signal decomposition technique, Meyer et al. (1988) have argued that two patterns of data have been obtained. In the original Meyer and Irwin (1981) study and Experiments 1 through 4 in Meyer et al. (1988) using a double-word lexical decision procedure, results show a rise of guessing accuracy from chance to a low asymptote, and this asymptotic accuracy plateau continues for about 150 to 200 ms (there are no data beyond this range). In contrast, recent experiments using other experimental tasks such as single-word lexical decision (Meyer et al., 1988, Experiment 5), semantic verification (Kounios, Osman, & Meyer, 1987), and item recognition (Experiment 1 in this article) show a monotonic growth of guessing accuracy *without* asymptote and with low accuracy (relative to regular responses). Meyer et al. (1988) concluded that these are two different patterns of results because, relative to regular reaction time distributions (i.e., over the range from the fastest regular responses to the median), both patterns occur in different experiments. That is, at the same point in time, measured from the regular response time distribution, one experiment shows a plateau of asymptotic accuracy, whereas the other shows a gradual rise.

However, the conclusion that the two patterns are different must be viewed as tentative because (a) there are significant differences in absolute times in the two cases; (b) an asymptote has only been demonstrated in the double-word lexical decision and there could be a gradual rise up to the asymptote (in the experiments performed so far, there is a gap of 200 ms from the measurement at chance to the next measurement at plateau in the double-word lexical decision task, so it is not known if there is a gradual rise in guessing accuracy or not); and (c) in the conditions demonstrating a monotonic growth, there could be an asymptote later in processing. Before these patterns can be used as a classification scheme as Meyer et al. (1988) have proposed, further experiments need to be performed to allow generalization of the results. For the purposes of the theoretical analyses that follow, the pattern of predictions I concentrate on is one in which guessing accuracy rises and asymptotes at an accuracy plateau lower than that for regular processes.

Meyer et al. (1988, see also Meyer, Yantis, Osman, & Smith, 1985; Yantis & Meyer, 1985) stressed the importance of the distinction between discrete and continuous processing. To the experimentalist, the framework of continuous models suggests a set of empirical questions that have little overlap with the questions one would ask from the framework of discrete models. For example, discrete models are often tested and interpreted with additive factors logic (Sternberg, 1969), whereas some versions of continuous models suggest that additive factors logic is flawed (e.g., McClelland, 1979; see Meyer et al., 1988, for further discussion). Also, discrete models are examined in a way that makes the behavior of errors and reaction time distributions of little importance, but many continuous models give error rates and reaction time distributions equal weight to mean reaction time. Given such major differences in focus between the two classes of models, new methods like that presented by Meyer et al. (1988) are of considerable importance to the field; they allow qualitatively new kinds of tests to be performed between models.

In this article, I show that Meyer and Irwin's (1981) analyses of some of the continuous models are incomplete, that one class of these models (the sequential sampling models) provides tight predictions for the form of the growth of the accuracy of guesses as a function of time, and that empirical data provide strong support for some members of this large class. Simulations of four sequential sampling models—the simple random walk (Feller, 1968), the diffusion model (Ratcliff, 1978, 1981; 1985), the runs model (Audley, 1960), and the counter or recruitment model (LaBerge, 1962; Pike, 1973)—are presented and predictions of these models are compared with the qualitative features

[1] It is interesting to note the genesis of the ideas in this article. I believed the claims made in the Meyer and Irwin article were correct, that their data ruled out continuous models, and decided to see how badly the diffusion model missed their data. Without altering the model at all (i.e., using the model described in Ratcliff, 1978), the model predicted their data qualitatively, and in this article I show that the unmodified diffusion model fit results from their procedure quantitatively.

of the data in Meyer et al. (1988). Following this comparison, a new experiment is presented that uses the study–test recognition memory procedure to examine the accumulation of partial information in item recognition. Finally, the diffusion model is fitted explicitly to the data from this new experiment.

Predictions of Sequential Sampling and Continuous Models

Meyer et al. (1988) examined the predictions of the cascade model of McClelland (1979) for the growth of partial information as a function of time and noted that the accuracy of guesses should rise continuously to the asymptotic accuracy of regular processes. They contrasted this prediction with that derived from a discrete model in which there are a number of information-processing stages. The discrete model predicts that accuracy should grow in steps so that initially accuracy is near zero and then rises to an intermediate level, with a separate intermediate level for each stage that provides some further partial information. One criticism that can be made of this kind of discrete model is that it is post hoc; the nature of the proposed serial processes is determined completely by the experimental results, and there is no theoretically motivated reason to expect any particular number of intermediate plateaus of guessing accuracy. In contrast, predictions from a sequential sampling model are determined by the preexisting structure of the model and cannot be easily changed in the light of experimental results. The estimate of partial information (guessing accuracy) is the estimate of accuracy for a process that has not terminated, that is, a process that has not reached a response criterion. It should be stressed that this estimate and how it changes as a function of time are determined by the structure of sequential sampling models. The predictions of these sequential sampling models are presented in the next sections.

Three of the models considered are the simple random walk, the runs model, and the counter model. These models fall between the classes of discrete and continuous models because they accumulate information over time (like a continuous model), but the information is accumulated in discrete packets. Because the accumulation of information is over time, they contrast with discrete serial stage models in the same way as continuous models. Predictions from each of these models are found with simple simulation programs using parameter values that produce reaction time distributions and levels of accuracy that mimic experimental data (reaction time distributions should be skewed to the right, and accuracy should be between 75% and 95% to cover choice reaction time and recognition memory paradigms, e.g., Vickers, Caudrey, & Willson, 1971). These simulations are sufficient to demonstrate the predictions of these models. While explicit solutions could probably be obtained, for the present purposes such derivations seem unnecessary because only the qualitative behavior of the three models is considered. The other model presented is the continuous version of the random walk, the diffusion model. Because this model will be fitted to data, explicit predictions in equation form are presented. The model is treated more fully than the others because (a) it has been applied quantitatively across a range of paradigms, (b) it is one of the continuous models that Meyer and Irwin (1981) specifically rejected, and (c) Meyer et al. (1988) claimed it has trouble handling some aspects of their data.

Simple Random Walk

The simple random walk can be understood best by analogy with a feature matching model. The process starts with some count, Z, and response boundaries are placed at 0 (for a nonmatch) and A (for a match). At each feature comparison, the counter is incremented one count for a feature match or decremented one count for a feature nonmatch until the process terminates at either A or 0. For the process to terminate with a match, there must be $A - Z$ more feature matches than feature nonmatches (conditioned on the total count not having reaching zero first). For the process to terminate with a nonmatch, there must be Z more feature nonmatches than feature matches (conditioned on the count not reaching A first). The parameters of the model are Z, A, and p, the probability of a feature match (i.e., taking a step toward the match criterion). Figure 1 (top panel) shows the simple random walk and parameters of the model. In a general model, there would also be a parameter representing the encoding, response preparation, and other nondecision processes, but this parameter is ignored for this model and for the runs and counter models because quantitative fitting to data is not performed.

In the case of a signal trial in which processing is interrupted and a response is required, the response has to be made on the basis of where the process is currently positioned. This can be done by placing a criterion at some position so that, for example, all processes with a count greater than Z give positive responses, all processes with a count less than Z give negative responses, and processes with counts equal to the criterion split the counts 50/50 positive and negative (note that in fitting the model to data, the criterion would usually be some value other than Z).

To examine the behavior of this model for signal trials, a simple simulation was performed. The model as just described was used, and 10,000 Monte Carlo simulations were performed for each of several sets of parameter values. For the simulations, the starting point Z was set to be k, the position of the upper boundary A was set to be $2k$ (i.e., boundaries equidistant from starting point), and the guess criterion was chosen to be k. When a guess terminated the walk at the criterion, a half score was given to both positive and negative categories of responses. The results of main interest were accuracy of regular responses and accuracy of guesses as a function of time (i.e., the stopping position in number of counts).

Table 1 shows the results from the Monte Carlo simulations. The accuracy of guesses rises rapidly (accuracy seems close to asymptote by 5 steps) and remains constant out to 40 steps (and more, though the variability becomes large because the number of observations becomes very small because most processes terminate earlier). These results are qualitatively consistent with the Meyer and Irwin (1981) and the Meyer et al. (1988) results for Experiments 1 through 4. They show a rise to an asymptotic level of accuracy below the level of accuracy for regular responses.

There is one major issue, and that concerns the relative positions of the minimum reaction time for regular processes and

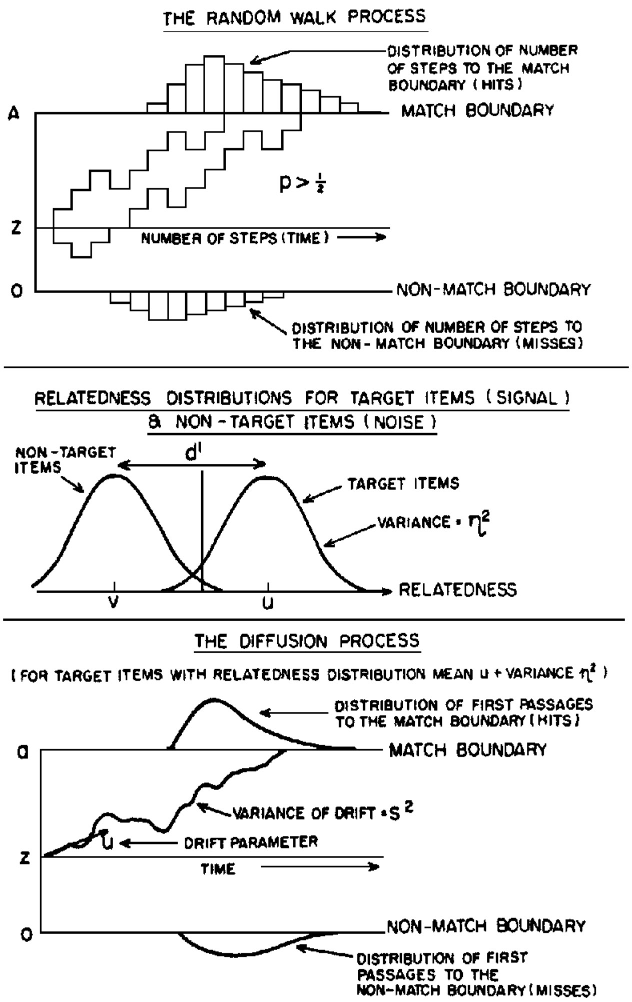

Figure 1. An illustration of the simple random walk (top panel), the diffusion process (bottom panel), and variability in drift rate over trials in the diffusion model (middle panel).

the time at which the accuracy of guesses rises above chance to asymptote. The simple random walk predicts that at the time the fastest regular processes begin to terminate, the accuracy of guesses is approaching asymptote, while the experimental data of Meyer et al. (1988) show that guessing accuracy is at chance just before the fastest regular processes begin to terminate. The resolution I present in detail later is that processing the signal to respond takes extra time and so the point at which guessing accuracy is measured actually reflects an earlier point in processing than an equivalent point in real time for regular processes. So guesses are at chance when fast regular processes are finishing because those guesses are based on the amount of information accumulated at an earlier point in time.

A second main point is that the accuracy of guesses is lower than the accuracy of regular processes. Using the first simulation and hit rate derived from the values in the table, with p the probability of a feature match at .6 and the probability of a mirror image process at .4 $(1 - p)$ for false alarm rates, values of d' can be calculated for both guesses and regular processes. These values are 0.9 for guesses and 2.4 for regular processes for walks of 10 or more steps. These values are quantitatively near the ratio found for the data of Meyer et al. (1988).

These simulations demonstrate that the simple random walk qualitatively predicts the results from the Meyer et al. (1988) studies: high accuracy for regular responses and low, relatively constant accuracy across lags for guesses after an initial rapid rise. No additional assumptions have to be made in the model to produce this pattern of results.

The prediction from the simple random walk model that the accuracy of guesses rises and asymptotes rapidly is difficult to understand intuitively. One would expect that accuracy of guesses would rise slowly to the accuracy of regular processes. This is prevented from happening by noise in the system. Consider the case in which the response boundaries are far from the criterion, and consider the behavior of a large number of processes each with the same feature match probability, thus giving a distribution across trials. As the number of steps increases, the distribution of processes will drift toward one response boundary, and the distribution of processes not terminated will spread. When processes begin to reach the response boundary, the processes with the greatest number of counts will terminate first and the rest will move closer to the boundary. All of the processes will not terminate, however, because noise will tend to move some processes away from the boundary (as well as bump some over the boundary). Therefore, noise in the system balances the tendency for processes to terminate at the response boundary. This works to keep some processes far away from the response boundary. There are three effects balancing each other: the tendency for a process to move closer to the boundary on average, the tendency for the process to exit the walk, and noise in the system that acts to move some processes away from the response boundary. As can be seen from this discussion, it is hard to guess what will happen from these component effects. The simple simulations shown above demonstrate that in fact accuracy of guesses is relatively low and asymptotes rapidly.

It is useful to note that the particular model just presented does not exhaust the range of possible versions of the simple random walk. It is possible to have the probability of a count of one kind vary as a function of the number of counts, or have the boundaries change position as a function of number of counts, or have the relationship between counts and milliseconds change as a function of number of counts (i.e., slow down or speed up). Any of these alternatives would alter the predictions, and it may be possible to obtain increasing or decreasing guessing accuracy as a function of time. However, none of these assumptions have been seriously considered and developed to produce reaction time models, and there are few explicit solutions for such variations of the random walk. Most of these same variations would be possible for the other models considered below, but again, few if any have been examined. Also, the aforementioned model does not exhaust the range of versions of the random walk with constant boundary positions and constant drift rate that have been examined. These other versions of the random walk (Laming, 1968; Link & Heath, 1975) would produce the same predictions as the model used for these simulations.

To summarize, the mathematics of the random walk requires that the distribution of nonterminated items moves close to the

Table 1
Probability of a Positive Response for the Simulations of the Simple Random Walk

Parameter			Cutoff									
p	*k*	Response	1	2	3	4	5	6	10	20	30	40
.6	5	Regular	—	—	—	—	.882	.897	.882	.880	.884	.884
		Guess	.600	.600	.648	.646	.666	.657	.668	.675	.668	.675
		N regular	—	—	—	—	903	886	2,913	6,461	8,281	9,096
.55	6	Regular	—	—	—	—	—	.788	.784	.766	.766	.767
		Guess	.549	.549	.574	.572	.597	.586	.592	.594	.609	.608
		N regular	—	—	—	—	—	340	1,481	4,233	6,127	7,409

Note. N regular refers to the number of trials out of 10,000 that terminated with a regular response (=10,000 − *N* guess).

response boundary and asymptotes in shape. From that point on, the shape does not change; the proportion of processes left in the walk simply decreases (i.e., the distribution collapses in size).

Diffusion Model

The diffusion model is a continuous version of the simple random walk (see Feller, 1968; see also Ratcliff, 1978, for applications) and can be derived from the simple random walk by taking limits as the step size becomes small. The bottom panel of Figure 1 illustrates the diffusion process and the parameters of the model. Expressions for accuracy and the distributions of finishing times for regular processes are available (see Ratcliff, 1978), as are expressions for the distributions of processes that have not terminated (Cox & Miller, 1965; Ratcliff, 1980). The expression for the distribution of nonterminated processes can be used to predict accuracy of guesses by setting a criterion as in the simple random walk. This expression for the distribution

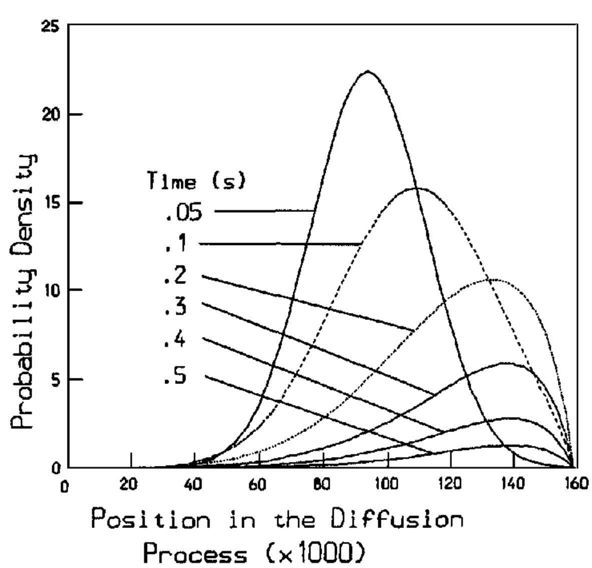

Figure 2. Distribution of nonterminated processes in a single diffusion process as a function of time. (Parameters used were as follows: $a = .16$, $z = .08$, $u = .3$, $s = .08$, and $T_{er} = 0$. Note that there was no variability in mean drift rate across trials in this example.)

of nonterminated processes as a function of position in the diffusion process and time is shown in Equation 1 (and is derived in Ratcliff, 1980),

$$p(x, t) = e^{u(x-z)/s^2} \sum_{n=1}^{\infty} \frac{2}{a} \sin\left(\frac{n\pi z}{a}\right) \times \sin\left(\frac{n\pi x}{a}\right) \exp\left\{-\frac{1}{2}\left(\frac{u^2}{s^2} + \frac{n^2\pi^2 s^2}{a^2}\right)t\right\}, \quad (1)$$

where x refers to the position in the diffusion process (between boundaries 0 and a), and where t represents time; u, the drift rate; z, starting point of the process; and s^2, variance in the drift rate. Figure 2 shows the distribution of nonterminated processes from Equation 1 as a function of position in the walk for several values of time for parameter values that are typical of fits of the diffusion model to data (e.g., Ratcliff, 1978, 1981). It can be seen that the distribution of nonterminated processes reaches an asymptote in shape as a function of time. Up to 0.2 s, the distribution moves toward the boundary a (set at 160/1000 = .16), while after that time the distribution collapses in size as more and more processes terminate. (Note that the distributions in Figure 2 are unnormalized probability density functions; the area under the function is the proportion of processes that have not terminated.)

This version of the diffusion process is the simplest case. In the model of Ratcliff (1978), an additional assumption is made: that there is variability in the mean drift rate across trials (the normal distribution is assumed with variance η^2). From now on the phrase "the diffusion model" will be used to refer to the diffusion process with a distribution of drift rates. Mathematically, this means that it is necessary to integrate over a range of drift values in Equation 1. The solutions are numerical but exact (the infinite series in Equation 1 has to be summed and this quantity integrated numerically over the distribution of drift rates u). Figure 3 shows an illustration of the diffusion process with variability in drift. The distribution over a large number of trials begins at the starting point, and as time elapses it spreads out, with both mean and variance increasing (the distribution is normal). When processes begin to terminate, the distribution begins to bunch up near the top boundary with a skew toward the bottom boundary. The difference between the unrestricted process (i.e., without response boundaries, as shown by the dotted distribution, which is presented for comparison) and the process with response boundaries represents the processes

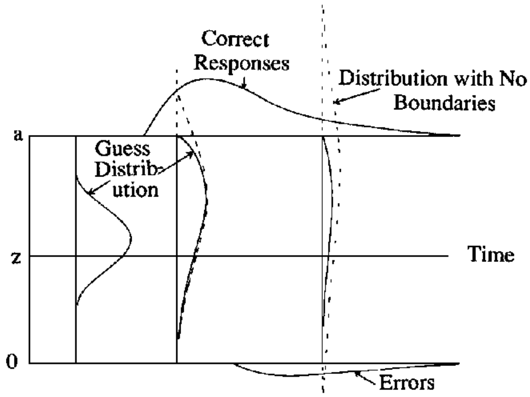

Figure 3. The diffusion process illustrating the distribution of regular processes (marked "correct responses" and "errors"), the distribution of nonterminated processes (marked "guess distribution"), and the distribution of processes that would occur with no response boundaries (the dotted line).

that have terminated. As time progresses further, the distribution becomes slightly less skewed because the processes with the larger values of drift tend to terminate more quickly (on average) leaving processes with lower values of drift that are (on average) less bunched toward the boundary. Thus, we would expect to see d' for nonterminated processes rise rapidly and then plateau and drop slowly.

Predictions for the behavior of several quantities are shown in Figure 4 for values of the parameters a, z, and u that are typical of fits of the diffusion model to empirical data (Ratcliff, 1978, 1981). The top panel shows the reaction time distribution for regular processes. The middle panel shows the growth of d' both for guesses (nonterminated processes) and for the diffusion process without boundaries (to contrast with guessing d', which has boundaries). Note the initial rise is the same because in both cases all the processes are involved in the calculation of d'; it is only when processes begin to terminate that guessing diverges from the process without response boundaries. These d' graphs were derived using a negative process with negative drift the same magnitude as positive drift (i.e., a mirror image process) and then using this negative process to give false alarms for the d' calculation. The bottom panel shows the growth of probability correct as a function of time.

For the diffusion process without boundaries, the distribution is normal and the equation is given by

$$p(x, t) = \frac{1}{\sqrt{2\pi s^2 t}} e^{-\frac{1}{2}(x - ut)^2/s^2 t}. \quad (2)$$

Thus, accuracy in terms of d' is given by

$$d'(t) = \frac{d'_a}{\sqrt{1 + s^2/(\eta^2 t)}}, \quad (3)$$

where $d'_a = (u - v)/\eta$; an example of this function is shown in the middle panel of Figure 4. For guesses, accuracy rises rapidly and decays more slowly, so for d' the peak is at $d' = 1.4$ and $t = .075$ s, and when $t = .25$ s, d' has fallen to 1.0. Note that the precise positioning, rate of growth, and height of this function are dependent on the parameter values used, but the shape is intrinsic to the model.

These results, like those for the simple random walk, demonstrate that important aspects of the data from Meyer et al. (1988)—rise to a relatively low level of guessing accuracy and relatively flat asymptote—are qualitatively predicted by a continuous model, the diffusion model. Possible decreases in accuracy of guesses at longer signal lags become difficult to examine because estimates of guessing accuracy become unstable at these longer times (this issue is considered later in this article).

Runs Model

The runs model is related to the simple random walk in that counts are accumulated with some probability p that a count is positive and $(1 - p)$ that a count is negative. The main difference between the two models is that in the runs model, counts of the same kind are accumulated until a count of the opposite kind occurs; then the counter is reset so the model assumes no memory beyond the current run. The stopping rule is a run of k counts in a row of the same kind (see Figure 5).

Discussion of this model can be found in Audley (1960) and Laming (1968). A simulation similar to that for the simple random walk was performed (using 10,000 trials per set of parameter values). For guesses, it was assumed that the last longest run type is stored and if the subject is required to respond, a response is produced based on this type. (If the response is based on the current run, the response will be based on the last count and thus will be p, the probability of a count, and will be con-

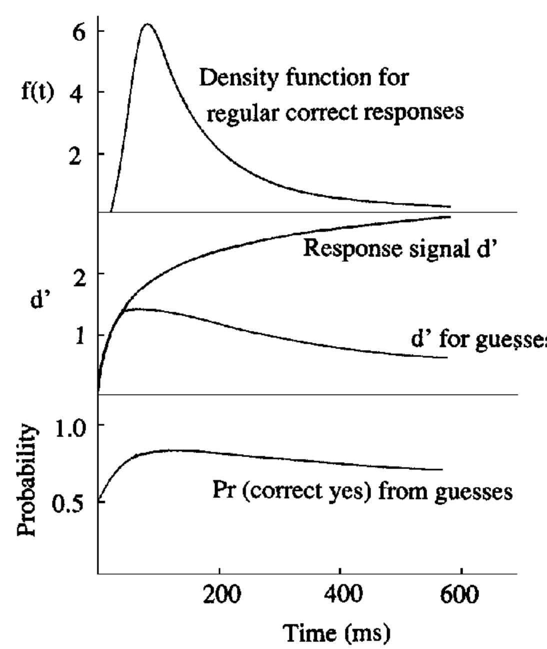

Figure 4. An example of predictions from a single diffusion process. (The parameters of the model that were used: $a = .1$, $z = .05$, $u = .3$, and $T_{er} = 0$. Note that the label *response signal d'* refers to predictions from the diffusion process without boundaries and reflects predictions for the response signal procedure from Ratcliff, 1978.)

Runs Model

p=probability of a "1" count

Respond on a run of length k (=4).

run example:

100011101001111

↑

Respond Here (run of length=4)

Figure 5. The runs model.

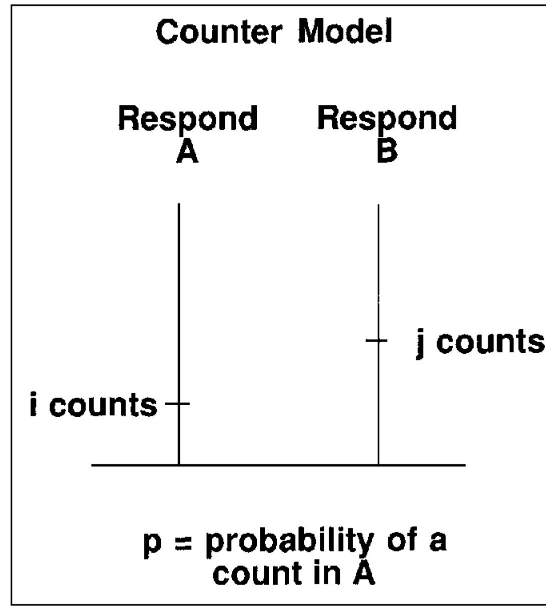

Figure 6. The counter model.

stant over the whole range.) Table 2 provides results for these simulations. For a probability p of .6 of one kind of count and a k of 6, the probability that a regular process will finish correctly is about .92 (corresponding to d' of 2.8 using a process with p = .4 to produce a false alarm rate of .08 [1 − .92]). This accuracy is roughly constant across a range of steps from 10 to 200. For guesses, the accuracy is about .80 (this corresponds to a d' of about 1.7) and is constant from 50 to 200 steps, showing a plateau of guessing accuracy.

One possibly important difference between the runs model and the simple random walk is that by the time the fastest processes begin to finish in the simple random walk, accuracy of guesses is very near asymptote, whereas in the runs model it is only by the time 30 to 40% of regular processes have finished that accuracy of guesses has risen to asymptote. Thus, the runs model provides the same qualitative results (i.e., guessing accuracy rising to a low asymptote relative to the accuracy of regular processes) as the simple random walk and explains qualitatively Meyer et al.'s (1988) data. However, to argue for a quantitative explanation of the data, note needs to be taken of the relative positions in time of fast-finishing regular processes and the point at which the accuracy of guesses asymptotes.

Counter Model

The last sequential sampling model considered here is the counter model (Pike, 1973). This model is related to the runs model and the random walk model, but there are two counters. One parameter is the probability p of a count to one of the two alternatives. Each counter accumulates counts until one reaches a criterion k, the other parameter of the model (see Figure 6). As before, a simple simulation was performed (with 10,000 trials per set of parameter values) to study the behavior of regular processes and guesses. For guesses, the counter with the largest number of counts is used; if the number of counts is the same, one counter is randomly chosen with a probability of 0.5.

The results are shown in Table 3 and provide a picture different from that seen in the runs and random walk models. As the number of steps increases from zero, the accuracy of guesses rises until processes begin to terminate. From then on, accuracy of regular processes and of guesses decreases. To understand the behavior of the counter models, consider a specific example: For

Table 2
Probability of a Positive Response for the Simulations of the Simple Random Walk

Parameter			Cutoff						
p	k	Response	10	20	30	50	100	150	200
.6	6	Regular	.921	.930	.922	.925	.917	.919	.919
		Guess	.700	.746	.760	.789	.810	.800	.796
		N regular	675	1,749	2,885	4,506	7,258	8,522	9,265
.6	5	Regular	.901	.892	.894	.888	.892	—	—
		Guess	.684	.720	.737	.743	.754	—	—
		N regular	1,387	3,300	4,734	6,689	9,072	—	—
.7	3	Regular	.948	.943	.948	—	—	—	—
		Guess	.753	.760	.733	—	—	—	—
		N regular	6,562	9,177	9,783	—	—	—	—
.55	6	Regular	.757	.782	.772	.767	.765	.771	.773
		Guess	.604	.630	.636	.663	.679	.671	.665
		N regular	445	1,362	2,097	3,463	5,938	7,442	8,447

Note. N regular refers to the number of trials out of 10,000 that terminated with a regular response (= 10,000 − *N* guess).

Table 3
Probability of a Positive Response for the Simulations of the Counter Model

Parameter			Cutoff								
p	k	Response	1	2	3	4	5	6	7	8	9
.65	5	Regular	—	—	—	—	.958	.931	.899	.870	.826
		Guess	.651	.653	.723	.719	.739	.680	.667	.5	—
		N regular	0	0	0	0	1,206	3,488	5,915	8,157	10,000
.6	4	Regular	—	—	—	.839	.789	.759	.719	—	—
		Guess	.599	.600	.647	.614	.596	.50	—	—	—
		N regular	—	—	—	1,575	4,224	7,259	10,000	—	—

Note. N regular refers to the number of trials out of 10,000 that terminated with a regular response (=10,000 − N guess).

a regular process to terminate after only 5 counts, when 5 is the criterion, it must have received 5 counts of the same kind in a row. This is much more likely for the counter with higher probability than for the counter with lower probability. For example, with p = .65, the probability of 5 counts in a row is .116; with p = .35 (1 − .65), the probability of 5 counts in a row is .00525, so that accuracy will be .959. In contrast, when both counters have 4 counts in them, the next count (9) will produce a response and the accuracy will be .65 (note the regular process accuracy in Table 3 is an average over all processes that terminated earlier). Thus, accuracy of regular processes decreases from .959 to .65 from the first regular responses to the last. Before regular processes begin to terminate, accuracy of guesses grows until processes begin terminating then accuracy decreases. For example, when the number of counts in each counter is one less than the critical number (the slowest possible guess), the accuracy of a guess must be 0.5. Thus the counter model makes a prediction for guesses that is at odds with the prediction made for continuous models by Meyer and Irwin (1981).

In addition, the counter model makes other predictions that are at odds with the real reaction time data: It predicts a maximum value of reaction time (with a criterion of 5 counts, there can be no longer run than 9 counts), and it predicts negatively skewed error reaction time distributions (the accuracy of regular processes falls as a function of the number of counts, which means that the number of incorrect responses rises [see Table 3]). Thus the counter model seems to fail on several grounds and cannot be considered a candidate to explain the data from the paradigm of Meyer et al. (1988).

Summary of the Models

None of these models predicts what might be expected from a continuous model (e.g., Meyer & Irwin, 1981), that is, that guessing accuracy will grow slowly and continuously to the accuracy of regular processes. Three of the models—the runs, the random walk, and the diffusion models—predict growth of guessing accuracy to a low level, with the level then constant for the random walk and runs models and with the level then declining slowly after a faster rise for the diffusion model. The counter model predicts rising then falling accuracy of guesses as a function of time. The simple random walk, the runs, and the diffusion models are all candidates to explain the data of Meyer et al. (1988). In the following section, the diffusion model is tested using results from a new recognition memory experiment.

Experiment

Meyer and Irwin (1981) argued that the pattern of data they observed in their double-word lexical decision data could not be accounted for by the diffusion model of Ratcliff (1978), and Meyer et al. (1988) argued that there were aspects of the data (the onset of the growth of guessing accuracy relative to the minimum reaction time for regular processes) that the diffusion model was incapable of fitting. To test whether the diffusion model is capable of making adequate quantitative predictions, I performed a new experiment using the study–test recognition memory procedure to which the diffusion model has been previously fitted, rather than attempt to modify the diffusion model by adding assumptions to deal with the processes involved in the double-word lexical decision task (note that this was done before the availability of Meyer et al.'s single-word lexical decision [their Experiment 5] and Kounios et al.'s, 1987, semantic memory experiments). A second reason for using the study–test recognition memory procedure is that accuracy is off the ceiling, typically 70% to 90%. Thus contamination of results by a small proportion of bad data would not be as serious as with experimental procedures in which accuracy is near ceiling (because it is possible for a large proportion of the errors to be spurious when error rates are low). A possible problem in using the study–test procedure is that averaging data over a range of study and test positions might result in a mixture of contributions from various long- and short-term components of performance. However, the importance of this problem is largely an empirical question and it is addressed in analyses of the effects of study and test position on performance.

The experimental procedure devised by Meyer and Irwin (1981) and Meyer et al. (1988) consists of the two types of experimental trials: regular and signal, *randomly intermixed.* On regular trials, subjects are free to respond in their own time, whereas on signal trials, subjects are presented with a signal to which they must respond immediately (within 200–300 ms). The experimenter determines the onset of the signal; in the Meyer et al. (1988) studies, the signal lags were not set at fixed values; rather, the values were set relative to the median response time of the prior block of trials. In the present experiment, the signal onsets were set at fixed values. A practical advantage of this is that programming is much simpler.

Theoretically, both methods of setting lags have some limitations from the viewpoint of the diffusion model, and if the parameters of the model fluctuate across trials (giving different median reaction times across blocks of trials), the two methods produce averaged curves with different properties. For example, one way regular reaction times can change systematically from block to block in the diffusion model is by changes in the response boundaries. If such changes are responsible for changes in regular reaction time, then tracking the changing median reaction time would result in the averaging of diffusion processes with different starting times. This is illustrated in the right panel of Figure 7, where the two processes (top right two graphs) are lined up with respect to the median reaction time (note that the median for processes with wider boundaries will be later in time, so that lining up the medians shifts the starting points). The third and fourth graphs in Figure 7 show the growth of accuracy of guesses for the top two panels, respectively, and the bottom graph is the average of the two above. Each individual process will have rapid initial rise followed by a more and more gradual approach to asymptote. The average shows a two-step rise, but this would not be observed in practice. What would be observed, averaging over a range of such varying processes, is a more constant (i.e., linear) and gradual rise than any individual process.

Fixed times for signal lags relative to the onset of the test item would keep the starting point of the diffusion process fixed (not dependent on boundary fluctuations), and this would result in averaging over the asymptotic portion of the curve, as shown in the left panel in Figure 7. The latter alternative would distort fits of the diffusion model less than would lining up medians, so fixed lags were chosen for this experiment. Note that for a serial stage model, the median will track a fixed point relative to the end of processing whereas a fixed time will track the beginning of processing.

The second main change in procedure was to use a visual signal to respond instead of an auditory signal. In other procedures using signals to respond, visual signals have been found to work just as well as auditory signals (Ratcliff, 1981; Ratcliff & McKoon, 1982).

Method

Subjects. The subjects were three Northwestern University undergraduates who participated in the experiment partly to fulfill a course requirement and partly for pay at a rate of $4 per hour. Each subject completed 5 practice sessions and 12 experimental sessions.

Materials. Words were selected randomly without replacement from a pool of 1,025 common two-syllable words not more than eight letters in length. There were no repetitions within a session, and words were assigned to conditions randomly.

Design and procedure. Stimuli were presented and responses recorded on a terminal driven by a Radio Shack color computer. The color computer obtained lists of materials from an Apple II+ computer that communicated with several color computers. Subjects responded by pressing one of two keys on the terminal keyboard (the slash key for "old" and the *Z* key for "new").

The first two practice sessions used a standard study–test recognition memory procedure without signal trials. On each study–test sequence, subjects studied 16 words presented individually for 1.5 s each. After a pause and a signal that the test list was about to begin, subjects were presented with 32 test words one at a time, to which they had to respond "old" or "new." The test list was composed of the 16 old words along with 16 new words, in random order. After a response, there was either a 500-ms delay if the response was correct or the word *error* was presented for 500 ms if the response was incorrect. After each study–test sequence, subjects were allowed a self-paced pause before proceeding to the next list.

The experimental sessions, preceded by three identical practice sessions (Sessions 3–5), were the same as the first two practice sessions except for the addition of signal trials. Half the trials (randomly chosen) were regular trials and identical to those in the first two practice sessions. The other half were signal trials. The test word was presented and then, after an experimenter-determined time, a signal to respond was presented. The signal was a row of eight asterisks presented directly under the test word. Subjects could respond before or after the signal was presented, and the test word remained on the screen until the response was made. On signal trials, response time feedback was presented and subjects were asked to keep the signal-to-response time to about 200 ms. The signal lags chosen were 200, 250, 300, and 400 ms. These lags were chosen to span the time after partial information had begun to accumulate to roughly the mean reaction time (note that it is necessary to add the subject's signal-to-response latency of about 200 to 300 ms to obtain total processing time on signal trials).

Instructions. One of the most important features of the use of signal trials in conjunction with regular trials is that it is extremely difficult to train subjects to respond adequately. The problem is that the two kinds

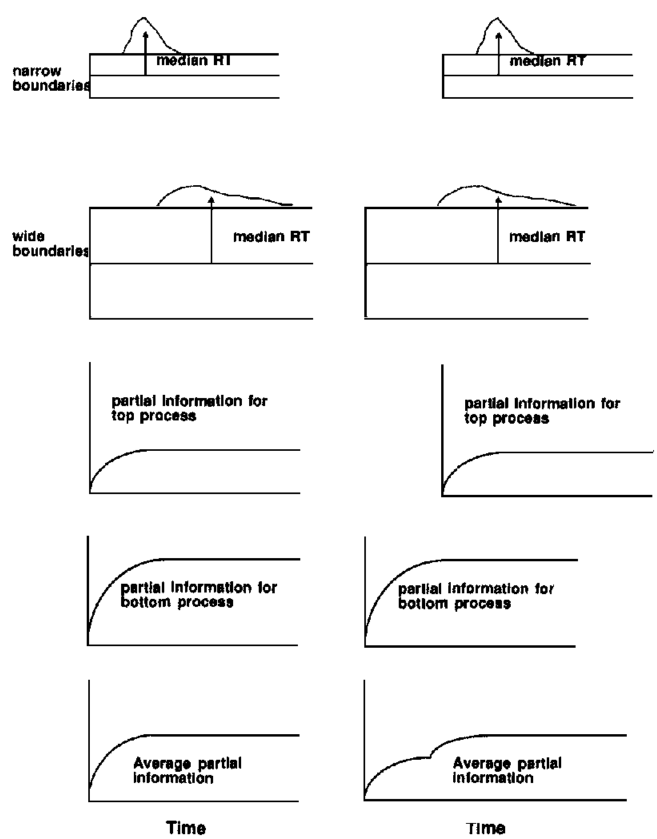

Figure 7. A theoretical comparison for the diffusion model between the average of cases in which median reaction time is tracked (right panel) and the average of cases in which fixed signals are used (left panel).

of trials require seemingly inconsistent behavior. On regular trials subjects are required to be accurate, whereas on the signal trials they are required to be fast. In a pilot run of this experiment, in which both signal and regular trials were presented in the practice sessions, subjects simply responded as quickly as possible so that on regular trials they actually responded more quickly than on the trials with the longest signal. It was after this that the following method was devised (with the consultation of John Kounios and David Meyer): Subjects were trained on the first two practice sessions with instructions to be accurate, and error feedback was given to emphasize accuracy. The next three sessions introduced the signal trials, and subjects were instructed to stay accurate on regular trials while gradually speeding up responses to the signals. By the third signal practice session, subjects were able to perform both tasks well, keeping regular trials accurate (and slow) and response times to the signal fast.

Results

The results from the practice sessions were discarded after determining that subjects' performances were acceptable. Preliminary analyses of the data showed that test position had a relatively large effect on performance (20–40 ms and 8% difference in reaction time and accuracy, respectively, between the first and second halves of the test list), but study position had little effect (less than 10-ms difference in reaction time and less than 2% difference in error rates). These analyses showed that within each half of the test list differences in performance were close enough to average, and so the data were split into two halves as a function of test position for data analysis (see Murdock, 1974; Murdock & Anderson, 1975; Ratcliff, 1978; Ratcliff & Murdock, 1976).

Signal trials and the race model. In order to extract the accuracy of guesses at each of the signal lags, it is necessary to perform an analysis in which the accuracy and reaction time of guesses are extracted from the mixture of guesses and fast-finishing regular trials that provides responses on signal trials. The first step involves deriving the cumulative distribution function for guesses. The second step uses this distribution to determine the probability that a guess will beat out a regular process, and this is used in deriving guessing accuracy.

According to the race model, the observed distribution of responses will reflect the minimum values of finishing times for samples drawn from regular processes and guesses. The equation for the cumulative distribution of guesses (Equation A2 in Appendix A) can be written in terms of the cumulative distribution functions of regular trials (observed) and signal trials (observed). In performing this derivation (see Appendix A and Meyer et al., 1988), it is assumed that the distribution of guesses for a particular response is independent of the duration of normal processes for a given type of stimulus and that the duration of the guessing process does not depend on whether the guess is correct or incorrect. The rationale for this method is discussed in Appendix A. Cumulative distribution functions were obtained using the group distribution method of Ratcliff (1979). For each session for each subject, reaction time quantiles were obtained (deciles). These were averaged across sessions to give the cumulative distributions used in the analyses (see also Meyer et al., 1988). Figure 8 shows the cumulative distribution functions for guesses averaged over three subjects for short test positions (2–16) (position 1 is discarded because these responses are slower by several hundred milliseconds, the result of warming up to the test list [Murdock, 1974]) and two subjects for long test positions (17–32).

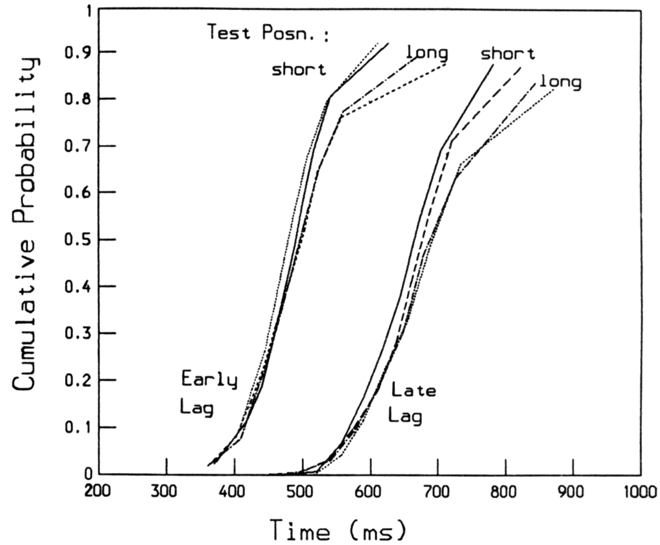

Figure 8. Cumulative guessing reaction time distributions for Experiment 1. (Short and long test position refers to positions 2–16 and 17–32, respectively, in the test list. Graphs for two of the four lags are presented and the data shown are for hits and correct rejections.)

Data from only two subjects were used at the longer lags because the data from the other subject were unstable at the long test positions. This was because accuracy was too low and the late signal trials were so slow that most of the responses were fast-terminating processes. The guessing distributions in Figure 8 differ little except at the highest quantiles. The slight differences observed are similar to those found by Meyer et al. (1988, Figures 14, 15, & 20).

The second step in obtaining guessing accuracy involves the use of a relationship among signal, guesses, and regular trials (using the cumulative reaction time distributions for guesses). There are three combinations that will lead to a correct response on signal trials: 1) when both the regular process and the guess are correct; 2) when the regular process is correct, the guess incorrect, and the regular process faster than the guess; and 3) when the regular process is incorrect, and the guess is correct and faster than the regular process. An expression for the accuracy of guesses using these three terms is shown in Equation B2 in Appendix B (see Appendix B and Meyer et al., 1988, for details).

Results for the accuracy of guesses as a function of time are shown in Figure 9. The accuracy of guesses grows slowly as a function of time at a level that is considerably lower than the accuracy for regular trials (see Table 5). For early test positions, accuracy is higher than for later test positions for both guesses and regular processes. Table 4 shows the hit and correct rejection rates for guesses from which the d' results shown in Figure 9 were derived. It is possible that averaging over individual subject's performance distorts the group results. However, the results for individual subjects show exactly the same trends (see the brief discussion of fits to individual subject's data).

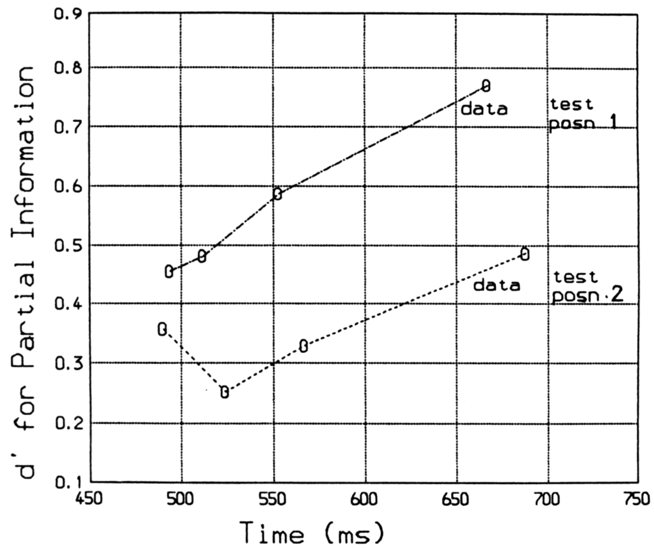

Figure 9. Guessing accuracy for results from Experiment 1. (Test Positions 1 and 2 refer to Positions 2–16 and 17–32, respectively, in the test list.)

Standard errors in guessing accuracy. In order to estimate standard errors, it is necessary to consider two sources of error. Because regular trial data are used across all signal lags, any error in the regular trial quantities will appear as a constant error in guessing accuracy across lags. In contrast, error in data from signal trials could be different for each lag so that there will be variability between signal lags. Estimating the variability in guessing accuracy is difficult because estimation of some of the terms in the equation for guessing accuracy (Equation B2) depends on observed reaction time distributions. However, it is possible to get estimates empirically by using simple Monte Carlo simulation. In the simulation, the quantities in Equation B2 are replaced by values drawn from a normal distribution, with mean and standard deviations derived empirically. Then the value of guessing accuracy is derived, and the process is repeated 1,000 times. These 1,000 sets of values of guessing accuracy are then used to determine the standard errors on guessing accuracy (both for hit and false alarm rates and d'). The standard error in p^* (probability of a response on signal trials; see Appendix B) is typically .03 for a single subject (derived from the binomial expression $\sqrt{(p(1-p)/N)}$. The standard error in p is .01 and the standard error in the probability $P(t_{ig} < t_j)$ (the three expressions in Equation B2) is roughly 0.02 at short lags and 0.026 at long lags. These were computed by a second Monte Carlo simulation of the race model: the distributions in Figures 8 and 10 were used to provide reaction times given random numbers between 0 and 1 (i.e., cumulative probability). Random reaction times were generated for guesses and regular processes, and the probability that guesses were faster than regular processes was thus obtained. Variability in this quantity was estimated using 50 Monte Carlo repetitions. Averaged over 3 subjects, a 2 standard error confidence interval in guessing accuracy is about ±.036. Most of the variability comes from the variability in p^*, so that the distinction between within and between lag variability has little practical consequence. These confidence intervals translate into 2 standard error confidence intervals in d' of approximately .13.

Fits of the Diffusion Model

The expressions shown in Equation 1 apply to the case in which a single diffusion process serves as the decision process; however, in the model of Ratcliff (1978), several diffusion processes proceed in parallel. Thus to obtain predictions for the data shown in Figure 9, it is necessary to obtain expressions for guessing accuracy in which several processes proceed in parallel. The decision rule is the same as that used in Ratcliff (1978, p. 95) for the response signal procedure: For guesses, if one process is above the criterion, a "yes" response is initiated; all processes must be below the criterion for a "no" response to be initiated. This rule is conditional, first, on the process's having not terminated (so it is necessary to sum over all combinations of processes from 1 to n still left in the walk) and second, on no other process's having terminated at the positive boundary. The derivation for guessing accuracy for the multiple parallel diffusion model is presented in Appendix C.

In order to fit the diffusion model to the guessing accuracy data, some method of limiting the number of free parameters must be found. The method I used involved fitting the model to the accuracy and reaction time distribution data from regular trials (as in Ratcliff, 1978), thus fixing the parameters of the model. These parameter values were then used to provide predictions for the accuracy of guesses as a function of time. The only free parameter was the time to process the response signal after it was presented, and this determined the position of the onset of guessing accuracy. In contrast, the level of accuracy for guesses is completely determined from the parameter estimates derived from the fits to data for regular trials.

The first result to discuss is the fit of the diffusion model to accuracy and reaction time for regular processes. The method used to achieve this fit is somewhat involved but is logically straightforward. First, a summary distribution is fitted to the hit and correct rejection reaction time distributions. The summary distribution used is the convolution of normal and exponential distributions, and the parameters, the mean of the normal (μ), standard deviation of the normal (σ), and the time constant (τ = mean) of the exponential are used as a summary of distribution shape. The next step is to fit the diffusion model

Table 4
Guessing Accuracy as a Function of Retrieval Time

t (milliseconds)	Hit rate	False alarm rate	d'
Test Position 1 (2–16)			
494	.561	.379	.456
512	.589	.398	.481
553	.638	.414	.586
667	.640	.337	.771
Test Position 2 (17–32)			
490	.500	.362	.358
524	.505	.408	.253
567	.523	.388	.329
688	.537	.353	.486

Table 5
Results for Regular Trial (RT) Data for Experiment 1

	Data				Fits			
Response type	Accuracy	RT (seconds)	μ (seconds)	τ (seconds)	Accuracy	RT (seconds)	μ (seconds)	τ (seconds)
Test Position 1 (2–16)								
Hit	.777	.801	.418	.382	.781	.780	.425	.353
Correct rejections	.752	.830	.446	.384	.745	.832	.425	.353
Test Position 2 (17–32)								
Hit	.686	.828	.430	.398	.686	.822	.422	.398
Correct rejections	.674	.850	.442	.408	.686	.861	.447	.407

Note. μ and τ refer to parameters of the convolution of normal and exponential distributions used as a summary of reaction time distribution shape. The parameters of the diffusion model were as follows: For Test Position 1, a = .157, z = .037, u = .182, v = −.349, and T_{er} = 243 s. For Test Position 2, a = .145, z = .039, u = .084, v = −.336, and T_{er} = .244 s.

with its parameters a, z, u, v, and T_{er} to the convolution summary distributions and accuracy. This is done by generating predictions from the diffusion model, fitting the convolution distribution to the theoretical reaction time distributions, and then minimizing the squared differences between theoretical and empirical values of μ, τ, and accuracy using a minimization routine (SIMPLEX, Nelder & Mead, 1965) that adjusts the parameters of the diffusion model. The parameters of the diffusion model that best fit the convolution distribution and accuracy are used as the diffusion model's account of the data. If there is any distortion due to use of the convolution distribution, it can only make the fits worse than they would be by fitting the data directly (see also Hockley, 1982; Ratcliff, 1978, 1979, 1981; Ratcliff & Murdock, 1976).

It should be noted that group average data for the reaction time distributions were used in these analyses. The data were averaged by first finding the 10 quantiles for the hit and correct rejection reaction time distributions for each experimental session for each subject. These were averaged across sessions for each subject, and the convolution distribution was fitted to these average distributions for each subject (see Ratcliff, 1979). The parameters of the convolution model were then averaged across subjects.

The results for the fit of the cumulative reaction time distributions are shown in Figure 10, and as can be seen, the fits are excellent (as noted above, fits achieved more directly without use of the convolution distribution as an intermediate summary can only be better). Table 5 shows the fits of accuracy and the reaction time distribution typical of those found in fits to the study test paradigm (see Ratcliff, 1978). The fits of the model show that for early and late test positions, almost identical values of T_{er} are obtained. This would be expected if variations in reaction time and accuracy were mainly due to variations in the decision process, and so this result adds some validity to the quality of the fits. Other parameter values remain within 10% of each other as a function of test position (a, z, and v) except u, which varies by a factor of 2. Loosely speaking, this is best interpreted by assuming that diffusion process boundaries are fixed as a function of test position, that the relatedness of negative test items is constant, and that the relatedness of positive items drops as a function of test position (i.e., forgetting). Thus this set of parameter estimates is nicely interpretable in terms of one parameter varying as a function of test position. Given the parameter values from the fits of the regular trials, the next step involves computing the accuracy of guesses using the derivations in Appendix C.

Fits of the diffusion model to guessing accuracy. The results for guesses are shown in Table 6 and Figure 11. Figure 11 shows the fit of d' as a function of time to the accuracy of guesses from Experiment 1. Table 6 shows the hit and false alarm rates for the theoretical predictions. As can be seen, the fit is excellent for both long and short test positions, given the lack of freedom in parameter values.

Along with the values of the hit and false alarm rates, Table 6 shows the values of the criterion setting. It should be noted that to fit the hit and false alarm rates accurately, it is necessary to allow the criterion to drift slightly as a function of time (note that often memory models do not attempt to fit hit rates and false alarm rates; they are content with fitting d').

The theoretical predictions fall within 2 standard errors of the data (d' of ±.13). Although the theory shows that the guessing accuracy peaks and then declines, it is possible that the theory could predict a much flatter function. For example, if the onset of any of the processes such as test item encoding or response signal processing were variable, then this would tend to flatten out the theoretical function shown in Figure 11. Thus the predicted peak seen in Figure 11 may be hard to obtain experimentally.

To illustrate an extreme version of the variable encoding and signal processing possibility, I took the theoretical predictions of d' as a function of time from Table 6 and averaged the curve with a copy that was shifted to the right by 50 ms. The top panel of Figure 12 shows the shifted function rising to a peak and then falling slightly (this is the prediction for test positions 2–16 in Figure 11). In the bottom panel is the average of the two. The average shows a more gradual rise (this could be taken to be a linear rise—see Kounios et al., 1987; Meyer et al., 1988, Experiment 5), followed by a leveling off in which the decline in d' is not particularly pronounced. Although this example is extreme, the effects of variability need to be considered in evaluating the fits, and I conclude that such effects would allow fitting the qualitative pattern of data more closely.

Other data. Besides fitting the group data, I fitted the individual subject data and found that the results were not quite as

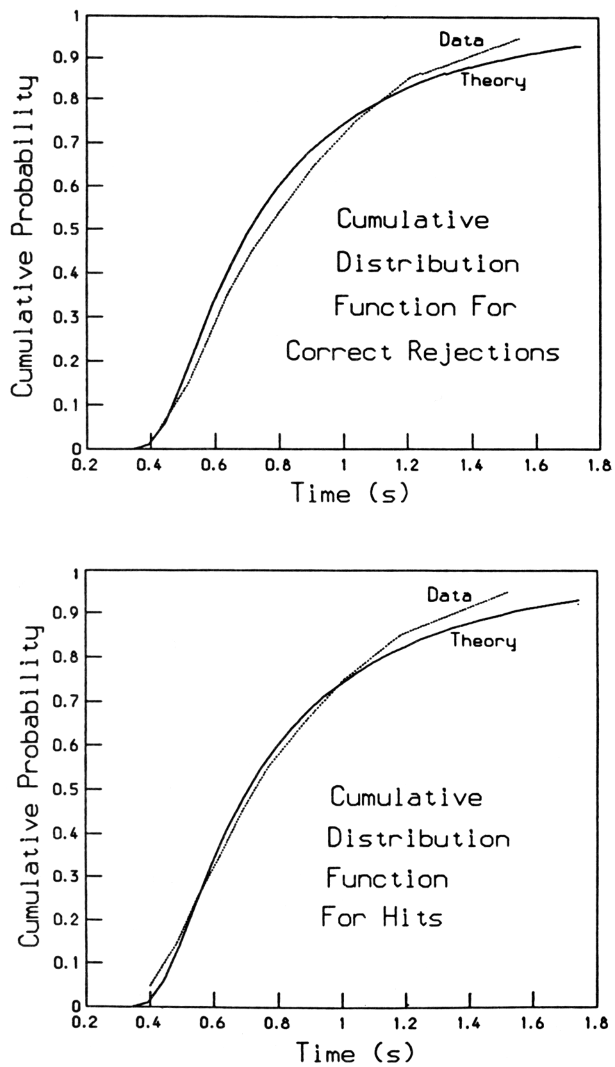

Figure 10. Cumulative reaction time distributions for the data from regular trials from Experiment 1. (Also shown are fits of the diffusion model.)

good as those found for the group. The regular trial reaction time distributions and accuracy were fitted by the diffusion model and the parameter values were used to calculate the accuracy of guesses. It turned out that for 2 of the subjects the estimate of guessing accuracy was too high by about 10% and for the other subject it was too low by 15%. However, these fits were within 2 standard errors of the data.

Gillund and Shiffrin (1984) noted that they would prefer a model in which there was only one random walk instead of several operating in parallel. I tried fitting the single diffusion process to the data for regular trials and then using the parameter values to obtain guessing accuracy as a function of time. Fits to the reaction time distributions and error rates for test positions 2–16 for regular trials were performed and were close to the fits for the multiple diffusion process model (above). The parameter values obtained were as follows: $a = .200$, $z = .103$, $u = .1376$, $v = -.133$, $T_{er} = .309$, $s = .20$, and $\eta = .166$. For the same values of t shown in Table 6 and Figure 11, the theoretical d' values were .568, .738, .796, .788, and .755. These values rise more rapidly than the multiple process model, peak earlier, and decline more slowly. The main discrepancy between the predictions and the data is the rapid rise; the data show a more gradual rise. In these and the other fits I have attempted with the single diffusion process model, I have found significant differences between the theory and data. This failure further supports the claim that the paradigm of Meyer et al. (1988) provides reasonably stringent tests for the sequential sampling and continuous models.

Discussion

The new response signal procedure developed by Meyer et al. (1988) has produced important results that provide strong tests for a class of sequential sampling models of decision processes. The procedure allows the examination of evidence available toward a decision during the time before the decision is initiated. This is extremely important because it provides a new class of tests that are paradigm independent (each experimental paradigm could have a different pattern of guessing accuracy). Most models prior to those presented in this article and those examined by Meyer and colleagues have not been used to predict guessing accuracy results, so this work provides new tests for all reaction time models. Results using this procedure show that the accuracy of guesses is much lower than the accuracy of regular processes and that the accuracy of guesses either grows slowly or remains constant (perhaps after slow growth) as a function of time. The stochastic models presented here (the runs, simple random walk, and the diffusion models) all make good qualitative predictions about the growth of accuracy of guesses, and the multiple process diffusion model is shown to fit the data from a recognition memory experiment quantitatively.

In the next section, critiques of the diffusion model's accounts of the new response signal paradigm and of error reaction times are discussed. In the final sections, the diffusion model is applied in a new way to results from the previously used response signal procedure (Reed, 1973, 1976) and the cascade model is evaluated with respect to the results presented in this article.

Meyer et al.'s (1988) Critiques of the Diffusion Model

There is one important issue that Meyer et al. (1988) raised with respect to the account provided by the diffusion model for the data from their response signal procedure. It concerns the dormant period before accuracy begins to rise above chance. They argued that the results from their experiments show that the diffusion model has to accommodate high accuracy of the fastest regular processes immediately after the dormant period of low guessing accuracy. Thus, the model requires "a large and very rapid rise in response strength, whose onset occurs at about the same time as the fastest normal processes reach their final high information level" (Meyer et al., 1988, p. 232). The basis for this conclusion is the assumption that the process of making a decision based on crossing a response boundary for a regular process takes the same amount of time as the process of making a decision based on partial information (see this as-

Table 6
Guessing Accuracy for the Fits of the Diffusion Model

	Test Position 1 (2–16)				Test Position 2 (17–32)			
t (seconds)	Hits	False alarms	Criterion	*d'*	Hits	False alarms	Criterion	*d'*
.05	.536	.371	.0575	.432	.472	.363	.060	.283
.10	.594	.335	.0625	.640	.514	.344	.065	.438
.15	.639	.329	.065	.798	.548	.346	.0675	.511
.20	.641	.324	.0675	.818	.546	.338	.070	.538
.25	.647	.355	.0675	.749	.530	.335	.0725	.488

Note. To scale time *t* to the real reaction times shown in Table 4 and Figure 8, it is necessary to add T_{er} = .243 s and a response signal processing time of .207 s.

sumption in footnote 30 of Meyer et al., 1988). My assumption is different. When a regular process crosses a response boundary, a fast automatic response preparation and execution process is initiated; in fact some of the response preparation may be performed as the process moves to the boundary (e.g., see the discussion of evoked potential measures in Meyer et al., 1988). In contrast, when the comparison process is interrupted, processes have to be executed to determine current position in the diffusion process relative to some criterion. I assume that these processes require significantly more time than firing off a response as a result of crossing a boundary. Meyer et al.'s (1988) criticism does not hold with this alternative assumption because within the framework of the diffusion model, guessing accuracy and regular responses are actually measured at different points in processing. Guessing accuracy represents the state of affairs about 200 ms (from theoretical estimates) earlier than regular processes that produce their response at the same physical time.

It should be stressed that this assumption about the time required to initiate a response to a signal is the only addition to the diffusion model that is required to account for the data from the study-test experiment using Meyer et al.'s (1988) new response signal procedure.

Limitations of the Diffusion Model

The diffusion model has one weak spot in fitting data, and that is error reaction times. The model predicts that error reaction times are very slow; however, the experimental results show them to be either slightly slower or slightly faster (depending on the subject) than correct reaction times. The results from the experiment reported here are similar in this respect to those reported in Ratcliff (1978, 1981) and show the major weakness in the present implementation of the diffusion model. The way to fix the model is to assume nonnormal relatedness distributions (i.e., distributions of drift rate that are not normal). Ratcliff (1978) performed some simple tests varying the shape of the relatedness distribution by including high tails and found that both accuracy and the shape of the reaction time distribution were robust to changes in shape of the relatedness distribution, whereas error reaction times varied from twice as slow to faster than correct responses. While it would be easy to assume some kind of high-tailed distribution here and fit all the data, such an assumption would be ad hoc. It is generally very difficult to work back from data to derive the shape of the signal and noise distributions in signal detection theory (e.g., Lockhart & Murdock, 1970), yet this is what would be needed here to fit the reaction times for error responses. Rather than provide an ad hoc fit, I decided to simply use the model as formulated before (Ratcliff, 1978, 1981) and indicate the problem with error reaction times. The qualitative fits of the model would be the same with nonnormal relatedness distributions, and extrapolating from experience with nonnormal distributions, the quantitative fits would be altered little.

Other Experimental Studies

Meyer et al. (1988) consider a study by Kounios et al. (1987) that examines the time course of retrieval in a semantic verification task. Kounios et al. (1987) find that the time course of guessing accuracy shows a slow rise in accuracy of guesses, with an almost linear trend over a range of about 150 ms. This is

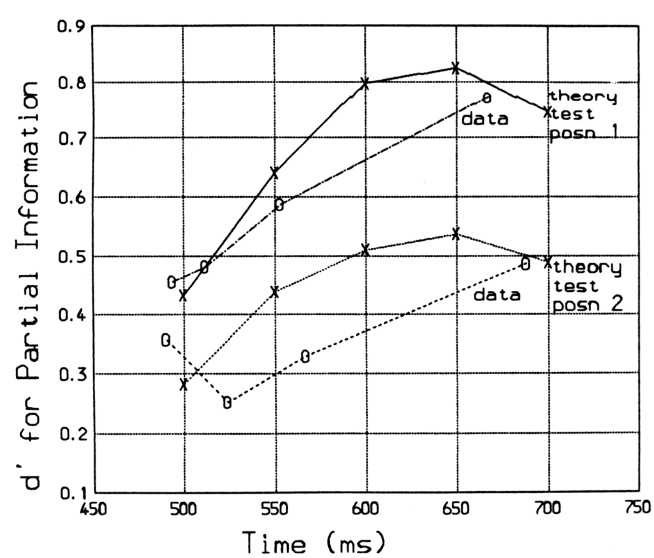

Figure 11. Fits to the data for guessing accuracy for Experiment 1. (Test Positions 1 and 2 refer to Positions 2–16 and 17–32, respectively, in the test list.)

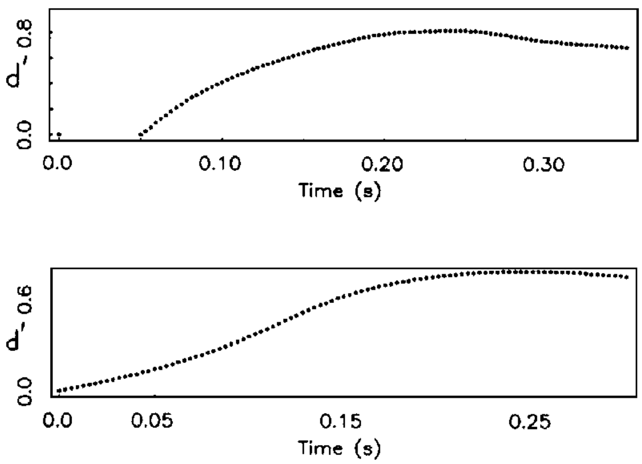

Figure 12. An example of the prediction of the diffusion model for guessing accuracy (from Figure 11) and the effect of averaging two of these curves separated by 50 ms.

similar to the results found in Meyer et al.'s (1988) single-word lexical decision Experiment 5 but possibly differs from the results from double-word lexical decision experiments (as noted earlier, the full range of the function needs to be examined in the double-word lexical decision task before a step function can be assumed). There are two things to note about Kounios et al.'s results. First, from the diffusion model (see Figure 4) the rise in accuracy of guesses follows the initial portion of the response signal curve. In Ratcliff and McKoon (1982), data are presented from the response signal procedure in which the initial rise in accuracy is quantitatively similar to the rise in the guessing accuracy curve obtained by Kounios et al. (1987). Thus there is every reason to believe that a model of the class of random walk or diffusion models (see Ratcliff & McKoon, 1982) could fit this rise in guessing accuracy. Specifically, to fit this data, it would have to be assumed (as in Figure 12) that the onset of the growth of accuracy was quite variable across trials because of variability in reading horizontally spaced words in the test sentences (this can be seen in Ratcliff & McKoon's, 1982, Experiments 1–4). The second point to note is that the accuracy of guesses in Kounios et al.'s (1987) studies is higher (e.g., d' up to 3) than that found in Experiment 1 above or in Meyer et al.'s (1988) experiments. The ratio of guessing accuracy to the accuracy of regular responses in Experiment 1 in this article is about .25 to .5, and in Meyer et al.'s (1988) experiments, it ranges from .2 to .5. However, it is hard to examine this ratio for Kounios et al.'s data because the accuracy of regular processes is very high and 95% confidence intervals ($\sqrt{pq/N}$) include 100% correct. Without reasonably precise estimates of the accuracy of regular processes, it would be hard to quantitatively evaluate the diffusion model.

Response Signal Procedures

Accounting for the data from the Meyer et al. (1988) response signal procedure suggests an alternative theoretical account of performance in the traditional response signal procedure in which subjects are presented with a test stimulus and are required to respond only after the signal is presented (Reed 1973, 1976; see also Dosher, 1979, 1981, 1984). The traditional technique is one half of the method used by Meyer et al. (1988) and Experiment 1 here because it uses only signal trials, and subjects cannot respond before the signal. The account provided by Ratcliff (1978) assumed that the boundaries of the diffusion process are moved far from the starting point (or removed) and the subject responds on the basis of position in the process. A different explanation involves the assumption that responses in the response signal procedure are a probability mixture of guesses and regular processes (that have terminated earlier than the signal) in a process with regular response boundaries. In the following, these two accounts are compared and it is shown that they mimic each other.

In the earlier account (Ratcliff, 1978), response boundaries are removed and the decision is based on position above or below some information-based criterion. The reason for this choice is that subjects would simply respond on the basis of information accumulated prior to the signal without any regard to response boundaries. With this assumption, it is possible to derive a simple expression for the growth of accuracy as a function of time, based on the spread of the positive and negative relatedness distributions. The expression for accuracy in terms of d' is given by

$$d'(t) = d'_a/\sqrt{1 + v/(t - T_{er})}, \qquad (4)$$

where v is the ratio of the variances, s^2/η^2. This expression has proved to be an excellent alternative to the more commonly used exponential approach to a limit, and there is little to choose between them based on goodness of fit (Dosher, 1981, 1984; Ratcliff & Iverson, 1984).

The account provided in this article for the Meyer et al. (1988) procedure suggests that response in the traditional response signal procedure could be a probability mixture of fast-finishing regular processes and guesses (see also Reed, 1976). The question is whether the diffusion model with boundaries set relatively close to the starting point (in positions normally found in fits to data) can produce functions that approximate Equation 4 above. Thus, at a particular time, some proportion of the processes will have terminated at diffusion process boundaries, leading to decisions that have some hit and false alarm rate, and the remaining decisions will be derived from guesses that have a different hit and false alarm rate. The two hit rates are combined and the two false alarm rates are combined and these are used to determine the overall accuracy and d'. Table 7 shows the probabilities of "yes" decisions for signal (old items in recognition memory) and noise (new items) categories as a function of time for guesses and regular processes. Parameter values used for this example are typical of those in fits of the diffusion model (Ratcliff, 1978, 1981). Adding the proportion of "yes" decisions for old items for regular processes and guesses gives the hit rate, and adding the equivalent proportions for new items gives the false alarm rate. These can then be combined into a d' measure producing a function that is monotonic as a function of time. I fitted the diffusion expression (Equation 4) to this set of d' values, and the fits are shown in Table 7 along with the recovered parameter values. It is important to note that the d' from the mixture of regular and guesses

Table 7
d′ Computed From a Mixture of Regular Processes and Guesses and Fits of the Diffusion Model Equation

Time (seconds)	Guess Hit	Guess False alarm	Regular Hit	Regular False alarm	d'	d' fit of diffusion equation
.05	.773	.227	.0	.0	1.48	1.46
.10	.817	.167	.016	.0	1.91	1.93
.15	.751	.136	.113	.0	2.16	2.19
.20	.626	.117	.256	.001	2.35	2.36
.25	.504	.103	.390	.003	2.47	2.48
.30	.405	.093	.497	.005	2.57	2.58
.35	.328	.084	.580	.008	2.64	2.64
.40	.270	.076	.644	.010	2.72	2.70
.45	.225	.070	.692	.013	2.77	2.75
.50	.191	.064	.730	.015	2.81	2.79

Note. The parameters of the fit of the diffusion model equation are as follows: T_{er} = 7.6 ms, v = 159.9 ms, d'_a = 3.20. The parameters of the diffusion model leading to the accuracy of guesses and regular processes are as follows: $T_{er} = 0$, $v = s^2/\eta^2$ = 197 ms, d'_a = 3.33. The criteria are set at z = .1 and a = .2, mean drift rates are u = .3 and v = −.3, and the variance parameters are set at values used in Ratcliff (1978), s = .08 and η = .18. This example assumes only one diffusion process, not multiple processes in parallel.

and the d' function from the diffusion process without boundaries mimic each other closely and that the recovered parameter values are close. This means that the diffusion expression (Equation 4) accurately describes the growth of accuracy for two versions of the model: (a) when the diffusion process boundaries are nonexistent and accuracy is based on the position of the process relative to some criterion, and (b) when the diffusion process has boundaries and accuracy is a mixture of regular processes and guesses.

Cascade Model

Meyer et al. (1988) argued that the cascade model of McClelland (1979) is inconsistent with the results from their experiments. In addition, Ashby (1982) has shown that the predictions of the cascade model for reaction time distributions do not fit experimental data adequately (but see Meyer et al., 1985, footnote 33) and that the model allows a proportion of processes to never reach the response criterion. The central feature of the cascade model that is responsible for all of these problems is the lack of a stochastic component (i.e., there is no source of noise in the model). For example, the probability of making a particular response is determined by a ratio of activations of the competing alternatives (using Luce's choice model; Luce, 1959). Also, the model cannot legitimately produce predictions for d' because there is no variance component in the model (the same is also true of McClelland & Rumelhart, 1981, but not true of the more recent model, McClelland & Rumelhart, 1985). To address this problem, it is necessary to introduce a noise component into the model. For example, McClelland (personal communication, March 1985) has suggested allowing each node to pass along activation with some probability within a time slice. This would allow activation to grow stochastically and would also overcome some of the problems raised by Ashby. In fact, processes of this kind with decision rules using response boundaries may mimic the discrete random walk. Another alternative is to use the activation function produced by the cascade model as the drift rate in a diffusion model (Ratcliff, 1980; see also Heath, 1981). In this way the continuous nature of the process is maintained and the combined model would produce noise in the decision (errors) and allow the kinds of data produced by Meyer et al. (1988) and Experiment 1 here to be at least qualitatively fitted.

Conclusions

The method that Meyer et al. (1988) have developed is important to cognitive psychology. With their method it is possible to extract the accuracy of responses based on information gathered prior to a decision. Although some of the results to date are consistent with several discrete models, these models are post hoc in their construction. However, the results provide important qualitative and quantitative support for some members of the class of stochastic sequential sampling models.

References

Ashby, F. G. (1982). Deriving exact prediction from the cascade model. *Psychological Review, 89,* 599–607.
Audley, R. J. (1960). A stochastic model for individual choice behavior. *Psychological Review, 67,* 1–15.
Cox, D. R., & Miller, H. D. (1965). *The theory of stochastic processes.* London: Methuen.
Crowder, R. G. (1976). *Principles of learning and memory.* Hillsdale, NJ: Erlbaum.
Dosher, B. A. (1979). Empirical approaches to information processing: Speed–accuracy tradeoff or reaction time. *Acta Psychologica, 43,* 347–359.
Dosher, B. A. (1981). The effect of delay and interference: A speed–accuracy study. *Cognitive Psychology, 13,* 551–582.
Dosher, B. A. (1984). Discriminating pre-experimental (semantic) from learned (episodic) associations: A speed–accuracy study. *Cognitive Psychology, 16,* 519–555.
Feller, W. (1968). *An introduction to probability theory and its applications* (3rd ed.). New York: Wiley.
Gillund, G., & Shiffrin, R. M. (1984). A retrieval model for both recognition and recall. *Psychological Review, 91,* 1–65.
Heath, R. A. (1981). A tandem random walk model for psychological

discrimination. *British Journal of Mathematical and Statistical Psychology, 34,* 76–92.
Hockley, W. E. (1982). Retrieval processes in continuous recognition. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 8,* 497–512.
Kounios, J., Osman, A. M., & Meyer, D. E. (1987). Structure and process semantic memory: New evidence based on speed–accuracy decomposition. *Journal of Experimental Psychology: General, 116,* 3–25.
LaBerge, D. A. (1962). A recruitment theory of simple behavior. *Psychometrika, 27,* 375–396.
Laming, D. (1968). *Information theory of choice reaction time.* New York: Wiley.
Link, S. W., & Heath, R. A. (1975). A sequential theory of psychological discrimination. *Psychometrika, 40,* 77–105.
Lockhart, R. S., & Murdock, B. B., Jr. (1970). Memory and the theory of signal detection. *Psychological Bulletin, 74,* 100–109.
Luce, R. D. (1959). *Individual choice behavior.* New York: Wiley.
McClelland, J. L. (1979). On the time relations of mental processes: An examination of systems of processes in cascade. *Psychological Review, 86,* 287–330.
McClelland, J. L., & Rumelhart, D. E. (1981). An interactive activation model of context effects in letter perception: Part 1. An account of basic findings. *Psychological Review, 88,* 375–407.
McClelland, J. L., & Rumelhart, D. E. (1985). Distributed memory and the representation of general and specific information. *Journal of Experimental Psychology: General, 114,* 159–188.
Meyer, D. E., & Irwin, D. E. (1981, November). On the time-course of rapid information processing. Paper presented at the meeting of the Psychonomic Society, Philadelphia. [Available as Technical Report No. 43, Michigan Cognitive Science Program, June, 1982.]
Meyer, D. E., Irwin, D. E., Osman, A. M., & Kounios, J. (1988). The dynamics of cognition and action: Mental processes inferred from speed–accuracy decomposition. *Psychological Review, 95,* 183–237.
Meyer, D. E., Yantis, S., Osman, A. M., & Smith, J. E. K. (1985). Temporal properties of human information processing: Tests of discrete versus continuous models. *Cognitive Psychology, 17,* 445–518.
Murdock, B. B., Jr. (1974). *Human memory: theory and data.* Potomac, MD: Erlbaum.
Murdock, B. B., Jr., & Anderson, R. E. (1975). Encoding, storage and retrieval of item information. In R. L. Solso (Ed.), *Theories in cognitive psychology: The Loyola symposium* (pp. 145–194). Hillsdale, NJ: Erlbaum.
Nelder, J. A., & Mead, R. (1965). A SIMPLEX method for function minimization. *Computer Journal, 7,* 308–313.
Ollman, R. T., & Billington, M. J. (1972). The deadline model for simple reaction times. *Cognitive Psychology, 3,* 311–336.
Pike, A. R. (1973). Response latency models for signal detection. *Psychological Review, 80,* 53–68.
Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review, 85,* 59–108.
Ratcliff, R. (1979). Group reaction time distributions and an analysis of distribution statistics. *Psychological Bulletin, 86,* 446–461.
Ratcliff, R. (1980). A note on modeling accumulation of information when the rate of accumulation changes over time. *Journal of Mathematical Psychology, 21,* 178–184.
Ratcliff, R. (1981). A theory of order relations in perceptual matching. *Psychological Review, 88,* 552–572.
Ratcliff, R. (1985). Theoretical interpretations of the speed and accuracy of positive and negative responses. *Psychological Review, 92,* 212–225.
Ratcliff, R., & Iverson, G. J. (1984, August). Computer intensive methods for examining parameter spaces of reaction time models. Paper presented at the annual meeting of the Society for Mathematical Psychology, Chicago.
Ratcliff, R., & McKoon, G. (1982). Speed and accuracy in the processing of false statements about semantic information. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 8,* 16–36.
Ratcliff, R., & Murdock, B. B., Jr. (1976). Retrieval processes in recognition memory. *Psychological Review, 83,* 190–214.
Reed, A. V. (1973). Speed–accuracy trade-off in recognition memory. *Science, 181,* 574–576.
Reed, A. V. (1976). List length and the time course of recognition in immediate memory. *Memory & Cognition, 4,* 16–30.
Sternberg, S. (1966). High-speed scanning in human memory. *Science, 153,* 652–654.
Sternberg, S. (1969). The discovery of processing stages: Extensions of Donders' method. In W. G. Koster (Ed.), *Attention and performance II* (pp. 276–315). Amsterdam: North-Holland.
Vickers, D., Caudrey, D., & Willson, R. J. (1971). Discriminating between the frequency of occurrence of two alternative events. *Acta Psychologica, 35,* 151–172.
Yantis, S., & Meyer, D. E. (1985). Dynamics of spreading activation in information processing. Paper presented at the annual meeting of the Psychonomic Society, Boston.

Appendix A

The Race Model and Guess Reaction Time Distribution

The derivation presented here outlines that presented in Meyer et al. (1988). The aim is to use the signal reaction time distribution and the regular trial reaction time distribution to extract the distribution of guesses. The race model assumes that responses on signal trials are composed of a probability mixture of fast-finishing regular trials and guesses. Thus, the response time on a signal trial is the minimum of the time taken on a regular trial and the time taken for a guess. If the two processes are independent, $t_s = \min(t_r, t_g)$. This can be rewritten as

$$Pr(t_s > T) = Pr(t_r > T)Pr(t_g > T) \qquad \text{(A1)}$$

because if time t is greater than some time T for a signal trial, then the individual times for regular responses and guesses must also be greater than T. Given that $Pr(t > C) = 1 - F(C)$ (where $F(C)$ is the cumulative distribution function), it is possible to substitute in Equation A1 and obtain

$$F_g(C) = (F_s(C) - F_r(C))/(1 - F_r(C)). \qquad \text{(A2)}$$

In performing the calculations leading to the estimates of the guessing cumulative distribution function, it is assumed that the guessing distribution is the same for responses independent of the stimuli, so that correct and error responses are combined. Thus, Equation A2 represents two equations, one for "yes" responses and another for "no" responses. Once the guessing distribution is obtained, the accuracy of the guesses can be obtained, as outlined in Appendix B.

Appendix B

Derivation of Guessing Accuracy

Again the derivation follows Meyer et al. (1988). As noted in the body of the text, there are three ways a positive response can occur. It can occur as the result of (a) both regular processes and guesses producing a positive decision; (b) a regular process producing a positive decision and a guess producing a negative decision, with the regular decision faster than the guess; and (c) a guess producing a positive decision and a regular response producing a negative decision, with the guess faster than the regular process. For a particular stimulus type (e.g., positive) we can write the probability that a positive response is made:

$$p_1^* = p_1 p_{1g} + p_1(1 - p_{1g})P_a + (1 - p_1)p_{1g}P_b, \quad \text{(B1)}$$

where the subscript 1 denotes a positive response (substitute 2 for a negative response), g refers to a guess, the asterisk refers to a signal trial response, and $P_a = P(t_1 < t_{2g})$ and $P_b = P(t_{1g} < t_2)$ where the absence of a g subscript refers to a regular process, and t_g is the time for a guess. Rewriting Equation B1 leads to

$$p_{1g} = (p_1^* - p_1P_a)/(p_1(1 - P_a) + p_2P_b), \quad \text{(B2)}$$

where p_1 is the probability of a hit on regular trials, p_2 is the accuracy of correct rejections on regular trials, and p_1^* is the accuracy of signal trial hits. All the quantities on the right side of the equation are derivable from the data. Note again that all the quantities are conditioned on one stimulus type (e.g., 1 denotes positive, thus p_{1g} refers to hits; if the negative stimulus type was used, p_{1g} would refer to false alarms). For more details see Meyer et al. (1988).

Appendix C

Predictions for Partial Information for Parallel Diffusion Processes

There is a complication in moving from the predictions for a single diffusion process to the predictions for several diffusion processes in parallel (exhaustive on negative termination, self-terminating on positive termination; see Ratcliff, 1978). There are two factors to be considered: First, it is necessary to consider all combinations of processes not yet terminated when the processes that have terminated have terminated with negative decisions. Second, the results have to be conditioned on no previous positive termination since a positive termination results in a response. Thus for a "yes" decision, the quantity to be calculated is *Pr*(one or more processes above the criterion and one or more diffusion processes not terminated and none have previously terminated at the positive boundary). For false alarms, this can be written as

$$\sum_{r=1}^{i} (r!(i-r)!/i!)p^{r-1}(1-p)^{i-r}(1-(1-y)^r)w^{i-r} \quad \text{(C1)}$$

where i is the number of processes left in the comparison, p is the probability that a process is still left in the diffusion process, y is the probability that a single process is above the criterion, and w is the probability that any process has terminated previously at the positive boundary. The quantities r and p are derived from the generalization of Equation 1, and w is derived from the expressions in Ratcliff (1978) for regular processes.

For hits there are two terms similar to those above, one representing the case in which the match comparison has not terminated and one in which it has terminated earlier with a negative decision:

$$\sum_{r=1}^{i-1} (r!(i-r-1)!/(i-1)!)p^r(1-p)^{i-r-1} \times (1-ph)(1-(1-y)^r)w^{i-r-1}wh + \sum_{r=1}^{i-1} (r!(i-r-1)!/(i-1)!)p^r(1-p)^{i-r-1}ph \times (1-(1-y)^r(1-yh))w^{i-r}, \quad \text{(C2)}$$

where ph and wh are parameters for the positive comparison that are equivalent to p and w. Note, to calculate accuracy for d' calculations it is necessary to conditionalize on (i.e., divide the Expression C2 by) the total number of processes still not yet terminated. This is done in Expression C2 by dropping the terms in y and yh and leaving the terms in w and p (and wh and ph). A check on this last expression can be made by setting y equal to yh and p equal to ph. The result is expression C1.

Received April 24, 1986
Revision received September 17, 1987
Accepted September 23, 1987 ■

Correction to Kosslyn

In the article "Seeing and Imagining in the Cerebral Hemispheres: A Computational Approach" by Stephen M. Kosslyn (*Psychological Review,* 1987, Vol. 94, No. 2, 148–175), an error in wording appeared on page 165. In column 1, paragraph 3, the second sentence should read as follows: "Taylor and Warrington (1973), Warrington and Rabin (1970), and Hannay, Varney, and Benton (1976) all found that right-hemisphere damage disrupts dot localization more than left-hemisphere damage does."