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# Levels of Selective Attention Revealed Through Analyses of Response Time Distributions

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The present research examines the nature of the interference effects in a number of selective attention tasks. All of these tasks result in interference in performance by presenting information that is irrelevant to task performance but competes for selection. The interference from this competing information slows the response time (RT) of participants relative to a condition where the competition is minimized. The authors use a convolution of an exponential and a Gaussian (ex-Gaussian) distribution to examine the influence of interference on the characteristics of RT distributions. Consistent with previous research, the authors show that interference in the Stroop task is reflected by both the Gaussian and exponential portions of the ex-Gaussian. In contrast, in 4 experiments they show that several other interference tasks evidence interference that is reflected only in the Gaussian portion of the ex-Gaussian distribution. The authors suggest that these differences reflect the operation of different selection mechanisms, and they examine how sequential sampling models accommodate these effects.



A common method for examining the operation of selective attention is to present individuals with competing sources of information and require these individuals to respond to one information source and ignore other, ostensibly irrelevant information. A prototypical example of this is the Stroop task (Stroop, 1935). In the Stroop task, individuals are instructed to ignore the identity of the word and simply name the color in which the word is displayed. In the incongruent condition, the identity of the word (e.g., blue) conflicts with the to-be-named color (e.g., RED), resulting in a slowing of the response time (RT) of individuals to name the color of the word, relative to the situation where the word presents little conflicting information (e.g., dog). This interference when the color and word mismatch is called the *Stroop effect,* and it would be an understatement to say that an enormous amount of theoretical and empirical work has focused on the mechanisms that underlie this effect (see MacLeod, 1991, for a review).

The present research is concerned with the nature of the interference effects that are usually indexed by measures of mean or median RT. Using a method for characterizing RT distributions, we examine how interference influences the RT distribution and whether such influences depend on the type of interfering information. We pursue this question in four steps. First, we introduce the method for modeling RT distributions and the motivation behind this approach. Second, we discuss some preliminary results of the application of this analytic method to performance from two selection tasks. Third, we present the results of several experiments that indicate that competition in spatial and nonspatial selective attention tasks differentially influence the shapes of RT distributions. Fourth and finally, we examine how the results of the experiments might be accommodated within the class of sequential sampling models.

## Response Time Distributions

Cognitive psychologists have relied very heavily on RT as the primary or sole dependent measure in behavioral studies. In most studies, researchers collect a number of observations within a condition and then collapse that sample of RTs into a single number, typically a measure of central tendency such as mean RT. The difficulty is that when analyses are limited to measures of central tendency, it is difficult to

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specify how the experimental manipulation influences RT. As shown in Figure 1, it is possible for a manipulation to increase mean RT either by increasing the skew of the RT distribution or by shifting the RT distribution. Moreover, it is possible that RTs may be affected by experimental manipulations but have no obvious effect on the mean RT (Figure 1, bottom panel). Indeed, there is growing interest in the possibility that theoretically interesting aspects of RT data are not captured in these measures of central tendency (Heathcote, Popiel, & Mewhort, 1991; Hockley, 1984; Ratcliff, 1978, 1979; Spieler, Balota, & Faust, 1996). The present research follows the approach that others have taken by fitting a mathematical function to empirical RT distributions to quantify characteristics of the entire RT distribution (e.g., Logan, 1992; Ratcliff, 1978). Analyses of response time distributions have been influential in some areas of experimental psychology, and one point that we emphasize is that considering the insights offered by analyses of RT distributions, these analyses deserve considerably broader usage than is currently the case.

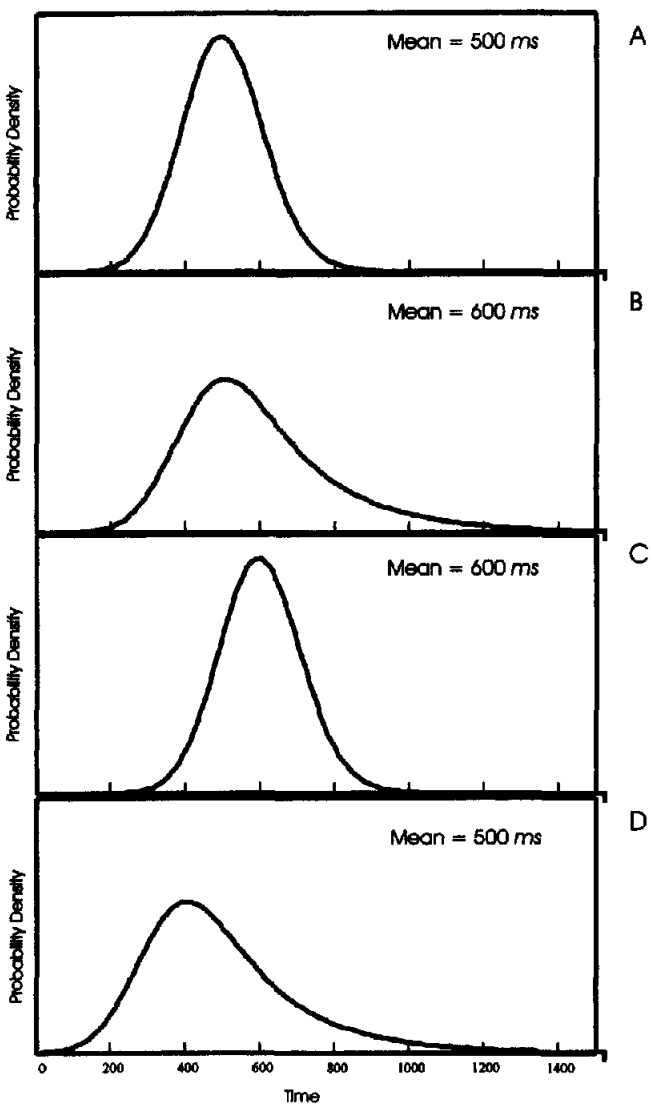


*Figure 1.* Equivalent changes in mean RT that arise either from increases in the skewing of the RT distribution (B) or a shift of the RT distribution (C), and offsetting effects (D).

In fitting an explicit mathematical function to empirical data, we obtain parameter estimates that characterize the shape of the empirical RT distribution. The convolution of a Gaussian and an exponential distribution called the *ex-Gaussian distribution* has been shown to yield a good fit to empirical RT distributions in a wide range of tasks and conditions (Heathcote et al., 1991; Hockley, 1984; Hohle, 1965; Luce, 1986; Ratcliff, 1978, 1979; Ratcliff & Murdock, 1976; Spieler et al., 1996). In fitting the ex-Gaussian distribution to an empirical RT distribution, one obtains estimates of three parameters: $\mu$, which reflects the mean of the Gaussian component of the distribution; $\sigma$, which reflects the standard deviation associated with the Gaussian component; and $\tau$, which reflects the mean and standard deviation of the exponential component. The mean of the ex-Gaussian distribution is simply $\mu$ plus $\tau$. The ex-Gaussian analysis offers a parsimonious way of characterizing the influence of factors on RT distributions. If an experimental manipulation increases mean RT, then the ex-Gaussian analysis allows one to see whether this effect arises from a shift of the RT distribution (a change in $\mu$; see Figure 1A and C), an increase in the tail of the RT distribution (a change in $\tau$; see Figure 1B) or both.

One of the original motivations for using the ex-Gaussian was the notion that different types of cognitive processes were reflected by the parameters of the ex-Gaussian. Hohle (1965) suggested that processes that lie on the input and output ends of processing are reflected by the Gaussian component, whereas more central, decision related processes are reflected in the exponential component of the distribution. Although there are several reasons to be skeptical of this claim (see Luce, 1986, for discussion), the notion that the parameters of the ex-Gaussian may be differentially sensitive to particular types of cognitive operations is certainly appealing. Indeed, it may be the case the parameters of the ex-Gaussian reflect theoretically meaningful components of the empirical RT distribution. Such a possibility is suggested by the finding that an experimental manipulation may consistently influence only one or two of the parameters of the ex-Gaussian (Balota & Spieler, 1999; Hockley, 1984; Spieler, 1998; Spieler et al., 1996). For example, there is evidence that certain factors in word recognition selectively influence parameters of the ex-Gaussian distribution (Balota & Spieler, 1999; Spieler, 1998). We (Balota & Spieler, 1999) have also shown that the word frequency by repetition interaction in the lexical decision task is entirely due to changes in the exponential component of the RT distribution.

At this juncture, it is important to sound several notes of caution. First, our present use of the ex-Gaussian distribution should not be interpreted as a claim that RTs are formed from the sum of an exponential and Gaussian random variables (the strict interpretation of the ex-Gaussian). Moreover, we think that it is highly unlikely that it will be possible to establish any one to one mapping of cognitive

processes to parameters of the ex-Gaussian (e.g., pattern recognition = Gaussian, response selection = exponential). Instead, we use the ex-Gaussian distribution because of the success that researchers have had in fitting the ex-Gaussian distribution to RT data in a wide variety of experimental contexts. The ex-Gaussian alone no more constitutes a theory of processing than does fitting a function in linear regression. However, fitting functions in both cases provides important insights by revealing regularities in the structure of the empirical data that in turn can guide and constrain theories of underlying cognitive processes. In this sense, the ex-Gaussian provides a language for describing the influence of experimental factors on components of RT distributions. We argue that this analytic method has provided some intriguing results in analyses of RT distributions in selective attention tasks. It is to the results that we now turn.

## Selective Attention and RT Distributions

As noted earlier, the Stroop task is a prototypical task for examining competition in the selection process. When the task is to name the color in which a word is displayed, individuals' RT for color naming is slowed when the color and word name nonmatching colors relative to a neutral condition in which the word may name a color unrelated word (e.g., dog). In an application of the ex-Gaussian analysis to data from the Stroop task, Heathcote et al. (1991) found the effect of interference evidenced in mean RT reflected as change in both the $\mu$ (60 ms) and $\tau$ (40 ms) parameters (estimated from Heathcote et al., 1991, p. 343). In these analyses, $\sigma$ also increased, although, because this is symmetric variability, this increase is not reflected in the mean RT. The pattern of interference in both $\mu$ and $\tau$ has also been replicated several times in our laboratories (e.g., see Spieler et al., 1996; Figure 2). This pattern indicates that the increase in mean RT when the color and word conflict is a reflection of a distribution that is both shifted and more skewed.[1]

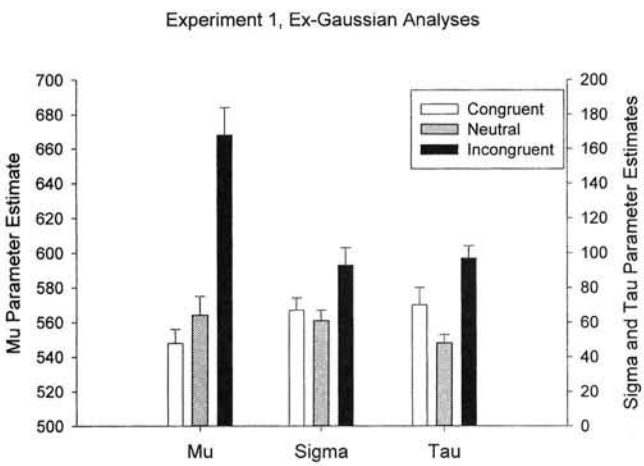


*Figure 2.* Mean ex-Gaussian parameter estimates from the Stroop task of Experiment 1 as a function of condition. Error bars represent one standard error.

The studies by Heathcote et al. and Spieler et al. have also shown that the effects in $\mu$ and $\tau$ can move in opposite directions (e.g., Figure 1, bottom panel). When the word and the color information match, there is facilitation that shifts the distribution (reflected by $\mu$) but this is accompanied by an increase in the tail of the distribution (reflected by $\tau$). Interestingly, in the literature on the Stroop task, it is not uncommon for there to be failures to find reliable facilitation in the congruent condition relative to the neutral condition (MacLeod, 1991). On the basis of the ex-Gaussian analysis, this appears to be due to the mixture of facilitation in $\mu$ and interference in $\tau$. Because the mean RT is simply $\mu$ plus $\tau$, effects that are in the opposite direction in these two parameters will tend to offset each other. Thus, in this case, the distributional analysis has not only provided more detailed information about the nature of effects that have already been identified in mean RT, it has also revealed effects that have been overlooked in analyses of mean RT. Present accounts for the opposite effects in $\mu$ and $\tau$ are at best, ad hoc, although in the General Discussion we discuss a possible mechanism that might account for this opposition.

Central to the purpose of the present article, there is evidence that the pattern of interference effects reflected in the parameters of the ex-Gaussian is different across tasks. This was shown using the local/global task (e.g., Navon, 1977). This task uses a display where a large letter is made from multiple smaller letters. The participant's task is to respond to the letter at one level while ignoring the identity of the letter(s) at the other level. Thus, the letter *H* may be formed from many small *S*s, and the participant's task is to make a button press to the local (small) letter while ignoring the global (large) letter. Navon (1977) showed that there was interference from the global letter information when individuals were to respond to the identity of the local letter (but see Kinchla & Wolfe, 1979; Martin, 1979). Mewhort, Braun, and Heathcote (1992) reported the results of an experiment showing that interference in a local/global task is reflected by increases only in the Gaussian parameters in contrast to both the Gaussian and exponential parameters for the Stroop task. Thus, interference in this task is evidenced primarily as a shift of the RT distribution.

These results indicate that the ex-Gaussian can reveal task-dependent changes in the nature of RT distributions (see also Hockley, 1984). This finding suggests that analyses of RT distributions might inform theories of selective attention to the extent that different influences on RT distributions reflect the operation of different processes. Of course, a substantial number of studies have used these tasks to examine the operation of selective attention and to explore neural substrates of attention (e.g., Pardo, Pardo, Janer, & Raichle, 1990; Perret, 1974; Robertson, Lamb, & Knight, 1988, 1991). These studies provide evidence that the selection mechanisms differ in these two tasks. In particular,

[1] Skew in the ex-Gaussian distribution is a function of both $\sigma$ and $\tau$, so although $\tau$ is correlated with skew, it is important not to interpret $\tau$ as a pure measure of skew.

the spatial information important in local/global task appears to rely more on posterior visual areas, whereas the Stroop task has traditionally been seen as a task with greater frontal involvement. In light of this, it is perhaps not surprising that the operation of different selection mechanisms might be revealed in analyses of RT distributions. Beyond this, if we can establish that different selection processes have different influences on characteristics of the RT distribution, the results of the distributional analyses will strongly constrain computational accounts of these processes and how information competes for selection.

In the studies that follow, we examine the possibility that the effect of interference on RT distributions reveals the operation of distinct selection mechanisms and go on to show how such results can constrain theoretical accounts of selection. We start with a replication of the initial results from the Stroop and local/global tasks. These replications are important because of the relatively small number of studies that have applied analyses of RT distributions to performance in selective attention tasks. At present we have little information about the replicability of these results, nor do we know how sensitive the ex-Gaussian analysis is to incidental variations in experimental context, stimuli, and participants. Thus, as a first step in this exploration, we begin with replications of the two critical empirical results by applying the ex-Gaussian analysis to performance in a standard Stroop task (Experiment 1) and a local/global task (Experiment 2).

## Experiment 1

The application of the ex-Gaussian analysis to Stroop task performance has revealed a relatively complex pattern of results. Stroop interference is evidenced as an increase in all three of the ex-Gaussian parameters in the incongruent condition relative to the neutral condition. In contrast, the congruent condition exhibited a decrease in $\mu$, an increase in $\tau$, and little effect on $\sigma$.

The present experiment has a somewhat different methodology from the experiment by Spieler et al. (1996) and Heathcote et al. (1991). One of the purposes of this is to verify that the subtle pattern of data revealed by the ex-Gaussian analysis is not dependent on incidental aspects of the experimental design. The mean RT results of this experiment were reported in Kanne, Balota, Spieler, and Faust (1998).

### Method

*Participants.* Twenty adult participants (mean age = 19.5 years; $SD = 2.0$) were recruited from the undergraduate student population at Washington University and were paid $5 for their participation.

*Apparatus.* Stimuli were presented on a 14-in. NEC Multisynch 2A VGA computer monitor with scan rate of 60 Hz interfaced with a CompuAdd 386 IBM compatible computer that controlled stimulus presentation and timing. The timing was accomplished using custom developed software routines that set the 8253 chip to generate 1 ms pulses used for timing all events. The presentation of stimuli was synchronized with the vertical raster of the monitor so that the display duration of all stimuli was a multiple of the 16.67 ms scan duration. Vocal RT was measured using a Gebrands 1341T voice-operated relay interfaced via the parallel port of the computer.

*Materials.* The stimuli consisted of four color names (*red, green, blue,* and *yellow*) and the corresponding colors. The neutral condition was a row of Xs. The colors were the VGA colors 1, 2, 4, and 14. The stimuli were presented in 40 column DOS text mode and subtended 1.5 to 3 degrees of visual angle. All stimuli were presented against a black background.

There was a word-naming and a color-naming block of trials, and the order of the blocks was counterbalanced across participants. Within each block, there were 48 congruent trials (4 colors and corresponding color names × 12 presentations); 48 incongruent trials (4 colors × 3 nonmatching color names × 4 presentations); and 48 neutral trials (4 colors × 12 presentations). The same congruent and incongruent stimuli were used in the word-reading and color-naming blocks. In the color-naming block, the neutral condition consisted of a row of four Xs displayed in one of the four colors. In the word-naming block, the words were color names presented in white on a black background. The logic used in selecting these neutral conditions was to minimize the influence of any distracting information in the irrelevant dimension as much as possible. The presentation was randomized within a block of trials with the restriction that no word or color could be repeated more than twice on consecutive trials. A different random ordering of trials was presented for each block of trials and for each participant.

*Procedure.* At the beginning of the experimental session, participants were provided with the directions for the first block of trials, and any questions that they might have regarding the experimental procedure were answered. Participants then saw 12 practice trials with congruent, incongruent, and neutral conditions present in equal proportions. The stimuli and the timing were identical to those used in the experimental session. The experimenter remained in the testing room with the participant throughout the experimental session.

On each trial, the following sequence of events occurred: (a) a white fixation stimulus (+ + +) appeared in the center of the computer screen for 700 ms; (b) the screen was blank for 50 ms; and (c) the test stimulus appeared centered on the position previously occupied by the fixation and remained on the computer screen until the onset of the participant's response. Response time was always measured from the reset of the vertical raster of the monitor marking the start of the scan that displayed the stimulus until the onset of the participant's response. The display of the stimulus was terminated at the screen refresh immediately following the onset of the participant's response. After the voicekey was triggered, the screen was cleared and the experimenter coded the participant's response. The experimenter pressed one key to signify a correct response and three other keys to code the type of error. The error types were: voicekey errors in which the voicekey either was not triggered by the onset of the individual's response or was triggered by a false start, stutter, or other extraneous noise; intrusion errors in which the participant responded to the incorrect dimension of the stimulus (e.g., reading the word when the task is to name the color); and an incorrect response that was not an intrusion error. When the experimenter pressed the key coding the response, there was a 1,750 ms intertrial interval before the start of the next trial. Participants were given breaks every 24 trials.

### Results

The RTs for those trials marked as errors were eliminated from all RT analyses. In addition, RTs that fell below 200 ms

or 3 standard deviations (*SD*s) below the condition mean or above 2,000 ms or 3 *SD*s above the condition mean were eliminated from all RT analyses. Using these trimming criteria, 2.4% of responses were eliminated from the analyses.

*Mean RT analyses.* As shown in Table 1, word naming was much faster than color naming. In the color-naming block, there appeared to be a large interference effect in the incongruent versus the neutral condition but no facilitation in the congruent condition relative to the neutral condition. On the other hand, there appeared to be very small differences between conditions in word naming. The absence of facilitation in the color-naming congruent condition was surprising, although it is generally the case that the facilitation effects in the Stroop task are smaller than the interference effects (see MacLeod, 1991), and it may be the case that the neutral condition in this experiment was particularly fast because it included virtually no interfering lexical information.

Unless otherwise noted, all statistics reported in this article are significant at the .05 level. The mean RT data were analyzed in a 2 (task) × 3 (condition) repeated measures analysis of variance (ANOVA). There were main effects of task, $F(1, 23) = 276$, $MSE = 4{,}234$, and condition, $F(2, 46) = 177$, $MSE = 552$. There was a Task × Condition interaction, $F(2, 46) = 124$, $MSE = 655$, that reflected the larger difference across conditions in the color-naming than in the word-reading block. There was an effect of condition on word naming, $F(2, 46) = 7.04$, $MSE = 62$. Although small, the interference effect in word naming was reliable, $F(1, 23) = 7.31$, $MSE = 51$, but the facilitation effect was not, $F(1, 23) = 1.19$, $MSE = 82$, $p > .10$, relative to the neutral condition. Turning our attention to the analyses of color-naming performance, as expected there was a main effect of condition, $F(2, 46) = 155.94$, $MSE = 1{,}144$. There was reliable interference, $F(1, 23) = 258$, $MSE = 1{,}087$, but no facilitation, $F(1, 23) < 1$.

*Error analyses.* Error rates were too low to allow statistical analyses. As reported in Table 1, there were more errors in the incongruent condition than in the neutral and congruent conditions.

*Ex-Gaussian analyses.* One of the primary advantages of using the ex-Gaussian analysis is that considerably fewer numbers of observations are required to capture the shape of the distribution than would be required to use the higher order moments (e.g., skew and kurtosis). Nonetheless, at least 100 observations per distribution are typically needed to fit the ex-Gaussian to empirical data (Ratcliff, 1979). When the number of observations per condition falls short of the number needed, a method for averaging across participants to create super-subjects, called *Vincentizing,* can be used. This method involves rank ordering the RTs for each condition for each participant and computing quantiles (e.g., fastest 10%, next fastest 10%, etc.). These quantiles can then be averaged across a number of participants, resulting in a smoothing of the RT distribution. In the present analyses, 20 quantiles were averaged across 3 participants to create a single super-subject.[2] Ex-Gaussian parameter estimates were obtained using the RTSYS software package (Heathcote, 1993). This software uses the Simplex algorithm (see Press, Teukolsky, Vetterling, & Flannery, 1992) to obtain maximum likelihood estimates of the three ex-Gaussian parameters. We evaluated goodness of fit by computing chi-square values for each distribution. There were a total of 8 super-subjects. Of the 24 distributions fit, none of the chi-squares were significant at the .01 level.

For the present analyses, we limit our attention to the color-naming performance. As shown in Figure 2, we replicated the results of Heathcote et al. (1991) and Spieler et al. (1996). Specifically, relative to the neutral condition, there was an increase in $\mu$, $\sigma$, and $\tau$ in the incongruent condition and an increase in $\tau$ and a decrease in $\mu$ in the congruent condition. Separate analyses of each of the three ex-Gaussian parameters confirmed these observations. For all three parameters, there were main effects of Stroop condition, $\mu$, $F(2, 14) = 57.43$, $MSE = 594$; $\sigma$, $F(2, 14) = 7.75$, $MSE = 303$; and $\tau$, $F(2, 14) = 14.13$, $MSE = 349$. Interference effects were evidenced by increases in all three of the ex-Gaussian parameters in the incongruent relative to the neutral condition, $\mu$, $F(1, 7) = 77.97$, $MSE = 561$; $\sigma$, $F(1, 7) = 10.47$, $MSE = 401$; $\tau$, $F(1, 7) = 34.97$, $MSE = 281$. Differences between the congruent and neutral conditions also replicated the pattern of results reported both by Heathcote et al. and Spieler et al. Thus, $\mu$ showed marginal facilitation effects, $F(1, 7) = 3.42$, $MSE = 281$, $p = .10$, and $\sigma$ did not differ in the two conditions $F(1, 7) = 2.09$, $p = .19$. Again, consistent with previous studies, $\tau$ increased in the congruent condition relative to the neutral condition, $F(1, 7) = 5.32$, $MSE = 409$, $p = .05$.

Table 1
*Mean RT and Error Proportions for Experiment 1*

| Condition | Measure | | |
|---|---|---|---|
| | Mean RT | *SD* | Error |
| Color naming | | | |
| Congruent | 619 | 83 | .002 |
| Incongruent | 764 | 96 | .037 |
| Neutral | 612 | 72 | .003 |
| Word reading | | | |
| Congruent | 481 | 61 | .000 |
| Incongruent | 490 | 62 | .001 |
| Neutral | 484 | 66 | .000 |

## *Discussion*

The results of Experiment 1 replicate the pattern of results reported both by Heathcote et al. (1991) and Spieler et al. (1996). Specifically, interference in color naming resulted in an increase in all three of the ex-Gaussian parameters relative to the neutral condition. As has also been reported previously, the congruent condition evidenced opposite

[2] Caution should be exercised anytime one collapses multiple participants into super-subjects. In our analyses, participants are always combined randomly. To ensure that our results did not capitalize on a particular combination of participants, multiple analyses were run in which each used a different combination of super-subjects. In all analyses, the pattern of results are qualitatively identical.

effects in μ and τ. Specifically there was a decrease in the μ parameter in the congruent condition but an increase in τ.

One interpretation of the interference effect observed in τ is that the influence of the word dimension is not consistent across trials. If every trial on which the word and color information mismatched resulted in a constant increase in RT, this would result in a change only in μ. If interference resulted in the addition of some normally distributed amount, then μ and σ may increase but there would be no change in τ. The change in τ in Experiment 1 suggests that on some trials, the interference effect may be small or even nonexistent, whereas on other trials, the interference effect is substantial. The larger interference effects on some trials than on others may occur because individuals occasionally switch attention to or otherwise devote more processing to the word dimension than is typically the case. Interestingly, there is some evidence that other aspects of selective attention may be similarly variable. For example, in dichotic listening tasks, there is some evidence that processing of the unattended channel may occur during periods in which individuals switch their attention to the unattended channel (Dawson & Schell, 1982; Newstead & Dennis, 1979). If the pattern of interference effects in the Stroop task are due to such attentional fluctuations, then the RT distributions are a mixture of performance from two different attentional states. The problem with this account is that, in the absence of some form of overt error, it is difficult to identify such responses. Parsimony favors a single mechanism capable of producing the increase in all three parameters of the ex-Gaussian. In the General Discussion, we return to this issue and suggest that one mechanism may indeed be sufficient to account for the increase in μ, σ, and τ in the incongruent condition.

The pattern of ex-Gaussian parameters in the congruent condition relative to the neutral condition is also intriguing although considerably more complicated. The match between the word and the color dimensions appears to result in facilitation in μ and interference in τ. Such opposing effects in μ and τ present a particular challenge to any modeling approach.

To summarize the results of Experiment 1, we successfully replicated the pattern of Stroop results reported by Heathcote et al. (1991) and Spieler et al. (1996). However, for the analyses of RT distributions to inform us about mechanisms underlying selective attention, we must identify a task that taps potentially different aspects of selective attention and show that interference in this task results in qualitatively different influences on components of the RT distribution. As noted earlier, a study by Mewhort et al. (1992) using local/global figures provided just such evidence. It is to this task that we now turn.

## Experiment 2

Mewhort et al. (1992) reported the results of a local/global figures task that indicated that the effect of interference from the irrelevant dimension was quite different from that observed in the Stroop task. Specifically, interference in this task was evidenced as an increase in the μ and σ parameters of the ex-Gaussian. Thus, these results suggest that interference in this task acts to shift the RT distribution (and increase variability). This experiment is the only demonstration of interference effects solely in the Gaussian component of the ex-Gaussian. To ensure that the results reported by Mewhort et al. are replicable, Experiment 2 applies the ex-Gaussian analysis to local/global task performance.

### Method

*Participants.* Twenty-five adults (mean age = 21.4 years, *SD* = 2.8) were recruited from the undergraduate student population at Washington University and were paid $10 for their participation in a battery of cognitive tasks of which the present task was one.

*Apparatus.* The equipment was identical to that used in Experiment 1 with the exception that button press RTs were used in the present experiment. Individuals made their responses on an IBM PC keyboard by pressing the *Z* key and the / key. These keys were raised approximately 5 mm above the height of the other keys on the keyboard.

*Materials.* On blocks where the participant was to respond to the local dimension, the local letters could be either *H* or *E*, and the global letter could be *E*, *H*, or a neutral *S*, and this was reversed when individuals were instructed to respond to the global dimension. Individuals were required to press one key when an *E* was presented in the relevant dimension and another key when an *H* was presented. There were a total of eight blocks of trials. Four blocks required local responses, and four required global responses. Each block consisted of 48 trials, with 16 trials each for the congruent, incongruent, and neutral conditions. The order of local and global responses was counterbalanced across participants. The order of trials within each block of trials was random with the constraint that there could not be consecutive trials of the same condition. The letters were displayed in Small Font graphics font. The size approximates 40 column text mode displays. The letters were block letters four characters wide and five characters tall. Stimuli were displayed in white on a black background.

*Procedure.* On each trial, the following sequence of events occurred: (a) a fixation consisting of a single plus sign (+) appeared in the center of the screen for 500 ms; (b) the stimulus appeared centered on the position of the initial fixation and remained on the screen until a response or 5,000 ms elapsed; (c) after the participant pressed one of the two buttons for a response, the screen was cleared, and there was a 1,200 ms intertrial interval. RTs were measured from the start of the raster scan that displayed the stimulus until the onset of the participant's button-press response. Participants were given breaks at the end of each block of trials.

### Results

The RTs for those trials where the individual pressed the incorrect button were eliminated from all RT analyses. In addition, RTs that fell below 200 ms or 3 *SD*s below the condition mean or above 2,000 ms or 3 *SD*s above the condition mean were eliminated from all RT analyses. Using these trimming criteria, we eliminated 2.0% of responses from the analyses.

*Mean RT analyses.* The details of the mean RT results and further discussion of these results are presented elsewhere (Faust & Balota, 1998). As shown in Table 2, local responses were somewhat faster than global responses and there was an effect of local information on global responses

Table 2
*Mean RT and Error Proportions for Experiment 2*

| Condition | Measure | | |
|---|---|---|---|
| | Mean RT | *SD* | Error |
| Global responses | | | |
| Congruent | 456 | 51 | .009 |
| Incongruent | 506 | 62 | .053 |
| Neutral | 478 | 55 | .014 |
| Local responses | | | |
| Congruent | 446 | 62 | .009 |
| Incongruent | 461 | 62 | .023 |
| Neutral | 464 | 63 | .012 |

and a much smaller effect of global information on local responses. These observations were confirmed in a 2 (local vs. global) × 3 (congruent, incongruent, and neutral) repeated measures ANOVA. Overall, local responses were faster than global responses, $F(1, 23) = 4.80$, $MSE = 3{,}957$, and there was a reliable effect of congruency, $F(2, 46) = 92.23$, $MSE = 139$. There was also a reliable interaction between level of the response (local or global) and congruency, $F(2, 46) = 22.39$, $MSE = 197$, reflecting the larger effect of congruency for global than for local responses. Congruency influenced responding for local responses, $F(2, 46) = 13.27$, $MSE = 174$, and for global responses, $F(2, 46) = 92.29$, $MSE = 161$. For local responses, there was no difference between the incongruent and neutral conditions, $F(1, 23) = 1.53$, $p > .20$; however, there was facilitation in the congruent condition relative to the neutral condition, $F(1, 23) = 19.12$, $MSE = 216$. Global responses, on the other hand, evidenced both interference, $F(1, 23) = 76.76$, $MSE = 121$, and facilitation, $F(1, 23) = 36.11$, $MSE = 159$.

*Error analyses.* As shown in Table 2, the error rates revealed a pattern of results similar to that observed in the mean RT results. An analysis of error proportions showed that there was a higher error rate for global responses than for local, $F(1, 23) = 15.57$, $MSE = .0003$. There was also an effect of congruency, $F(2, 46) = 36.04$, $MSE = .0003$, and an interaction between level and congruency reflecting the fact that the effect of congruency was larger for global responses than for local responses, $F(2, 46) = 11.90$, $MSE = .0003$.

*Ex-Gaussian analyses.* Super-subjects were created in the same manner as in Experiment 1. The data from three participants were combined to form each super-subject, and chi-square statistics were computed to evaluate the goodness of fit. None of the 48 distributions resulted in chi-square values that were significant at the .01 level. As shown in Figure 3, there were quite sizable effects in $\mu$ and $\sigma$ but much smaller effects in $\tau$. The ex-Gaussian parameters were analyzed in three separate 2 (level) × 3 (congruency) repeated measures ANOVAs. There was a main effect of level in $\mu$, $F(1, 7) = 18.60$, $MSE = 320$, and a marginal effect in $\sigma$, $F(1, 7) = 4.53$, $MSE = 150$, $p = .07$, but not in $\tau$, $F(1, 7) < 1$. Congruency was also significant in $\mu$, $F(2, 14) = 14.14$, $MSE = 160$, and $\sigma$, $F(2, 14) = 6.50$, $MSE = 78$, but not in $\tau$, $F(2, 14) = 1.09$, $p > .20$. The interaction between level and congruency was also significant in $\mu$, $F(2, 14) = 20.42$, $MSE = 106$, and $\sigma$, $F(2, 14) = 5.48$, $MSE = 40$, but not in $\tau$, $F(2, 14) = 1.49$, $p > .20$. These interactions were due to effects of congruency on global responses but not on local responses. For local responses, the effect of congruency was nonsignificant for all three parameters, $Fs < 2.50$, $ps > .10$, whereas for global responses, the effect of congruency was reliable for $\mu$, $F(2, 14) = 24.72$, $MSE = 168$, and $\sigma$, $F(2, 14) = 7.39$, $MSE = 94$, but not for $\tau$, $F(2, 14) < 1$. For the global responses, relative to the neutral condition, $\mu$ and $\sigma$ decreased in the congruent condition, $\mu$, $F(1, 7) = 24.55$, $MSE = 96$; $\sigma$, $F(1, 7) = 7.28$, $MSE = 18$; and increased in the incongruent condition, $\mu$, $F(1, 7) = 7.04$, $MSE = 258$; $\sigma$, $F(1, 7) = 4.33$, $MSE = 145$, $p = .08$. Again, none of these effects were significant in the $\tau$ parameter.

## *Discussion*

Although the initial observation of interference in the local/global task was that global information interferes with local information (Navon, 1977), the pattern of interference in this task has been shown to be sensitive to a variety of display variables (e.g., Martin, 1979). The finding that local responses were made more quickly than global responses suggests that with the particular display parameters used in Experiment 2, local information was more discriminable than global information. This in turn accounts for the fact that local information interfered with global responses but not the reverse.

The most important aspect of these results is that we replicated Mewhort et al.'s (1992) finding that interference effects in the local/global task are reflected only by the Gaussian component of the ex-Gaussian and has little effect on the portion reflected by the exponential component. These results contrast with the results from the Stroop task in Experiment 1 in which interference was evidenced as increases in all three of the ex-Gaussian parameters. Experi-

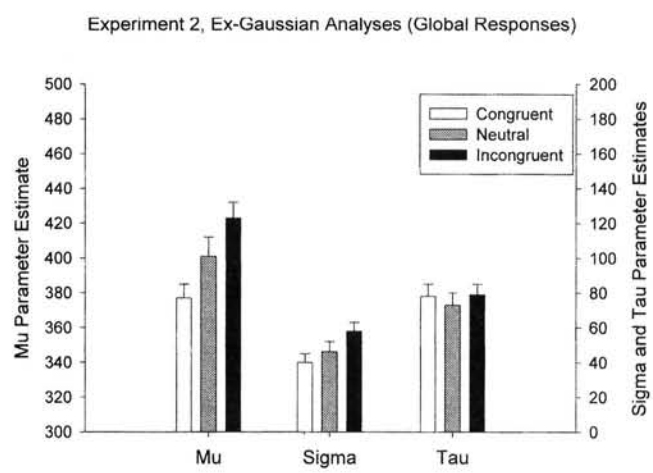


*Figure 3.* Mean ex-Gaussian parameter estimates from the local/global figures task of Experiment 2 as a function of condition. Data are from global judgments. Error bars represent one standard error.

ments 1 and 2 establish that the influence of interference on the parameters of the ex-Gaussian is replicable.

The central question is why interference influences characteristics of the RT distribution differently in these two tasks. The Stroop task and the local/global task differ along a number of dimensions, each of which may influence how interference is reflected in the underlying RT distribution. For example, these two tasks differ in the relation between the relevant and irrelevant dimensions of the stimuli. In the Stroop task, the two dimensions are integrated into a single object and selection is between attributes of this object. For the local/global task, the two dimensions overlap in terms of their spatial position but are less obviously integrated as in the Stroop task. For example, Robertson (1996) argued that hierarchical forms as in the local/global task might be similar to spatially separated stimuli except that instead of being distributed across Euclidean space, the forms are distributed across hierarchical space. The analogy provides some suggestion as to the interpretation of the present results. The perceptual system may process the distracting information in the Stroop task as an attribute of the selected object, whereas distracting information in the local/global task is treated as information from a different object or objects.

There is evidence that the multiple attributes of a single object may be processed differently from the same attributes if associated with different objects. Duncan (1984) showed that individuals are equally adept at reporting either one or two different dimensions of a stimulus provided that the dimensions were part of the same object. In contrast, individuals were poorer at reporting two rather than one dimension of a display if the two dimensions were part of different objects (see also Duncan, 1993; Triesman, Kahneman, & Burkell, 1983). This result was present even when Duncan took into account distance between the two dimensions. These results are consistent with the suggestion of Kahneman and colleagues that multiple attributes of an attended object are processed to a greater extent than the same attributes if associated with multiple objects (Kahneman & Triesman, 1984; Kahneman, Triesman, & Gibbs, 1992; Kramer & Jacobson, 1991; Treisman et al., 1983).

In light of the preceding discussion, it should be possible to identify other selection tasks in which the relevant and irrelevant dimensions are spatially separated. Any interference in such tasks should be evidenced as a change in $\mu$ and $\sigma$ with little effect on $\tau$. To some extent, this suggestion depends on our argument that the relation between dimensions of a stimulus arranged hierarchically is similar to dimensions that are spatially separated (e.g., attributes of different objects). To test this, we next apply the ex-Gaussian analysis to performance in a spatial selection task in which the relevant and irrelevant information is presented in different locations on the display.

## Experiment 3

The first task that we turn to is the flanker task (Eriksen & Eriksen, 1974). If the spatial component to these tasks is important in determining the nature of interference effects, then this leads to an interesting prediction for the flanker task. This task requires individuals to make a simple identification response on the basis of the identity of a central letter in a display. For example, individuals may press one button when a central letter in a display appears (e.g., *H*) and press a different button when another letter appears (e.g., *S*). In the conflict condition, the display typically consists of a central letter requiring one button press and flanking letters associated with a different button press (e.g., *S S H S S*). The conflict between the central letter and the flanking letters slows an individual's response compared with a condition where the flanking letters are mapped onto the same response as the central letter.

In this task, selection may be accomplished by selecting the target location and filtering out the irrelevant locations. If the effect that interference has on the shape of the RT distribution is influenced by whether or not spatial selection can be used, then the ex-Gaussian analysis of the flanker task should reveal results similar to that observed in the local/global task. There is some evidence suggesting this to be the case. Using a memory scanning task in which the targets were sometimes flanked by response compatible or incompatible noise letters, Eriksen, Eriksen, and Hoffman (1986) found that incompatible noise letters appeared to result in a fairly constant increase of approximately 30 ms for all parts of the RT distribution. In the ex-Gaussian analysis, this would translate into an effect primarily in $\mu$. Experiment 3 attempts to verify this by applying the ex-Gaussian analysis to RT performance in a standard flanker task.

### Method

*Participants.* Twenty-four adults participated (age $M = 21.3$ years, $SD = 2.4$). These participants were recruited from the undergraduate student population at Washington University and were paid $10 for their participation in a battery of cognitive tasks of which the present task was one.

*Apparatus.* Equipment was identical to that used in Experiment 2.

*Materials.* The letters used in the present experiment were *H*, *C*, and *S*. The letters *H* and *C* were each mapped to a response, and the letter *S* was the flanker in the neutral condition and was not mapped to any response. Target letters appeared flanked by two letters on each side. There were a total of eight blocks of 48 trials each. As in Experiment 2, the letters were displayed in Small Font graphics font. The order of trials within each block of trials was random with the constraint that there would not be consecutive trials of the same condition. There were a total of 384 trials in the experiment.

In the present experiment, there was a manipulation in addition to the consistency of the targets and the flankers. On half of the trials, the flankers preceded the target by 100 ms, whereas on the other half of the trials, the onset of the targets and the flankers would be simultaneous. There is no theoretical motivation for this manipulation in the present context, so the analyses will be limited to the 0 ms stimulus onset asynchrony (SOA) condition.

*Procedure.* Each trial began with a fixation consisting of a single plus sign (+) appearing at the center of the screen for 500 ms. After the 500 ms had elapsed, the flankers and target appeared on the screen with the central target letter centered at the position of the fixation. The stimuli remained on the screen until a response or 5,000 ms elapsed. After the participant pressed one of the two

buttons for a response, the screen was cleared, and there was a 1,200 ms intertrial interval. Participants were given breaks at the end of each block of 48 trials.

### Results

The RTs for those trials where the individual pressed the incorrect button were eliminated from all RT analyses. In addition, RTs that fell below 200 ms or 3 *SD*s below the condition mean or above 2,000 ms or 3 *SD*s above the condition mean were eliminated from all RT analyses. Using these criteria, 1.7% of responses were eliminated from the analyses.

The mean RT results are shown in Table 3. The more detailed discussion of the mean RT results are presented elsewhere (Faust & Balota, 1998). Note that there appears to be both interference and facilitation effects relative to the neutral condition. A three-way repeated measures ANOVA confirmed these results. There was a main effect of congruency, $F(2, 46) = 100.88$, $MSE = 172$. Relative to the neutral condition, there were both facilitation in the congruent condition, $F(1, 23) = 72.32$, $MSE = 681$, and interference in the incongruent condition, $F(1, 23) = 65.76$, $MSE = 198$.

*Error analyses.* An analysis of error proportions revealed a pattern of results that paralleled the mean RT results. A three-way ANOVA on error proportions revealed a significant effect of congruency, $F(2, 46) = 32.36$, $MSE = .004$.

*Ex-Gaussian analyses.* As in Experiments 1 and 2, we averaged the data across 3 participants to create each super-subject. We assessed the ability of the ex-Gaussian distribution to fit the empirical distributions by computing chi-square statistics for each distribution. Of the total of 24 distributions fit in the present analysis, none resulted in chi-square values that were significant at the .01 value.

As shown in Figure 4, the pattern in $\mu$ and $\sigma$ largely paralleled the results in the mean RT analyses. On the other hand, the only effect evident in the $\tau$ parameter is a decrease in the incongruent relative to the neutral condition. The ex-Gaussian parameter estimates were analyzed in three separate three-way repeated measures ANOVAs. There were main effects of congruency for all three parameters, $\mu$, $F(2, 14) = 58.13$, $MSE = 211$; $\sigma$, $F(2, 14) = 33.22$, $MSE = 73$; and $\tau$, $F(2, 14) = 6.69$, $MSE = 205$. There were reliable differences between the incongruent and neutral conditions in all three parameters, $\mu$, $F(1, 7) = 45.81$, $MSE = 267$; $\sigma$, $F(1, 7) = 57.56$, $MSE = 62$; and $\tau$, $F(1, 7) = 7.14$, $MSE = 285$. Of course, the effect in $\tau$ was in the opposite direction from the effects in $\mu$ and $\sigma$. Of the three parameters, only $\mu$ showed a reliable difference (in the direction of facilitation) between the congruent and neutral conditions, $F(1, 7) = 9.04$, $MSE = 185$.

Table 3
*Mean RT and Error Proportions for Experiment 3*

| Condition | Measure | | |
|---|---|---|---|
| | Mean RT | *SD* | Error |
| Congruent | 460 | 51 | .009 |
| Incongruent | 513 | 53 | .051 |
| Neutral | 480 | 51 | .013 |

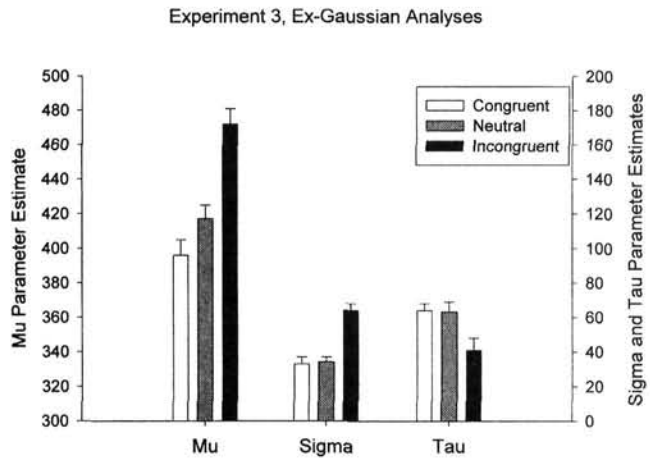


*Figure 4.* Mean ex-Gaussian parameter estimates from the flanker task of Experiment 3 as a function of condition. Error bars represent one standard error.

Thus interference in the flanker task results in a distribution that is shifted up the RT scale (with a concomitant increase in variability) but also becomes somewhat less skewed. This is opposite the effect of interference in the Stroop task.

### Discussion

Experiments 2 and 3 indicate that the influence of competing information in the local/global and flanker tasks are primarily on the component of the RT distribution reflected by the Gaussian parameters of the ex-Gaussian. In contrast to the robust interference effects observed in the $\tau$ parameter in the Stroop task, both the local/global task and the flanker task show either no interference effect in $\tau$ (Experiment 2, local/global task), or an actual reversal of the pattern observed in the $\mu$ estimates (Experiment 3, flanker task).

The results of Experiment 3 provide support for the notion that the difference in interference effects revealed in the ex-Gaussian analysis may reflect the distinction between spatial and attribute selection. However, before pursuing this possibility, there were two possible limitations in Experiment 3 that we address in Experiment 4.

## Experiment 4

The design of the flanker task in Experiment 3 was somewhat different from the original flanker task. Specifically, there was only one letter associated with each of the two responses. Previous studies have typically used at least two letters associated with each response. By pairing two letters to each response, this adds an additional factor to the design, that is, compatibility. On some trials, a participant is presented with flanking letters that are different from the

target but are associated with the same response (compatible), whereas on other trials the flanking letters are associated with a different response (incompatible). Increasing the number of stimuli in the experiment decreases the number of repetitions of specific stimuli and increases the lag between these repetitions. Experiment 4 uses two letters for each of two responses, thereby increasing comparability to other experiments in the literature. This change also makes the number of stimuli in the flanker task equal to that in the Stroop task.

The second issue has to do with the use of Vincentizing to create super-subjects for fitting the RT distributions. We have no a priori reason to believe that this procedure might systematically influence the pattern of interference effects. However, another goal of Experiment 4 was to replicate the effect of flanker interference on parameters of the ex-Gaussian distribution in an experiment that included sufficient observations per participant per condition that it is possible to fit the ex-Gaussian distribution to individual participants.

## Method

*Participants.* Twenty adults were recruited from the undergraduate student population at Washington University. Participants were 19 to 22 years old ($M$ = 19.5, $SD$ = 1.4) and had 13 to 17 years of education ($M$ = 14.2, $SD$ = 1.2). Individuals participated for course credit.

*Apparatus.* The apparatus was identical to that used in Experiments 2 and 3.

*Materials.* Letters were written in a Courier font, and each letter subtended approximately .3 degrees of visual angle. The letters were *C*, *S*, *H*, *K*, and *Y*. All letters were displayed in upper case in white on a black background. The letters were divided into two pairs where one pair (e.g., *C* and *S*) was assigned to the left response key and the other (e.g., *H* and *K*) assigned to the right response key. The assignment of letter pairs to side was counterbalanced across participants. The letter *Y* served as the neutral flanker, and it was not associated with any response. The flanking letters appeared offset to the left and right by 8 pixels or approximately .3 degrees of visual angle.

There are two factors that describe the relation between targets and flankers. First, there is the congruency of the targets and flankers. This refers to whether the targets and flankers are the same (congruent) or different (incongruent). Second, there is the compatibility of the targets and flankers. The targets and flankers may be associated with the same response (compatible) or the opposite response (incompatible). Thus, there are three conditions in the traditional flanker task—congruent-compatible, incongruent-compatible, and incongruent-incompatible—that are compared with the neutral condition. The neutral condition consisted of flankers that were not associated with any response. There were 192 trials in each of the four conditions, giving a total of 768 trials in the experiment and 32 practice trials. The order of trials was randomized for each participant.

*Procedure.* At the beginning of the experiment, participants were given the instructions that included the key mapping (e.g., *C* and *S* mapped to the left key, *H* and *K* mapped to the right key or vice versa). Individuals were told to make their responses as quickly and as accurately as possible.

On each trial, the following sequence of events occurred: (a) a single plus sign appeared in the center of the screen for 500 ms; (b) the screen was blank for 200 ms; (c) the target and flankers appeared and remained on the screen until the participant responded or until 2500 ms had elapsed; and (d) a 1,000 ms intertrial interval was initiated before the start of the next trial. In the event of an error, which was defined as an incorrect button press or 2,500 ms elapsing before the response was made, there was a 700 Hz tone presented for 500 ms and the message ***Error*** was displayed in the center of the screen for 1,000 ms.

Thirty-two practice trials appeared at the beginning of the session. The sequence and timing of events for each trial was the same as in the experimental portion. Breaks were provided every 100 trials. Feedback in the form of speed and accuracy information was given after every block of trials. The entire experimental session lasted approximately 45 min.

## Results and Discussion

The RTs for trials where the individual pressed the incorrect button were eliminated from all RT analyses. In addition, RTs that fell below 200 ms or 3 *SD*s below the condition mean or above 2,000 ms or 3 *SD*s above the condition mean were eliminated from all RT analyses. Using these criteria, we eliminated 1.65% of responses from the analyses.

*Mean RT analyses.* As shown in Table 4, the mean RT results revealed the expected ordering of conditions. Indeed there was a reliable effect of condition, $F(3, 57) = 74.97$, $MSE = 62$. Relative to the neutral condition, the incongruent–incompatible condition showed reliable interference, $F(1, 19) = 123.98$, $MSE = 45$, and the congruent–compatible condition showed reliable facilitation, $F(1, 19) = 22.45$, $MSE = 70$. The incongruent–compatible condition did not differ from the neutral condition ($F < 1$).

*Error analyses.* As also shown in Table 4, the ordering of conditions in error rate generally paralleled the results found in the RT analyses, with a reliable effect of condition, $F(3, 57) = 20.22$, $MSE = .0003$. Relative to the neutral condition, participants made fewer errors in the incongruent-compatible condition, $F(1, 19) = 9.82$, $MSE = .0001$, and more errors in the incongruent–incompatible condition, $F(1, 19) = 27.87$, $MSE = .0003$. The congruent-compatible condition did not differ reliably from the neutral condition, $F(1, 19) = 1.45$, $MSE = .0001$, $p = .25$.

*Ex-Gaussian analyses.* Turning to the ex-Gaussian analyses, there were 192 trials for each of the four conditions, allowing the ex-Gaussian to be fit to each of the four conditions for each participant. Thus, there were a total of 80 distributions fit in this analysis. Three of the eighty distributions resulted in chi-square values that were significant at the .01 level. Visual inspection of these empirical distributions

Table 4
*Mean RT and Error Proportions for Experiment 4*

| Condition | Measure | | |
|---|---|---|---|
| | Mean RT | *SD* | Error |
| Congruent-compatible | 471 | 80 | .017 |
| Incongruent-compatible | 482 | 88 | .013 |
| Incongruent-incompatible | 507 | 87 | .050 |
| Neutral | 483 | 87 | .021 |

and the corresponding ex-Gaussian fits indicated that the fits were generally good. Analyses were done on the parameter values both with and without these distributions, and the results were qualitatively identical. The following results are for analyses that included these distributions. As shown in Figure 5, the results are straightforward. There was a reliable effect of condition on $\mu$, $F(3, 57) = 32.73$, $MSE = 101$. Paralleling the results in the mean RT analyses, there was interference in the incongruent-incompatible condition, $F(1, 19) = 33.42$, $MSE = 140$, and facilitation in the congruent-compatible condition, $F(1, 19) = 5.16$, $MSE = 148$, whereas the incongruent-compatible condition did not differ from the neutral condition ($F < 1$). For $\sigma$, there was a reliable main effect of condition, $F(3, 57) = 16.26$, $MSE = 43$. The effects in $\sigma$ followed those found in $\mu$; namely, there was interference in the incongruent–incompatible condition, $F(1, 19) = 17.57$, $MSE = 46$, and facilitation in the congruent–compatible condition, $F(1, 19) = 4.87$, $MSE = 51$, whereas the incongruent–compatible condition did not differ from the neutral condition ($F < 1$). In contrast, there was no main effect of condition in $\tau$, $F(3, 57) = 1.31$, $MSE = 103$, $p = .28$.

The results of Experiments 3 and 4 clearly demonstrate that conflicting information in the flanker task primarily influences the Gaussian component of the ex-Gaussian distribution. The slight decrease in $\tau$ in the incongruent relative to the neutral condition in Experiment 3 was not replicated in Experiment 4. We turn next to a strong test of the hypothesis that competition in spatial selection should exert its primary influence on the portion of the RT distribution reflected by the Gaussian component of the ex-Gaussian.

## Experiment 5

In Experiment 5 we examine interference effects in the Stroop task when the color and word dimensions are spatially separated (e.g., Gatti & Egeth, 1978; Kahneman & Chajczyk, 1983; Kahneman & Henik, 1981). Previous studies have shown that separating the two dimensions in the Stroop task tends to reduce the interference effects, although interference is still observed with separations of as much as five degrees between the color and word (Gatti & Egeth, 1978). If the influence of interference on RT distributions depends on whether the relevant and irrelevant dimensions are represented as attributes of a single integrated object or of different objects, then spatially separating the color and word dimensions in the Stroop task should result in interference effects similar to those observed in Experiments 2, 3, and 4. Experiment 5 tested this prediction using a version of the Stroop task where the color and word dimensions are spatially separated.

There are four differences between the Stroop and the spatial tasks that could also account for the difference in interference effects. First, in the local/global and flanker tasks, the number of possible responses has been limited to two while in the Stroop task, the number of responses is four. The separated Stroop task uses the same number of responses as in the standard Stroop task. Second, the spatial tasks required manual responses, whereas the Stroop task requires a vocal response. The separated Stroop task also requires vocal responses. Third, the spatial tasks had competing information that was closely matched to the relevant dimension in terms of the strength with which it was associated with the response. In the flanker and local/global tasks, the irrelevant dimension was always mapped to an arbitrary button press in the same manner as the target dimension. The separated Stroop task preserves one of the important characteristics of the standard Stroop task, namely the distracting word is considerably more closely tied to the required response (e.g., Sugg & McDonald, 1994; Virzi & Egeth, 1985). Fourth, there are semantic relations between the dimensions in the Stroop task that are generally lacking in the spatial tasks. Because we eliminate all of these differences in Experiment 5, this experiment provides a strong test of the hypothesis that interference in spatial selection influences the RT distribution differently from competition in nonspatial selection.

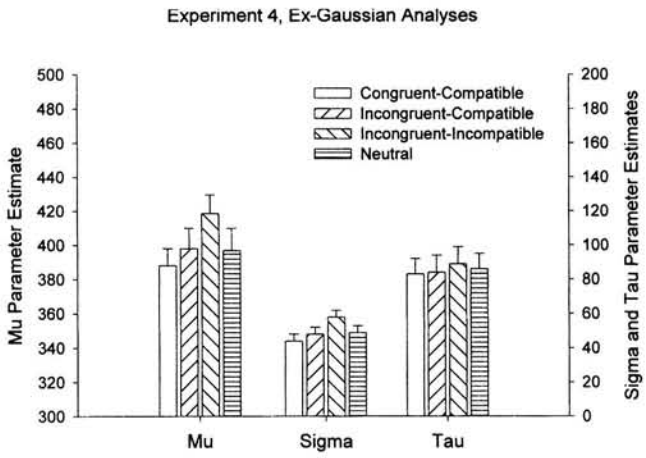


*Figure 5.* Mean ex-Gaussian parameter estimates from the flanker task replication of Experiment 4 as a function of condition. Error bars represent one standard error.

### Method

*Participants.* Twenty-two adults were recruited from the undergraduate student population at Washington University and participated for course credit. Participants were 18 to 22 years of age ($M = 19.8$, $SD = 1.3$) and had 13 to 16 years of education ($M = 13.7$, $SD = 1.2$). The data from one participant were lost because of equipment failure.

*Apparatus.* The apparatus was the same as for Experiment 1.

*Materials.* Four colors and the corresponding color names were used in the experiment: *RED, BLUE, GREEN,* and *YELLOW.* In addition, there were four neutral words (*DOG, BEAR, MOUSE,* and *TIGER*) used as distractors in the neutral condition. The words were presented in Courier font, and each letter subtended approximately 0.3 degrees of visual angle. The color consisted of a rectangular patch of uniform color 30 pixels wide and 7 pixels tall. The colors were the same as those used in Experiment 1 and by Spieler et al. (1996). The color patch always appeared at the fixation. The word appeared either 35 pixels above the fixation or 30 pixels below (approximately 1.2 degrees of visual angle). The

position of the color and the word remained constant for each participant and was counterbalanced across participants.

The colors and words occurred in the following combinations: the congruent condition consisted of 128 trials (4 color words and matching color names × 32 occurrences of each); the incongruent condition consisted of 132 trials (4 colors × 3 nonmatching color names × 11 occurrences of each); and the neutral condition consisted of 128 trials (4 colors × 4 neutral words × 8 occurrences of each). This resulted in 388 trials total in the experiment. The order of trials was randomized for each participant with the constraint that a word or color could not appear on more than two consecutive trials.

*Procedure.* Each trial consisted of the following sequences of events: (a) a fixation consisting of three plus signs (+ + +) appeared in the center of the screen for 500 ms; (b) the screen went blank for 200 ms; (c) the stimulus appeared and remained on the screen until the VOR was triggered by the participant's naming response; (d) the experimenter pressed one of 5 keys coding the response (4 keys corresponding to 4 colors and 1 key corresponding to a VOR error); and (e) the screen cleared for a 1,000 ms intertrial interval prior to the start of the next trial.

At the beginning of the experiment, 32 practice trials were presented to familiarize the participants with the task. The sequence of events was the same as for the experimental trials. During the experiment, participants were given breaks at the end of each block of 50 trials. Feedback in the form of speed and accuracy information was given after every block of trials. The experiment lasted approximately 45 min.

## Results

The RTs were screened using the same criteria as in Experiments 1 through 4. A total of 1.3% of responses were eliminated from the analyses.

*Mean RT analyses.* As shown in Table 5, there were both interference and facilitation effects in this task, and as is typically found, such effects are somewhat smaller than in the standard Stroop task. A three-way repeated measures ANOVA revealed a significant effect of congruency, $F(2, 40) = 55.35$, $MSE = 708$. Relative to the neutral condition, there was facilitation in the congruent condition, $F(1, 20) = 54.93$, $MSE = 369$, and interference in the incongruent condition, $F(1, 20) = 38.54$, $MSE = 490$.

*Error analyses.* Also shown in Table 5 are the error proportions for each condition. As can be seen, the error rates paralleled the mean RT results. An analysis of error proportions revealed a main effect of congruency, $F(2, 40) = 12.95$, $MSE = .0006$.

*Ex-Gaussian analyses.* Turning to the ex-Gaussian analyses, a total of 63 distributions were fit using a chi-square test to evaluate goodness of fit for each condition for each participant. None of the chi-square values were significant at the .01 level, indicating that the ex-Gaussian was fitting the empirical distributions quite well. As shown in Figure 6, the robust interference and facilitation effects observed in the analyses of mean RT were reflected entirely in the $\mu$ parameter. Three separate three-way repeated measures ANOVAs confirmed these observations. There were effects of congruency in $\mu$, $F(2, 40) = 42.51$, $MSE = 811$, and $\sigma$, $F(2, 40) = 18.77$, $MSE = 242$, but not in $\tau$, $F(2, 40) < 1$. Relative to the neutral condition, there was significant interference in the incongruent condition for both $\mu$, $F(1, 20) = 15.61$, $MSE = 846$, and $\sigma$, $F(1, 20) = 8.50$, $MSE = 341$. There was also facilitation in the congruent condition for both $\mu$, $F(1, 20) = 44.72$, $MSE = 483$, and $\sigma$, $F(1, 20) = 12.02$, $MSE = 141$.

Table 5
*Mean RT and Error Proportions for Experiment 5*

| Condition | Measure | | |
|---|---|---|---|
| | Mean RT | *SD* | Error |
| Congruent | 560 | 115 | .015 |
| Incongruent | 647 | 146 | .051 |
| Neutral | 604 | 124 | .021 |

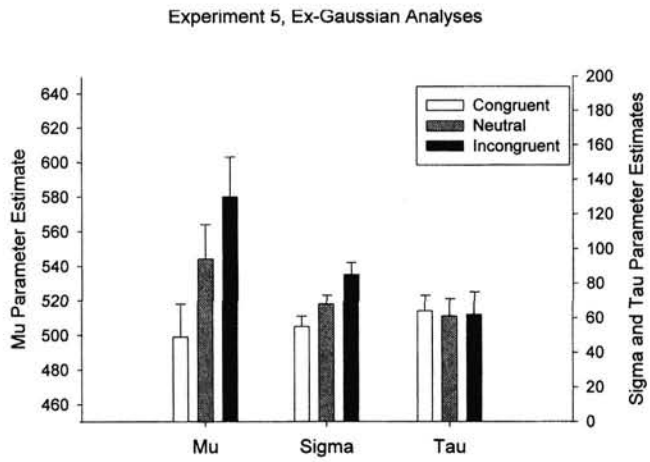


*Figure 6.* Mean ex-Gaussian parameter estimates from the separated Stroop task of Experiment 5 as a function of condition. Error bars represent one standard error.

## Discussion

The results from this experiment were straightforward: Competition between the color and the word in the separated Stroop task resulted in shifts of the RT distribution, with no change in the tail of the distribution. This is in marked contrast to the results of previous Stroop experiments that used integrated stimuli and found that interference influenced $\mu$, $\sigma$, and $\tau$ (Experiment 1; Heathcote et al., 1991; Spieler et al., 1996). The results for the separated Stroop task also rule out a number of alternative accounts for the different effects that interference has on RT distributions. First, the separated Stroop task had the same number of response alternatives as the original Stroop task, ruling out number of responses as an account for the observed task differences. Second, the responses were verbal as in the original Stroop task, ruling out response modality as an account. Third, the distracting word dimension was equally related to the nature of the verbal response as in the original Stroop task. Finally, the separated Stroop task preserved the semantic relation between the competing dimensions found in the standard Stroop task. Each of these alternative accounts were contradicted by the results of Experiment 5,

whereas the distinction between spatial and attribute selection was supported.

## General Discussion

The goal of this research was to examine the influence of selective attention processes on the shapes of underlying RT distributions. Experiment 1 replicated the complex pattern of ex-Gaussian results for Stroop performance reported by Heathcote et al. (1991) and Spieler et al. (1996). Experiment 2 showed that interference effects in other selective attention tasks may be quite different from that found in Stroop task performance. Specifically, Experiment 2 showed that interference in a local/global task influences only the Gaussian parameters of the ex-Gaussian, hence replicating the finding by Mewhort et al. (1992). A tentative account based on the distinction between spatial and attribute selection was then drawn, and the prediction was made that interference in a letter flanker task (Eriksen & Eriksen, 1974) should only influence the Gaussian parameters. This prediction was supported by Experiments 3 and 4. Finally, we showed that spatial separation of the color and word dimensions in the Stroop task eliminates the interference in the exponential component of the ex-Gaussian and leaves only the effects on the Gaussian parameters.

These results appear to provide strong support for the notion that competition in spatial selection influences the portion of the RT distribution reflected by the Gaussian parameters, whereas attribute selection influences the portions of the distribution reflected by both the Gaussian and exponential parameters of the ex-Gaussian. The next step is to explore the computational mechanisms that might give rise to these distinct influences revealed in the present experiments. Before pursuing this, we turn to a remaining alternative account for the present results.

### *Effect Size and Difficulty*

One suggestion offered by a reviewer is that the present results may be a reflection of differences in difficulty across the spatial and Stroop tasks. More explicitly, the difference in difficulty between the incongruent and neutral conditions is larger in the Stroop task than in the other selection tasks. As the difference in difficulty between two conditions increases, the likelihood that one might observe differences in all three parameters of the ex-Gaussian distribution might also increase. If we make the assumption that differences in difficulty across conditions maps onto differences in effect size across conditions, then there are several experimental results that suggest that there can be large differences in mean RT that do not result in differences in all three parameters of the ex-Gaussian. First, Hockley (1984) showed that increasing the number of elements in a visual search task resulted in quite large increases in mean RT that were in turn evidenced as increases in $\mu$ and $\sigma$ with little change in $\tau$. Second, Balota and Spieler (1999) have reported that the difference in time between *yes* and *no* responses in a rhyme-judgment task (~100 ms) also was evidenced as a change in $\mu$ and $\sigma$ and no change in $\tau$. Finally, several experiments (Balota, Watson, Cortese, & Spieler, 1998; Spieler, 1998) have shown that semantic priming effects in the lexical decision task (~70 to 100 ms) may be reflected only in the Gaussian parameters of the ex-Gaussian. In sum, the size of an experimental manipulation does not appear to be a strong predictor of how a manipulation might influence the RT distributions.

The relation between difficulty and parameters of the ex-Gaussian can also be explored in the present data. If one assumes that individual differences in interference effects map onto individual differences in perceived difficulty, then one can ask whether individuals that exhibit large interference effects are more likely to exhibit effects in all three parameters of the ex-Gaussian compared with those individuals that show smaller interference effects. To examine the relation between effect size and $\tau$, we computed interference effects in mean RT for each individual in the separated Stroop task and performed a median split on the size of the interference effect. This divided participants into those individuals that showed large (54 ms) and small (19 ms) interference effects. Examination of the $\tau$ estimates revealed that the group showing large interference effects had larger $\tau$ estimates overall, but neither group showed any evidence of effects of condition on $\tau$ estimates (47, 44, and 44 for the congruent, incongruent, and neutral conditions, respectively, for the small interference group and 82, 81, and 79 for the corresponding conditions in the large interference group).

Taken as a whole, these analyses and the available literature seem to argue against difficulty or effect size as a sufficient explanation of how factors influence the shape of RT distributions. However, we do not want to argue that difficulty is irrelevant to the observation of effects on the parameters of the ex-Gaussian distribution. If one were to gradually decrease the difference in difficulty between two conditions, then it is possible the effects in one of the parameters such as $\tau$ may be eliminated, whereas significant differences might still be observed in $\mu$ or $\sigma$. Our argument here is simply that we have identified one psychologically relevant factor (e.g., spatial separation) that is important in determining how competition in selection influences components of the RT distribution.[3]

[3] Another aspect regarding the ex-Gaussian analysis that one should be concerned about is the possibility that there may be parameter tradeoffs such that changes in one parameter will impact the value of the other parameters. $\sigma$ and $\tau$ are frequently negatively correlated such that large $\sigma$ estimates are generally associated with smaller $\tau$ estimates. One concern in particular is that the increase in $\sigma$ in the incongruent conditions in all of the spatial selection tasks may make it difficult to observe effects in $\tau$. To address this, we conducted correlations between the $\sigma$ and $\tau$ parameter estimates for Experiments 1 through 5. The correlations were .18 for Experiment 1, −.38 for Experiment 2, −.54 for Experiment 3, .64 for Experiment 4, and .22 for Experiment 5. Thus, the results are mixed. For Experiments 2 and 3, the relatively high correlations between $\sigma$ and $\tau$ means that the possibility of parameter tradeoffs cannot be excluded. However, the other two spatial selection tasks show no such evidence for parameter tradeoffs (Experiments 4 and 5). Thus, although we cannot rule out the possibility that there are some tradeoffs between $\sigma$ and $\tau$, in the aggregate it seems unlikely that a tradeoff between $\sigma$ and $\tau$ accounts for the present results.

### *Random Walk Models and RT Distributions*

The results of five experiments suggest that spatially integrated dimensions (e.g., Garner, 1974) may result in qualitatively different influences on components of RT distributions than spatially separate dimensions. We have also suggested that differences between tasks in difficulty is insufficient in accounting for these results. We now turn to an exploration of computational mechanisms that might produce these effects.

We explore quantitative accounts for the present results using sequential sampling models. These models require very limited assumptions about the nature of processing and can be framed at a level that is well suited to modeling differences between tasks. Specifically, evidence for a particular response accumulates over time. At each time step, a piece of evidence (e.g., a feature) is taken as consistent with one of the possible responses. Evidence for a particular response moves one step closer to the criterion for that response. The probability that evidence is consistent with a particular response is a measure of the signal strength entering the decision process. Thus, if a signal for a response is particularly strong, then evidence accumulates for that response with a higher probability compared with a weaker signal. A single piece of evidence is insufficient to make a response. Instead, a criterion is set, and once the amount of evidence reaches a criterion, a response is made. The same response criterion is set for all of the responses. This criterion may be either an absolute criterion such that a response is made once evidence for a response reaches a predetermined level, or it may be a relative criterion such that a response is made once evidence for a response exceeds its nearest competitor by a specified amount. Because processing in these models is stochastic, these models generate predictions at the distributional level.

The first of the sequential sampling models that we use is the random walk model. In the present simulations, both time and evidence are unit valued. Other instantiations of random walk models may allow either time or evidence or both to be continuous random variables. Although parameter values will differ, both the continuous and discrete random walks will generate similar fits to the data.

In the first set of random walk simulations, there are three parameters. First, the probability that incoming features are consistent with a particular response represents the *signal strength* for the particular response. Second, there is the relative *response criterion* for each response (for all simulations, response criterion is equal for all responses). The response criterion specifies the amount of evidence that a particular response must have over the nearest competitor in order for a response to be made. Third, because the random walk represents the time for the decision process, we assume that there is also some *residual time* taken for low level encoding of the stimulus, execution of the response, etc. This residual time is held constant across conditions. In all of the present simulations, a single piece of evidence is allocated to a response at each cycle, and each cycle has a duration of 1 ms. Figure 7 shows the pattern of ex-Gaussian parameters as a function of signal strength with response criterion constant, and Figure 8 shows ex-Gaussian parameters when response criterion is varied but signal strength is held constant. The qualitative pattern shown in these figures is important. The exact shape of the functions will depend on the specific parameter values. The fits of the ex-Gaussian distribution to the simulated RTs from the random walk model were excellent. In the next section, we examine how the Stroop interference effects might be modeled using the random walk model. Although there are some differences, a

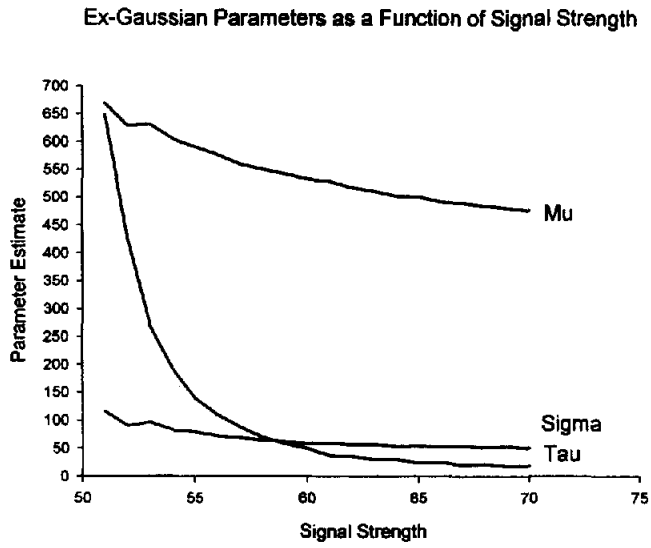


*Figure 7.* Ex-Gaussian parameter estimates from an RT distribution generated by the random walk model when signal strength is varied (residual = 400, *SD* = 50, criterion = 40, strength varies .51 to .70).

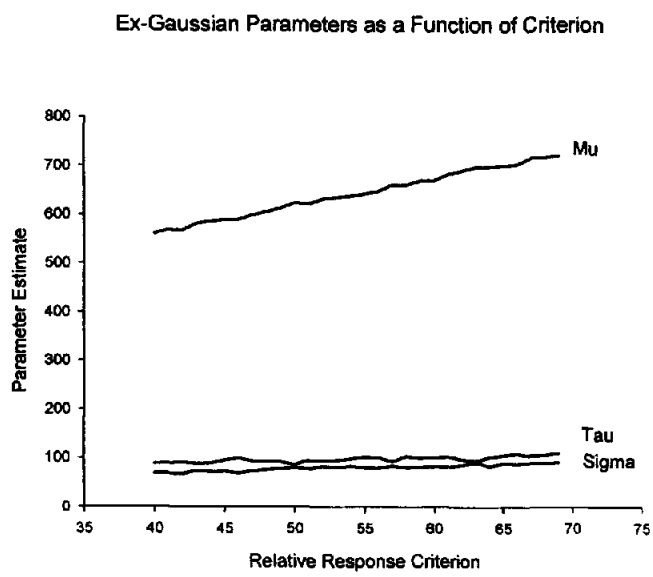


*Figure 8.* Ex-Gaussian parameter estimates from an RT distribution generated by the random walk model when response criterion is varied (residual = 400, *SD* = 50, strength = .57, criterion = 40 to 69).

similar random walk approach to modeling Stroop performance can be found in Trainham, Lindsay, and Jacoby (1997).

### *Models of Stroop Performance*

It should be apparent from Figure 7 that variations in signal strength are a promising starting point for modeling the Stroop interference effect. In the incongruent condition, incoming evidence may reflect a mixture of evidence from the color and the word dimension. The word dimension steals evidence from the color dimension, resulting in a loss of signal strength in the incongruent condition relative to the neutral condition. We conducted five separate simulations in which the model generated 700 RTs per condition, the ex-Gaussian distribution was fit to the simulated RTs and the ex-Gaussian parameters were averaged across the five runs. As shown in Figure 9, a decrease in signal strength does a remarkably good job of fitting the neutral and incongruent conditions from Experiment 1 (compare with Figure 2). These results are consistent with the notion that the influence of the word dimension acts to reduce the overall strength of evidence that comes into the correct color response.

To simulate the facilitation effects in the Stroop task, the preferable approach would be to have the congruency of the word and the color information increase signal strength in the same way that the mismatch of the two dimensions decreases signal strength. The results of Experiment 1 suggest that one cannot model the facilitation effects as simply an increase in signal strength. Note that in the congruent condition, $\mu$ decreases while $\tau$ increases (see Figure 2). As shown in Figure 7, an increase in signal strength tends to reduce all three parameters of the ex-Gaussian. Thus, the opposing effects in $\mu$ and in $\tau$ in the congruent condition requires a mechanism that is different from that generating the interference effect.

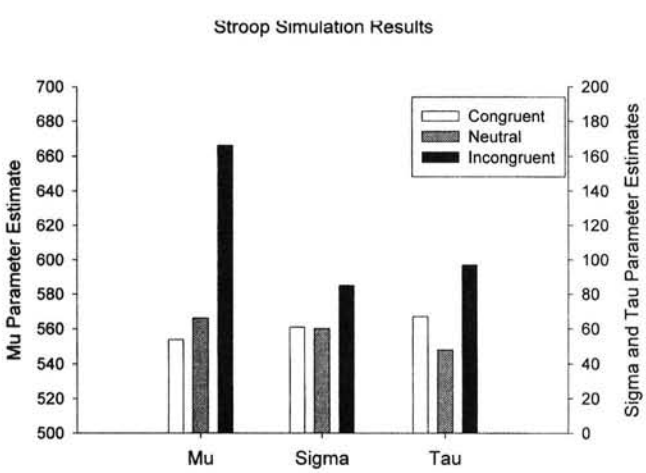


*Figure 9.* Mean ex-Gaussian parameter estimates generated by the random walk model to model the Stroop results (residual $M = 370$, $SD = 50$; criterion = 62; neutral strength = .62; incongruent strength = .57; congruent strength = .62, $SD = .02$).

### *Mixtures of Correct Responses and Intrusion Errors*

One possibility is that there are intrusion errors in the congruent condition that are just not detectable (MacDonald & MacLeod, 1996). Because these are detected in the incongruent condition, they are removed from the analyses, but an intrusion error in the congruent condition is a correct response (even though based on the incorrect dimension) and hence is retained for all analyses. This suggests that the congruent condition, unlike the other conditions, is a mixture of correct color-naming responses and incorrect word-reading responses. In an attempt to test the viability of this account, we generated an ex-Gaussian distribution with $\mu$, $\sigma$, and $\tau$ values of 600, 60, and 100, respectively, and mixed simulated word-reading responses from a distribution with $\mu$, $\sigma$, and $\tau$ values of 450, 50, and 50, respectively. The values for the word-naming distribution are similar to ex-Gaussian parameters obtained for word naming by Balota and Spieler (1999). To obtain 15 ms of facilitation in $\mu$, 10% of the responses had to be drawn from the word-reading distribution. When this was done, we obtained $\mu$, $\sigma$, and $\tau$ estimates of 586, 84, and 93, respectively. This should be compared with the 600, 60, and 100 values for $\mu$, $\sigma$, and $\tau$ for the original distribution. Note that this mixture can generate the decrease in $\mu$ but cannot accommodate the increase in $\tau$ relative to the neutral. On the basis of these simulations, the strong form of the mixture account can be rejected.

A weaker version of the mixture account may still be viable. It may be unrealistic to suggest that the influence of the word dimension is either all or nothing. Although individuals might avoid overt responses on the basis of the word dimension, individuals could still use information in the word dimension, if only because the fluency with which word information is processed. Of course, in the incongruent condition, any processing of the word dimension can only hurt performance (with some boundary conditions, Logan & Zbrodoff, 1979; Logan, Zbrodoff, & Williamson, 1984). On the other hand, in the congruent condition, the word information can be used to arrive more quickly at the correct response. We suggest that ultimately individuals respond on the basis of the identity of the color but that word information may be used when possible to speed processing. The tendency to use such word information is likely to be sensitive to such factors as the proportion of congruent and incongruent trials and the sequence of trials. In situations where the proportion of congruent trials is high, or when there have been several congruent conditions in a row, individuals may be more likely to use information gleaned from the word dimension (Logan & Zbrodoff, 1979; Logan, Zbrodoff, & Williamson, 1984). On the other hand, when there are few congruent trials, or when there have been several incongruent trials in a row, individuals may be more likely to treat a congruent trial as similar to an incongruent trial. This account does not require that individuals be able to predict the upcoming trial but rather simply suggests that individuals may be aware of information in the word dimension sufficiently early in processing that it may be used for arriving at a response. In random walk simulations, we modeled this as an increase in variability in signal

strength in the congruent condition relative to the neutral condition. Specifically, the signal strength on a particular trial was drawn from a Gaussian distribution that had a mean signal strength equal to that in the neutral condition but with a standard deviation of 0.01. As shown in Figure 9, this increase in variability can generate the tradeoff in $\mu$ and $\tau$ observed in the data. We acknowledge that this account is post hoc, but we find the fit of the model compelling.

In summary, the results of the random walk simulations suggest that the Stroop interference effects are nicely modeled as a decrease in signal strength. The congruent condition presented more difficulty, but we were able to generate RT distributions very similar to those observed in the empirical data via an increase in variability in signal strength in the congruent condition relative to the neutral condition.

### *Spatial Selection*

In light of the empirical results from Experiments 2 through 5, and because changes in signal strength tend to move all three ex-Gaussian parameters, signal strength is an unlikely candidate for modeling the results of the spatial selection experiments. There are two additional parameters in the random walk model, namely, response criterion and the residual time.

It is possible to generate effects on RT distributions similar to that observed in the spatial selection tasks by varying response criterion across condition. Specifically, increasing response criterion in the incongruent condition relative to the neutral condition can result in an influence that is primarily reflected by the Gaussian portion of the ex-Gaussian distribution. In justification, one might suggest that if individuals detect any conflict in the stimulus, then they increase their response criterion for that trial. There are two problems with this argument. First, it is unclear why this might occur for the spatial selection tasks and not for the Stroop task. Indeed, the increased competition in the Stroop task would seem to make increases in response criterion even more likely in the Stroop task than in the spatial selection tasks. Second, it may not be realistic to suggest that individuals systematically vary response criterion across conditions when the conditions are randomly intermixed within a block of trials. It is also possible to fit the results by allowing the residual time parameter to vary across conditions although this would be a trivial exercise that would offer little insight into underlying mechanisms.

In the next section, we develop two accounts for the results of the spatial selection tasks. Each of these two accounts have both advantages and disadvantages. However, both lead to the conclusion that the manner in which individuals arrive at a correct response in the spatial selection tasks is different from that used in arriving at a correct response in nonspatial selection tasks. Thus, the development of these accounts for spatial selection emphasizes the constraint that analyses of RT distributions place on the development of computational accounts of selective attention.

With the demonstration that an unelaborated random walk model is unable to generate effects in $\mu$ with justifiable changes in parameters in the model, we have two options. First, we can attempt to continue working within the random walk modeling framework but make modifications to some aspects of processing in this model. Second, we can look to another type of sequential sampling model to account for the results of the spatial selection tasks. In the absence of a compelling argument for one of these options, we pursue both and demonstrate that the results of the spatial selection tasks may be modeled in two ways. In one sense, the ability to devise two different models to account for these results suggests that the behavioral data provide inadequate constraint on the theoretical accounts. Although this is true, this is likely true about almost all results of experiments using only behavioral measures. We suggest, however, that the more important point is that both of these accounts suggest that the selection process operates differently for spatial selection compared to nonspatial selection.

### *Random Walk With Attentional Gradient*

Clearly location information plays an important role in selective attention, and this is emphasized by the metaphors used in describing the operation of selective attention (e.g., zoom lens, spotlights, etc.). These attentional metaphors suggest that processing in attended locations is generally enhanced relative to unattended locations. In general, spatial attention can be viewed as distributed over a particular region of space, and individuals have some control over the size and perhaps shape of the attended region (e.g., LaBerge, 1983; LaBerge & Brown, 1989; Logan, 1996; Sperling & Weichselgartner, 1995).

Applied to the Stroop task, the assumption is that unless the letters of the word are presented in a very large format, attention will select a region of space that covers the word. Once attention has selected this region, the sampled features are a mixture of the color and the word dimensions (e.g., Logan, 1980). Under normal circumstances, the automaticity of lexical processing may make it difficult to reduce the size of the attended region below the size of the word. Moreover, even if this is possible, there is evidence that only a few letters from a nonmatching color can produce interference (Singer, Lappin, & Moore, 1975). This can be contrasted with the situation in the spatial selection tasks where it may be possible to restrict the size of the attended region to minimize the sampling of features from the irrelevant dimension and maximize the sampling of features from the relevant dimension.

So far this description only predicts that in the spatial tasks it may be easier to restrict the sampling of irrelevant features that in turn only predicts less interference in spatial tasks than in nonspatial tasks. However, there is some reason to think that the distribution of attention over the target and distractors is not constant during the course of a trial. Take the flanker task as an example. Although the task minimizes the need for individuals to search for the target letter, the target is defined not only in terms of absolute position, but

also it is defined in reference to the flankers (e.g., "respond to the center letter in the display"). Clearly individuals register and encode some information from the flankers as evidenced by their sensitivity to information such as target-flanker correlations (e.g., Carlson & Flowers, 1996; Miller, 1987) and, of course, the presence of flanker interference. However, during the course of the trial, to ensure that the sampling of target letter information is sufficiently strong, the attentional distribution must be sharpened over the central letter resulting in a decreased probability of sampling features of the distractors. This sharpening of attention results in a signal strength that increases during the trial as attention is progressively focused. It is this lower selectivity early in the course of a trial that we suggest results in the interference effects observed in the spatial selection tasks.

To evaluate the possibility that an increase over time in the probability of sampling from the target dimension influences RT distributions in a manner similar to that observed in the present experiments, we used the same random walk model as was used in the Stroop task with one important difference. The initial distribution of attention at the start of a trial was over all of the letters, and this distribution results in a mixture of features sampled from the target letter and the flankers. In the incongruent condition, this distribution results in initially lower signal strength relative to the neutral condition because the sampling of features from the flankers moves the available evidence toward an incorrect response. However, as attentional selection was sharpened over the central letter, signal strength increased to a maximum that was no greater than that in the neutral condition. In the present simulations, we used a linear increase in signal strength, although other simulations suggest the form of the increase in signal strength is not crucial. The neutral condition was simulated using a constant signal strength throughout the trial. To simulate the difference between the congruent and the neutral conditions, we took the same approach by assuming that the distribution of attention over the redundant stimuli would result in a higher signal strength and that the sharpening of attention to the central letter reduced the influence of this redundancy and, hence, reduced the signal strength. It may not be entirely realistic to suggest that individuals continue to narrow their attentional focus in the presence of redundant stimuli, although the rate at which we reduced signal strength during processing was sufficiently slow that in many cases the model generated a response prior to the maximal reduction in signal strength (equal to the neutral condition). As shown in Figure 10, an initially low signal strength that increases during the course of a trial results in increases in $\mu$ and $\sigma$ with little change in $\tau$ relative to a neutral condition where the signal strength remains constant during the course of a trial. Similarly, the congruent condition with the initially higher signal strength that decreased equivalently over the course of the trial exhibited decreases in $\mu$ and $\sigma$ with little change in $\tau$.

The random walk simulation demonstrates a mechanism that is capable of producing the pattern of results observed in Experiments 2 through 5. These simulations suggest that attention acts to progressively attenuate the sampling of competing information from spatially adjacent locations. This attenuation reflects the sharpening of the distribution of attention over target information. The initially broad distribution of attention at the start of processing may result from limits on the ability to select the small region of space not presently occupied by any stimuli or an automatic broadening of attention with the onset of the stimuli (e.g., Yantis & Jonides, 1984). Alternatively, it could reflect more strategic processes that arise because the instructions to the participants require them to respond to a target that is partially defined on the basis of the distractors (e.g., the center letter in the display).

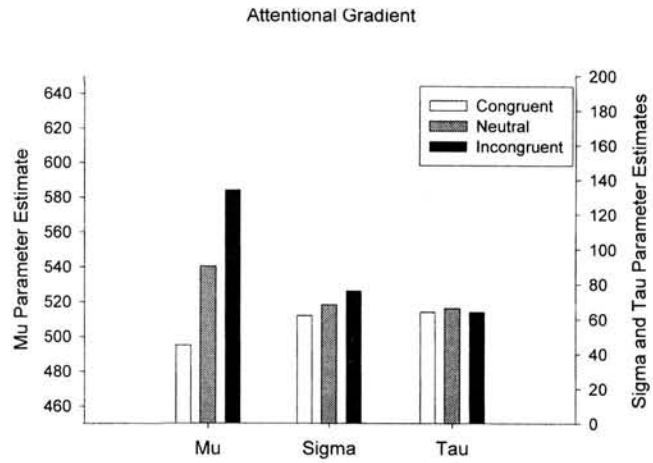


*Figure 10.* Mean ex-Gaussian parameter estimates generated by the random walk model to model the spatial selection tasks (residual $M$ = 300, $SD$ = 50; criterion = 53; signal change = .00108/sample).

The time course of attentional selection suggested in the random walk simulations is similar to that implemented in several other computational models. Our account is essentially a gradient model of attention, and there are several examples of how such an attentional mechanism might be implemented in a neurally plausible model (e.g., LaBerge, Carter, & Brown, 1992). In these models items are represented by location with mutually inhibitory connections to adjacent spatial locations. Higher order processes provide a biasing input to the central location that allows processing in this location to eventually dominate. However, early on in processing, the targets and flankers are nearly equally activated because the within level inhibitory connections have not had sufficient time to dampen activation of the flanking letters. A mechanism such as mutually inhibitory connections within levels and a biasing top–down influence to enhance processing in the targeted location is one mechanism for implementing the time course of selection reflected in the random walk model. A similar process of initial activation followed by lateral inhibition can also be seen in a model of the flanker task (Cohen, Servan-Schreiber, & McClelland, 1992) and is consistent with at least one account for how selection is accomplished between levels in the local/global task (Robertson, 1996).

### *Accumulator Models and Spatial Selection*[4]

An alternative for modeling results from the spatial selection tasks is to use a different type of sequential sampling model. The random walk model uses a single evidence accumulator that moves toward one of two boundaries representing one of two response alternatives. If we think of the two response alternatives as representing the relevant and irrelevant dimensions of the stimulus (e.g., evidence from the color and word dimensions), then these two dimensions are completely interactive at the level of accumulating evidence. This interactivity comes from the fact that information converges onto a single evidence accumulator, meaning that information favoring one response automatically counts against the alternative response. Hence, incoming information always influences evidence for both response alternatives. Suppose we retain the assumption that evidence for both the relevant and irrelevant dimensions are accumulated in parallel but we suggest that when the two dimensions are spatially separated, that evidence no longer shows the complete interaction found in the random walk model. Rather, evidence for the response alternatives accumulates in such a way that evidence for one response is neutral with respect to the alternative, and evidence favoring one response has no influence on the other evidence accumulators. This describes a type of sequential sampling model that has been referred to as an *accumulator model* (see Smith & Vickers, 1988, for a review).

The influence of signal strength on characteristics of RT distributions generated by accumulator models is different from the influence of signal strength in the random walk models. Both types of models require more samples to reach the response criterion as signal strength decreases. However, the random walk model shows increasing skew with decreasing signal strength (see Figure 7), while the accumulator models show decreasing skew with decreasing signal strength. This characteristic leads to a pattern of results that are similar to that observed in Experiment 3 where interference resulted in an increase in $\mu$ and $\sigma$ but a decrease in $\tau$.

To verify that an accumulator model is able to generate a pattern similar to that observed in the spatial selection experiments, we implemented an accumulator simulation. The basic parameters were similar to those in the random walk simulations. Signal strength represented the relative strength of evidence for the two response alternatives, where for each sample, information favored one response with a probability of $p$ and favored the other with probability of $1 - p$. Response criterion was equal for both response alternatives. As for the random walk, we included a Gaussian distributed residual time based on the assumption that the decision process did not take up the entire processing time. We assume, as we did for the Stroop simulation, that signal strength in the incongruent condition was lower than in the neutral condition. In the congruent condition, we assumed a higher signal strength than in the neutral condition. In the accumulator simulations, signal strength was held constant throughout the trial.

Note that for the time dimension, the random walk model sampled one unit of information each millisecond, and there might be 200 to 300 samples before one of the response criteria was met. Distributions generated by the accumulator models would be insufficiently skewed if several hundred samples were needed to make a response, and so the number of samples was lower for the accumulator simulations. The reason for the difference in the number of samples needed to reach the response criterion in these two models should be more clear with the example of one unit of information favoring each of the two response alternatives. In the random walk model, one unit to each response alternative will cancel one another out, and there will be no net movement toward either boundary, but in the accumulator model, both accumulators will move toward the boundary. Because of this lower number of samples, we assumed that the time between each sample was a Gaussian distributed random variable with a mean of 20 and an *SD* of 5.

In the accumulator simulations, the evidence was an exponentially distributed random variable with a mean and *SD* of one (see also Smith & Vickers, 1988). The accumulator simulation involved generating 1,000 simulated RTs for each condition and fitting the ex-Gaussian distribution to the simulated RTs. The overall fits of the ex-Gaussian to the simulated data was as good as the ex-Gaussian fit to the random walk simulations. The results of the accumulator simulation are shown in Figure 11. As expected, the accumulator shows that decreases in signal strength result in increases in $\mu$ and $\sigma$ and a decrease in $\tau$. This reversal is similar to that observed in Experiment 3. However, the accumulator simulations tend to generate values for $\sigma$ that are larger than those observed in the spatial selection experiments.

In Experiments 2, 4, and 5, we were able to observe increases in $\mu$ and $\sigma$ without opposite effects in $\tau$. However, it is not possible at this time to suggest that the results of Experiment 3 are not replicable because a direct replication was not attempted of these results in any of the subsequent experiments. Thus, we cannot say that we have identified the cause for the reversal of effects in $\mu$ and $\tau$ observed in Experiment 3. One distinction between the accumulator model and the gradient account for spatial selection is that using the present assumptions about how signal strength changes over time, it is not possible for the gradient random walk account to generate the opposite patterns in $\mu$ and $\sigma$ on one hand and $\tau$ on the other. In the event that other selection tasks evidence a pattern of results similar to that observed in Experiment 3, then this would support the accumulator account at the expense of the gradient account. However, because the other experiments use a range of other spatial selection tasks, it appears that such reversals are not the rule.

The application of the accumulator suggests that the difference between the spatial and nonspatial selection results arises from how information from competing dimensions is combined. Suppose there exists an array of evidence accumulators each corresponding to a particular spatial location or frequency channel. When target and distracting stimuli occupy different spatial locations, then evidence for each stimulus feeds into distinct accumulators, and the

[4] We thank Philip Smith for suggesting this modeling argument.

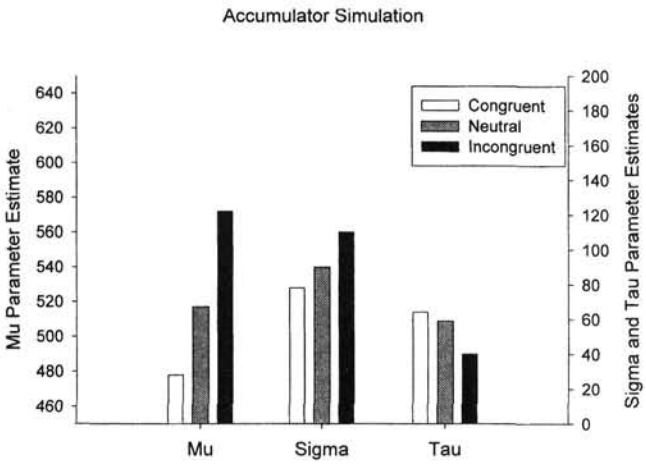


*Figure 11.* Mean ex-Gaussian parameter estimates generated by the accumulator model to model the spatial selection tasks (residual $M = 200$, $SD = 10$; criterion = 13; neutral strength = .59; incongruent strength = .56; congruent strength = .62; sample duration = 20, $SD = 5$).

decision process is best represented by the accumulator model. However, if target and distracting stimuli are spatially integrated, then evidence for each converge on the same accumulator, and the decision process is best represented as a random walk. Such an account is similar in spirit to the distinction made by Garner regarding separable and integrated dimensions (e.g., Garner, 1974).

### *Limitations and Caveats*

We find the results of the present set of experiments in conjunction with the results from the random walk and accumulator simulations consistent and compelling. However, we acknowledge some limitations to our present account. First, in drawing a distinction between the spatial and attribute selection, we are drawing a distinction between the Stroop task and all of the other tasks. Because of this, it may be possible to identify other possible distinctions that are also consistent with the present data. This objection is perhaps best addressed by the results of Experiment 5 in which we conducted a directly analogous Stroop experiment with a single change in one psychologically relevant dimension by introducing a spatial separation between the word and the color dimension. The fact that we eliminated $\tau$ effects would seem to invalidate several alternative accounts. For example, the presence of a semantic relation between the relevant and irrelevant dimension does not appear to account for this data because there remains a semantic relation between the dimensions in the separated Stroop task. We have also presented an analysis of the present data and drawn on other sources of evidence that argued against effect size as a possible account. Nonetheless, it is certainly possible that each of these could, under some circumstances, influence the nature of the interference effects. Additional studies will be required to more fully examine the possibility that either semantic influences or differences in effect size might influence how interference is evidenced in the parameters of the ex-Gaussian.

With respect to the random walk and accumulator simulations, we have identified two approaches that are able to influence the RT distributions in a manner similar to that revealed in the spatial selection experiments and contrasted that with the random walk simulations of Stroop performance. Each of these modeling approaches is consistent with other views of how attention might be allocated to locations or perceptual dimensions. However, there may be alternative computational frameworks that may, with modifications, be able to model these influences on RT distributions (e.g., Cohen, Dunbar, & McClelland, 1990; Phaf, Van der Heijden, & Hudson, 1990). Of course, further careful empirical work is needed to distinguish between the alternative models. Nonetheless, we remain confident that any modeling framework will require distinct selection mechanisms to account for the different effects that interference has on components of the RT distributions revealed in the present set of experiments.

To summarize, the results of the present set of experiments, in conjunction with the random walk simulations, strongly support the notion that mechanisms underlying selection in the spatial tasks is quite distinct from that in the Stroop task. One could hardly call this conclusion revolutionary, but we argue that the important point is that such a conclusion appears to be required by the results of the ex-Gaussian analyses and simulations using sequential sampling models. Thus, in a more general sense, the present article provides a demonstration of the utility of analyses of RT distributions for developing and constraining theories of cognitive processes.

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