

Location Cuing and Response Time Distributions in Visual Attention

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Abstract

The allocation of visual attention was investigated in two experiments. In Experiment 1 (n = 24), a peripheral cue was presented, and in Experiment 2 (n = 24), a central cue was used. In both experiments, cue validity was 90% and the task was 4-choice target identification. RT distributions were collected for valid trials over 5 cue-target SOAs, and ex-Gaussian parameters were extracted. In both experiments, only the mean of the Gaussian component decreased as a function of cue-target SOA, which implied a strict time-axis translation of the distributions. Results were consistent with sequential sampling models featuring a variable delay in the onset of information uptake.

In location-cuing studies of visual attention, a particular location in the visual field is indicated (cued) by a marker, after which a target is presented. The most general finding from this type of study is that target identification or detection is faster and more accurate at cued (valid) than at uncued (invalid) locations (Cheal & Lyon, 1991; Jonides, 1981; Posner, 1980). A secondary finding is that the time interval between cue and target onset (stimulus onset asynchrony, or SOA) affects both response time (RT) and accuracy. Specifically, as SOA increases, identification RT generally decreases at valid locations and increases or remains constant at invalid locations (Remington & Pierce, 1984), whereas identification accuracy increases at valid locations and decreases or remains constant at invalid locations (Cheal & Lyon, 1991; Gottlob & Madden, 1998). The time signatures of these RT- and accuracy-SOA curves have been studied under a wide variety of stimulus and task demands (Cheal & Lyon, 1991; Cheal, Lyon & Gottlob, 1994; Posner, 1980; for a review, see Wright & Ward, 1998).

Much work on visual attention has attempted to describe its movement or allocation, often employing metaphors such as spotlight (Posner, Snyder, & Davidson, 1980), zoom lens (Eriksen & St. James, 1986), gradient (LaBerge & Brown, 1989; Cheal et al., 1994), and stagelight (Sperling & Weichselgartner, 1995). These metaphors for allocation, however, do not identify the mechanism by which attention improves processing of the target. To address that issue in the context of target detection (simple RT), models have been formulated to distinguish between bias and sensitivity changes due to attention (Hawkins et al., 1990; Smith, 2000). On the other hand, when target identification rather than

detection is measured, change in bias is no longer tenable as an explanation, and researchers propose mechanisms more directly involved with sensitivity. For instance, Cheal (1997) and LaBerge (1994) both propose that attention works to increase the rate of information flow at the attended location. Other studies have suggested that attention works through mechanisms such as improved localization (Treisman & Gelade, 1980) and exclusion of distractor information (Shiu & Pashler, 1994).

A few recent studies have identified attention mechanisms by using psychophysical functions relating target and distractor quality to accuracy. Lu and Doshier (2000) concluded that location cues improved identification accuracy due to perceptual effects such as stimulus enhancement and external noise exclusion. Cameron, Tai, & Carrasco (2002) also found evidence for stimulus enhancement (which they called *contrast gain*) as the mechanism of attention. These studies looked directly at improvements in accuracy due to effects on perceptual representations, but they did not examine directly the speeding-up of responses due to attention. This change in response time due to attention will be examined in the present study, by the examination of RT distributions, which offer more information than mean RT.

RT distributions have been tied to underlying mechanisms through the use of sequential sampling models such as the random walk and the diffusion model (Ratcliff, 1988; Ratcliff, Van Zandt, & McKoon, 1999). Sequential sampling models for two-choice identification tasks are well established in the literature (for recent empirical papers, see Ratcliff, 2002; Ratcliff, Thapar & McKoon, 2001;

Van Zandt, Colonius, & Proctor, 2000; for analytic treatments, see Luce, 1986; Townsend and Ashby, 1983). Random walk models treat information accumulation as occurring in discrete time; diffusion models are continuous generalizations. Both types of models have three major parameters: In the diffusion model, these are named drift rate, which is the rate of evidence accumulation, drift rate variance, and boundary, which is the amount of evidence required to emit a response. Each boundary in the standard two-choice model corresponds to a single choice (A or B); movement toward boundary A implies movement away from boundary B. A response is emitted when either boundary is crossed. In the two-choice diffusion model, information accumulation for A and B are perfectly (negatively) correlated. Ratcliff, who has developed the 2-D diffusion model and fitted it to two-choice data, adds other factors such as variability in starting state, and contaminant reaction times, in order to fit the model to data (Ratcliff, 2002; Ratcliff & Tuerlinckx, 2002).

Generalizations of sequential sampling models to n choices have been discussed by Luce (1986), Karpiuk, LaCouture, and Marley (1997), Shiffrin (1997), Nosofsky (1997), and Ratcliff & McKoon (1997). As Luce (1986) notes, n -choice models are potentially much more complex than 2-choice models, especially if evidence accumulation is dependent among the choices (Shiffrin, 1997). However, as noted by several researchers (Marley & Colonius, 1992; Van Zandt et al., 2000; Van Zandt, 2002), an n -choice random walk, with any degree of correlation among the choices, can be equivalently represented as a race across n independent counters. (It should be noted, however, that there are

restrictions on the types of models which can be mimicked by independent parallel processes; see Townsend, 1976.) According to this equivalence between dependent and independent parallel models, diffusion models and race models are not identifiably different, although if there is a reason to model particular dependencies between the choices (such as for fitting), then they can serve to constrain a model. In that vein, Van Zandt et al. (2000) compared race and diffusion models for perceptual matching data and found that the fits were comparable for that particular data set. Many other fits of race models have been reported, including those of Karpiuk et al., Nosofsky (1997), and Ratcliff & McKoon (1997).

The task in the current paradigm is a four-choice identification, which offers certain advantages over a two-choice identification in the study of visual attention. These advantages include a lower “chance” rate of accuracy, which discourages guessing and increases the information value of locating the target. In accordance with the above findings regarding the equivalence of diffusion and race models, the four-choice identification can be modeled either by a four-boundary diffusion process with a complex (but underdetermined) correlation across responses, or alternatively, as a four-counter race model. The race model that most simply describes this task maps individual, independent counters to target responses (e.g., “target A” counter produces only a “target A” response). This model contains two important features that preserve mappings between single counters and responses: (a) The model does not converge counters onto responses, as opposed to some models that contain “or” processes (e.g.,

response A could arise from counter A or counter B), and (b) the counters have “context independence” (Van Zandt, 2002) in that the marginal distributions for the single counters are identical to the single-counter distributions. Because the counters are non-converging and context independent, RT distributions for correct trials can be assumed as identical to the finishing time distributions of the single counters associated with each response. These finishing time distributions can be modeled by the one-dimensional diffusion (Wiener) process (Luce, 1986; Ratcliff, 1993). The equation for this process (Cox & Miller, 1965) expresses the RT probability density function (pdf), $g(t)$, as

$$g(t) = \frac{L}{\sqrt{2\pi d^2 t^3}} \exp\left(\frac{-(L - rt)^2}{2d^2 t}\right) \quad (1)$$

where L is the boundary, r is drift rate, and d is drift rate variability. This distribution is called the Wald or inverse Gaussian (Burbeck & Luce, 1982; Luce, 1986; Ratcliff, 1993; Schwarz, 2001; Zabel & Anderson, 1997), and fits empirical reaction time distributions well (Luce, 1986; Ratcliff, 1993).

In the interests of generality, it will be assumed that the four identification targets form an equivalence class, because the targets are “t” shapes in different orientations, with minimal semantic content and equal visibility. This allows collapsing the counters for the four targets onto a single one-boundary diffusion process. This assumption, along with the direct mapping between component counters and responses, will allow us to simplify our model so as to draw general conclusions about the finishing time distributions of the 1-D diffusion process, which will be inferred from the shapes of RT distributions.

A useful distribution for describing RT distribution shape is the ex-Gaussian (Brown & Heathcote, in press; Hockley, 1984; Luce, 1986; Ratcliff, 1993; Ratcliff & Murdock, 1976), which can closely approximate both the empirical RT distributions and the Wald. The ex-Gaussian is a distribution formed by the convolution of a Gaussian and an exponential distribution; the RT pdf, $f(t)$, is given by

$$f(t) = \frac{e^{-[(t-\mu)/\tau] + \sigma^2/(2\tau^2)}}{\tau\sqrt{2\pi}} \int_{-\infty}^{\{[(t-\mu)/\sigma] - \sigma/\tau\}} e^{-y^2/2} dy \quad (2)$$

It is determined by three parameters, μ and σ (mean and variance of the Gaussian), and τ (exponential parameter). The mean of the ex-Gaussian is $\mu + \tau$ and the variance is $\tau^2 + \sigma^2$. In describing RT distributions, variance is dominated by τ because τ is usually four times as large as σ (Ratcliff, 1993).

In many cases, the ex-Gaussian fits both empirical RT distributions (Brown & Heathcote, in press) and diffusion model simulations (Ratcliff et al. 1999, Spieler et al., 2000) at least as well as any other distribution. The ex-Gaussian and Wald are very close in appearance; often they can only be distinguished by examination of the hazard functions in the tails (Van Zandt, 2002). Furthermore, it will be shown in the discussion section that changes in boundary and drift rate in the Wald map on to changes in the parameters of the ex-Gaussian.

Previous research using fitting ex-Gaussians to RT distributions has found that the parameters seem to react in a lawful manner to experimental manipulations. For instance, Hockley (1984) found that for visual search, increasing set size produced increases in μ and σ , whereas for memory search, increasing set size produced increases in τ only. These differential effects were

interpreted as reflecting a fixed search rate (visual search) versus a search rate that was affected by load (memory search). Similar differences, attributed to fixed- versus load-affected search rate, were found in judgment-of-recency and recognition tasks. In the same vein, Spieler et al. (2000) compared interference effects in the Stroop task (which involves non-spatial selectivity), with other tasks such as global/local figures, and flankers tasks (which involve spatial selectivity). Stroop interference in color naming produced increases in μ , σ , and τ , whereas interference in the four spatial tasks was manifested in μ and σ , but not τ . One interesting aspect of both Hockley's (1984) and Spieler et al.'s findings is that when there was an effect in μ , there was always a corresponding effect in σ , indicating that when the Gaussian portion of the distribution was affected, it was always affected in both of its parameters. Many other papers have used ex-Gaussian parameters to link experimental manipulations to RT distributions, including Ratcliff (1988; 1993) and Ratcliff & Murdock (1976).

In addition to the relationship between experimental manipulations and changes in ex-Gaussian parameters, there are mappings between parameter changes in the diffusion process (as represented in the present context by the Wald) and parameter changes in the ex-Gaussian. In the most general sense, a change in any single diffusion parameter will affect all three parameters of the ex-Gaussian. This relationship between the diffusion process and the ex-Gaussian will be explored more fully in the discussion section of this paper. In the current study, RT distributions from a location-cuing task were fitted with ex-Gaussians, and the attention effect as reflected in the ex-Gaussian parameters provided

constraints on a diffusion model interpretation of mechanisms involved in attention.

Experiment 1

Experiment 1 was designed to investigate attention in a location-cuing task by analyzing RT distributions for target identification. Previous research using identification accuracy has shown that accuracy for valid trials increases as a function of cue-target SOA and asymptotes at 100 - 150 ms for cues presented near the target (peripheral cues; Cheal & Lyon, 1991; Gottlob & Madden, 1998). The implication has been that very short SOAs do not allow for sufficient attentional preparation by the time the target appears, but that slightly longer SOAs allow for attentional processes to be fully engaged at target onset. The asymptotic behavior indicates that perceptual processes are affected maximally by attention at very short time scales.

Studies investigating RT have found that identification RT for valid trials also decreases over a similar time scale (Eriksen & Hoffman, 1972; Posner, 1980), although asymptotic performance is difficult to confirm with RT because of the possibility of generalized warning effects. The decrease in mean RT due to attention over a range of short cue-target SOAs should implicate (at least partially) the same perceptual processes that are involved with the increase in accuracy. If that is the case, the shapes of the RT distributions may also change as a function of SOA. For instance, if attentional engagement improves the perceptual representation of the target at longer SOAs, then one might predict ex-Gaussian parameter changes that would be consistent with increases in drift

rate in a diffusion process. In Experiment 1, RT distributions for five successive cue-target SOA values were compared in terms of shape, using ex-Gaussian decomposition.

Successive cue-target SOAs were chosen as a basis for comparison for several reasons. First, because the goal was to compare various levels of attentional preparation, three different potential “baseline” conditions were considered but rejected. (1) Invalid trials as a baseline were considered, as has been used previously in studies looking at RT distributions (e.g., Johnson & Yantis, 1995). There are some potential pitfalls to that method, however, in that the responses to valid and invalid trials may be qualitatively different in some way. For instance, if probability matching were used by observers, then valid and invalid trials would consist of different mixture distributions of discrete attentional states such as spotlight vs. spread of attention (Jonides, 1983, but see Johnson & Yantis, 1995). This would make comparisons of RT distributions problematic. (2) Another possibility would be to use a neutral cue condition as a baseline and compare valid RT to that, but there are methodological problems involved in comparing neutral to valid trials (Jonides & Mack, 1984). For instance, a neutral cue consisting of four markers (one for each possible target location) may trigger a different type of attention allocation than a cue that indicates a single target location with 90% probability. The only exception to the neutral/valid distinction is when non-informative cues are used. (3) A third possible baseline that was rejected was that of a 0 ms SOA trial (simultaneous cue and target). This comparison would also be problematic because the perceptual representation of

a simultaneous cue and target is very much different from the target presented alone. For instance, at 0 ms SOA, for peripheral cues, there may be lateral masking between the cue and target (Lyon, 1990), and with any type of cue, the total luminance on 0 ms SOA trials is higher than when the target is presented alone. On the basis of the potential problems with these three measures of baseline performance, it was decided that it would be best to compare RT distributions across different cue-target SOAs. In that manner, the trials would be comparable in every way except for the time interval between cue and target.

The cue validity was fixed at 90%; the 10% of trials that were invalid allowed the comparison of invalid and valid RTs, to ensure that observers were allocating in response to the cue. Another reason for using a 90% valid cue is that high probabilities (high cue predictabilities) have been found to induce stronger cuing effects (Gottlob, Cheal, & Lyon, 1999), and if any probability matching strategy is used (Johnson & Yantis, 1995; Jonides, 1983), trials would consist mostly of a single type of response. This would minimize the mixing of RT distributions, which would be problematic for any analyses based on their shape.

Method

Observers. Twenty-four University of Kentucky students between 19 and 25 years of age participated. All observers had a minimum of 12 years of education. Corrected near visual acuity was measured from a four-foot distance. Acuity ranged between 4/4 and 4/8 for all observers. The observers were paid \$10 per 1-hour session.

Apparatus and stimuli. Stimuli were presented on a Viewsonic PF775 color monitor, operating in 600 x 800 mode at 120 Hz, controlled by a Pentium 4 computer. Responses were recorded on a standard IBM keyboard. An adjustable chin rest fixed the eye-to-screen distance at approximately 80 cm, with the eye at center-screen level. Eye movement was monitored with a video camera connected by cable to a monochrome monitor located at the experimenter's desk. During training sessions, observers were instructed to suppress eye movements, which were observed to occur on fewer than 1% of trials (which were not excluded or replaced).

Stimuli consisted of white characters on a black background. Luminance was fixed at 330 cd/m^2 for all screen stimuli. Figure 1 contains a schematic of the events in a trial. The first display consisted of a fixation point, which was a 0.5 deg dash in the center of the screen, presented for 1000 ± 50 ms. The 50 ms variability was due to machine delay in setting up the visual stimuli for each trial, but within each trial, bitmaps loaded into video memory ensured accurate presentation time. A 33 ms cue appeared which was 1 deg to the outside of one of the target locations. On 90% of trials, the cue appeared adjacent to the location containing the target (valid trials), while on 10% of trials, the cue appeared adjacent to the location diametrically opposite the target (invalid trials). Following a variable (blank screen) delay, the target (100 ms) along with three distractors appeared. Stimulus onset synchronies (SOA; time between onsets of cue and target) were 33, 66, 83, 100, and 133 ms, presented randomly.

[Insert Figure 1 about here.]

The target was a "T" subtending 2.2 deg in one of four orientations (pointing right, left, up, or down), centered in one of four locations 2.6 deg to the top, bottom, left or right of the fixation point. The distractors consisted of 2.2 deg plus ("+") signs at the other three locations. The distractors were included so that there would not be a single abrupt onset when the target appeared. Sole abrupt-onset targets may attract attention automatically (Yantis, 1993; but see Folk, Remington, & Johnston, 1993) and would thus eliminate the need for a cue. Following the target and distractors, a 2.3 deg contour mask was presented, which consisted of an outline of the four superimposed targets, at all target and distractor locations. The observer's task was to identify the target by pressing one of four possible arrow keys on the numeric keypad, according to which way the tail of the target was pointing. The mask was terminated at observer response, and accuracy feedback was provided by a green "+" on correct trials, and a red "X" on incorrect trials. Cue-target SOA, target location, and target orientation were presented in random order on each trial.

Procedure. Observers practiced for two sessions, and data was collected on the third. Observers were instructed that fast response time was of primary importance, low error rate was secondary, and eye movements were to be suppressed. Eight blocks of 90 trials were presented, with observer-terminated breaks between blocks, to produce 648 valid trials and 72 invalid trials per observer.

Results and Discussion

The results will be presented, followed by a brief discussion, for both Experiments 1 and 2. The General Discussion section will address the interpretations of the findings for both experiments.

Statistics. Because the observations (trials) were repeated within observers, the assumption of independence of observations was not met. In addition, cell means were not derived from equal numbers of observations; 90% of trials were valid & 10% were invalid. Therefore, the generalized linear mixed model, as implemented in PROC MIXED (Littell, Milliken, Stroup, & Wolfinger, 1996), was employed. The variable of SOA was assumed randomly variable over observers, which yielded a repeated measures analysis over observers, equivalent to the standard repeated-measures analysis of variance (ANOVA). The models implemented in PROC MIXED are evaluated using likelihood functions instead of sums-of-squares as in ANOVA. In PROC MIXED, generalized F ratios are calculated using (restricted) maximum likelihood estimates of variance components and generalized least-squares estimates of treatment differences (Littell et al., 1996).

Mean accuracy as a function of cue-target SOA and cue validity, is presented in Figure 2 (which also presents the results of the second experiment). There was no main effect of SOA, but there was a main effect of validity, $F(1, 23) = 1461.53$, $p < .001$, due to the higher accuracy for valid trials (.97, $SE = .18$) than for invalid trials (.68, $SE = .17$). There was a significant interaction of SOA x Validity, $F(4, 92) = 2.99$, $p < .05$. Pre-planned simple effects analyses found no

significant effect of SOA for invalid trials, but a significant effect of SOA for valid trials, $F(4, 92) = 2.60$, $p < .05$. Post-hoc paired comparisons among valid trial accuracies, using the Sidak correction (SAS Institute, 1989), yielded no pairwise differences at $p < .05$.

[Insert Figure 2 about here.]

For RT analyses, fast responses ($RT < 300\text{ms}$) and slow responses ($RT > 1000\text{ms}$) were removed. This eliminated 1.6% of observations for valid trials and 4.8% of observations for invalid trials. The censoring did not materially change the results of the statistics performed on the data. Mean correct RT as a function of cue-target SOA and cue validity, is presented in Figure 2. There were more total observations in the valid condition than the invalid condition (14,751 vs. 1085) due to both the 9:1 valid/invalid trial ratio and the difference in accuracy across conditions. There was a significant main effect for SOA, $F(4, 92) = 7.19$, $p < .001$, and a significant effect of validity, $F(1, 23) = 1830.86$, $p < .001$. The main effect of validity was due to a lower mean RT for valid trials (486.32 ms, $SE = 13$) than for invalid trials (612.49, $SE = 13$). The Validity x SOA interaction was not significant, $F(4, 92) = 1.73$, $p > .05$.

In addition, pre-planned simple-effects analyses were run on RT for valid and invalid trials separately. For invalid trials, there was no main effect for SOA, $F(4, 92) = 0.39$, $p > 0.05$; for valid trials, there was a main effect of SOA, $F(4, 92) = 25.26$, $p < .001$, indicating that RT decreased significantly as a function of SOA. Post-hoc paired comparison tests of valid mean RT, using the Sidak correction, yielded significant differences for all pairs of observations except for those

between SOAs of 83 and 133 ms, 83 and 100 ms, and 100 and 133 ms.

Maximum difference for the significant comparisons was 33 ms; minimum difference was 9 ms.

As can be seen in Figure 2, valid trials produced higher accuracy and lower RT than invalid trials; this indicates that observers were using the cue to allocate attention. In addition, RT decreased as a function of SOA for valid trials, but not for invalid trials, which indicates that effects of attention are confined to valid locations for these SOAs. In previous research, it has been found that effects of peripheral cues are often maximal by an SOA of 100 ms (Cheal & Lyon, 1991; Jonides, 1981; Gottlob & Madden, 1998; Muller & Rabbit, 1989). It is impossible to establish asymptotic behavior with only a few data points; however, it appears in the current data that the benefit of the cue levels off by 100 or 133 ms.

Ex-Gaussian Analysis. Because of errors, the mean number of observations for each RT distribution, per observer, was 123 (SD = 7.5). According to Brown and Heathcote (in press), the minimal number of observations required to produce good parameter estimates for ex-Gaussians is about 40. Ex-Gaussians were fitted to the 120 individual RT distributions (24 observers x 5 SOAs) using QMLE (Brown & Heathcote, in press; Heathcote, Brown, & Mewhort, 2002) as the fitting procedure, and all fits converged to stable solutions. In order to evaluate the fits, Kolmogorov-Smirnov tests were performed on the data points vs. the fitted values; the mean p -value was .95 (SD = .11) with a median of .99. Of the 120 fits, one fit had a p -value of less than .3, one was in the range of .4 - .5, 6 were in the range of .7 - .8, 5 were in the range of .8 - .9, and 107 were

between .9 and .999. The Kolmogorov-Smirnov test is not sensitive to deviations in the tail, because it is based on the maximum deviation between data and predicted values. An alternative test, the Cramer-von Mises (SAS Institute, 1989), is based on the integrated difference between data and predicted values, and so has a little more sensitivity to differences in the tail. None of the Cramer-von Mises tests were significant at the .15 level. (It is generally accepted that a high p -value is not sufficient to accept a model; however, it may be used to infer that the model is sufficient to describe the data.) Means for the best-fit values for μ and σ (Gaussian mean and variance, respectively), and τ (exponential parameter), along with the standard errors for parameter estimates, are presented in Figure 3. Parameters σ and τ do not change with SOA, but μ shows a consistent decrease with SOA. These parameter-SOA relationships were tested on the individual observer level for monotonic decreasing trends, using Kendall's τ , which is an ordering coefficient based on paired comparisons (Gottlob & Madden, 1999; Kendall, 1970). Kendall's τ ranges from -1 (strictly decreasing) to 1 (strictly increasing); random trends would have a mean score of 0. Mean Kendall's τ values were -.68, .05, and -.05 for μ , σ , and τ respectively, which indicates that the shapes of the individuals' RT distributions corresponded to that of the mean parameter estimates.

[Insert Figure 3 about here.]

Figure 3 indicates that the two ex-Gaussian "shape" parameters (σ and τ) were constant over SOA, whereas μ , which determines the mean of the entire distribution, decreased as a function of SOA. This is describing a translation of

the distributions to the left as SOA increases, without any changes in shape. (One would also expect generalized warning effects to produce some sort of leftward translation as SOA increases, but these effects seem to be small or absent because invalid RTs do not decline with SOA). The leftward translation (change in μ) is of a smaller magnitude than the change in SOA; increasing the SOA from 33 to 133 ms only translated the distribution to the left by 30 ms. This yielded a mean μ -SOA slope of .3; maximum slope for any limb of the μ -SOA curve was about 0.5. Thus, it appears that RT changes produced by the response to a peripheral cue consist of similar RT distributions that vary only by translation along the time axis. The generality of this finding to another type of cue response will be examined in Experiment 2. On the basis of both sets of results, it will be asserted in the General Discussion that this pattern is consistent with a restricted class of sequential sampling mechanisms.

Experiment 2

In Experiment 1, a peripheral cue was used. Previous studies have found that the responses to peripheral cues are predominantly automatic (Yantis, 1993; but see Folk, Remington, & Johnston, 1993) and fast, as if attention is “pulled” to the target location. In contrast, responses to central cues are believed to require effort, because they must be interpreted first, and then attention must be “pushed” to the target location. Whereas maximal responses to peripheral cues are often observed by 100 ms cue-target SOA, in most cases the maximal response to central cues is observed only after 300 ms (Cheal & Lyon, 1991; Jonides, 1981; Muller & Rabbit, 1989). It has been suggested that responses to

peripheral cues are mediated by a “posterior” visual cortical pathway, whereas central cue responses are mediated by an “anterior” visual cortical pathway (Posner, Walker, Friedrich, & Rafal, 1984). The purpose of Experiment 2 is to test whether RT facilitation by central cue is manifested by a strict translation of the RT distribution to the left, as found in Experiment 1 using a peripheral cue. This would be expected if, despite the differences in cue type and (presumably) the mechanism that processes the response to the cue, the manner in which attention speeds processing is the same.

Method

The observer demographics and apparatus were the same as for Experiment 1. One observer had participated in Experiment 1; the rest were naïve. The procedure was identical to Experiment 1, except for the use of a central cue instead of a peripheral cue, and the timing of the events on the computer screen (Figure 1). The cue consisted of an 1.7 deg arrow with centroid at fixation, indicating 1 of 4 locations on the screen. The arrow was presented for 100 ms, followed by a 100 ms target, with cue-target SOAs of 100, 150, 200, 250, or 350 ms. Targets and masks were identical to those used in Experiment 1.

Results and Discussion

Statistics. PROC MIXED analyses were performed as in Experiment 1. Mean accuracy as a function of cue-target SOA and cue validity, is presented in Figure 2 (which also presents the results from the first experiment). There was a main effect of validity, $F(1, 23) = 1287.51$, $p < .001$, with valid trials ($M = .97$, $SE = .17$) higher in accuracy than invalid trials ($M = .67$, $SE = .18$). There was also a main

effect of SOA, $F(4, 92) = 13.23$, $p < .001$, and a significant interaction of SOA x Validity, $F(4, 92) = 10.26$, $p < .05$. Follow-up simple effects analyses found no significant effect of SOA for invalid trials, but a significant effect of SOA for valid trials, $F(4, 92) = 37.55$, $p < .001$. Post-hoc paired comparisons ($p < .05$) among valid trial accuracies, using the Sidak correction, yielded accuracy differences between SOAs 100 and all other SOAs, and between SOA 150 and all other SOAs. Maximum and minimum difference for the significant comparisons was .048 and .013, respectively.

As in Experiment 1, for RT (and ex-Gaussian) analyses, fast responses (RT < 300ms) and slow responses (RT > 1000 ms) were removed. This eliminated 1.8% of observations for valid trials and 7.6% of observations for invalid trials. Mean correct RT as a function of cue-target SOA and cue validity is presented in Figure 2. As in Experiment 1, there were more total observations in the valid condition than the invalid condition (14,531 vs. 1032) due to both the 9:1 valid/invalid trial ratio and the difference in accuracy across conditions. In the PROC MIXED analysis, there was a significant main effect for SOA, $F(4, 92) = 6.96$, $p < .001$, and a significant effect of validity, $F(1, 23) = 1319.37$, $p < .001$. The main effect of validity was due to a lower mean RT for valid trials (526.74 ms, $SE = 17$) than for invalid trials (643.52 ms, $SE = 17$). The Validity x SOA interaction was significant: $F(4, 92) = 15.66$, $p < .001$.

In addition, pre-planned analyses were run on RT for valid and invalid trials separately. For invalid trials, there was no main effect for SOA, $F(4, 92) = 0.13$, $p > 0.05$; for valid trials, there was a main effect of SOA, $F(4, 92) = 40.63$, $p < .001$,

indicating that RT decreased significantly as a function of SOA. Post-hoc paired comparison tests of valid mean RT, using the Sidak correction, yielded significant differences for all pairs of observations, with a maximum difference of 68 ms and a minimum difference of 11 ms.

Just as in Experiment 1, valid trials produced higher accuracy and lower RT than invalid trials, which indicates that observers were using the cue to allocate attention. Also, RT decreased as a function of SOA for valid trials, but not for invalid trials, which indicates that effects of attention were confined to valid locations. Thus, it appears that the central cues produced attention effects similar to those produced by the peripheral cue, but over a more extended time scale. In Experiment 1, the RT facilitation was effected by a strict translation of RT distributions along the time axis; therefore an ex-Gaussian analysis was performed on these data in order to compare results.

Ex-Gaussian Analysis. As in Experiment 1, ex-Gaussians were fitted to the individual observers' RT distributions for correct responses on valid trials, at each SOA, using QMLE. All 120 fits (24 observers x 5 SOAs) converged successfully; mean parameter values are shown in Figure 4. Kolmogorov-Smirnov tests yielded a mean p -value of .97 (SD = .06) with a median of .998. Of the 120 fits, one fit had a p -value of less than .7, 3 were in the range of .7 - .8, 7 were in the range of .8 - .9, and 109 were between .9 and .999. Cramer-von Mises tests were also performed; none were significant at the .15 level. As in Experiment 1, parameters σ and τ do not change with SOA (except for a 12 ms change in τ between SOAs of 100 and 150 ms), but μ shows a consistent decrease with

SOA. Applying Kendall's τ test for monotonicity yielded values of $-.79$, $-.04$, and $-.29$ for μ , σ , and τ respectively, again indicating that the distributions on the individual level were consistent with the means.

[Insert Figure 4 about here.]

Similar to the findings in Experiment 1, increasing the SOA from 100 to 350 ms had the effect of translating the RT distribution to the left by 55 ms. Maximum μ -SOA slope for any individual limb was about 0.37, as μ decreased from 477 to 458 between SOAs of 100 and 150. Because τ also decreased by 12 ms over the interval ($\mu + \tau = \text{mean RT}$), RT-SOA slope between those two SOA values was 0.62.

General Discussion

The results from both Experiment 1 and 2 are consistent with previous studies of location cuing and visual attention: Mean RT was lower for valid trials than for invalid trials, and valid RT declined as a function of cue-target SOA. The SOA values that were chosen (33 – 133 ms for peripheral cues, and 100 – 350 ms for central cues) corresponded to previous research which found that identification accuracy reaches asymptotic values during this time interval (Cheal & Lyon, 1991), meaning that perceptual processes subject to attention are not affected at later SOAs. Therefore, the processes that are bringing about a decrease in valid RT during this time interval probably have a large perceptual component. In addition, generalized warning effects may have contributed to the decrease in valid RT, but if they existed, they were not apparent in the invalid mean RTs.

The current experiments expanded mean RT to a complete RT distribution, which revealed a constancy in distribution shape as a function of cue-target SOA. To summarize the RT results, in Experiment 1 (peripheral cue), the RT distribution shifted to the left (μ decreased) by 30 ms as SOA increased from 33 to 133 ms, and in Experiment 2 (central cue), the μ shift was 55 ms as SOA increased from 100 to 350 ms. Both types of cue produced a leftward shift of the RT distribution without any changes in shape; there is a decrease in μ , but no changes in σ or τ , with SOA (except a change in τ over the first two SOAs in Experiment 2). These results may be contrasted with those of Hockley (1984) and Spieler et al. (2000) who always found changes in σ when the value of μ varied.

It is possible that probing a larger range of SOAs might produce evidence for RT distribution shape changes on valid trials. Those changes, however, would be difficult to differentiate from generalized warning effects, because as stated above, perceptual changes due to attention seem to be asymptotic by 100-150ms for peripheral cues and 300-350 ms for central cues (Cheal & Lyon, 1991; Cheal et al., 1994). Also, longer SOAs might permit eye movements to occur, which would change the character of late-SOA responses.

The shape constancy of the current experiments, when put into the context of a diffusion model, may reveal the mechanisms at work in visual attention that serve to decrease identification RT. Because the diffusion model has been the preferred model to account for identification RT (e.g. Ratcliff, 2002), it was important to determine whether it could easily account for the current results. As

stated previously, the pdf of the 1-D diffusion process is described by the Wald distribution (Eqn. 1), which has three parameters, L (boundary), r (drift rate), and d (drift rate variability). In order to explore the behavior of the Wald with respect to its parameters, many representative Wald pdfs, over a large variety of parameter values, were constructed over the interval $x = 0$ to 1 second. Then, for each distribution, 1000 simulated observations were sampled and fitted to ex-Gaussians. Fits were excellent between the sampled Wald values and the ex-Gaussians (mean $r = .99$). It was found that varying a single Wald parameter (L , r , or d) in order to reduce mean finishing time (RT) produced characteristic ex-Gaussian parameter changes. Decreasing the boundary produced decreases in μ and σ , with τ approximately constant. Increasing the drift rate (the most likely candidate for an attention-related parameter) produced decreases in μ , τ , and σ . Increasing drift rate variability produced a decrease in μ , an **increase** in τ , and no change in σ . According to the simulations, it is not possible to create, by varying a single parameter, a family of identical-shape Wald distributions that differ only in location along the x axis (i.e., where μ and no other parameter in the fitted ex-Gaussian is changed). This result can be confirmed by comparing Equations 1 and 2. For Equation 2 (ex-Gaussian), μ is additive with respect to t , so the effects of changing μ and t are equivalent. On the other hand, for Equation 1, (Wald), no parameter has a simple additive relationship with t .

The results of the above simulations, and inspection of the Wald and ex-Gaussian equations, run parallel to previous inferences drawn about the diffusion model and ex-Gaussian parameters. Zabel and Anderson (1997) plotted Wald

densities and observed that, with changes in drift rate and drift rate variability, there were always corresponding changes in distribution shape. Ratcliff (1993), noted that changes in the Wald drift rate corresponded to changes in both μ and τ in the ex-Gaussian fits. Similarly, Spieler et al. (2000) simulated random walks in which single parameters (drift rate or boundary) were manipulated, after which they fitted ex-Gaussians. When boundary was increased, there were monotonic increases in μ , τ , and σ , although the increase in μ was about five times the increases in τ and σ . Spieler et al. also found that when they increased drift rate, there were monotonic decreases in μ , τ , and σ , although the decrease in τ was highly nonlinear over the range of drift rates they tested. These three studies confirm the above results that single parameter changes in the Wald would not produce simple x-axis translations of RT distributions. Of course, it is possible that coordinated parameter changes could effect a strict translation in the RT distributions, but these would have to take effect over all SOAs and both experiments. Therefore, the shape invariance of the RT distributions suggests that the diffusion process cannot model the present data by varying drift rate, drift rate variability, or boundary singly. This result was not anticipated, because drift rate is the most reasonable candidate for a diffusion model parameter that corresponds to differences in attention or task difficulty.

One way for a diffusion model to produce a set of translated RT distributions is by adding a parameter which corresponds to a variable delay in the onset of information uptake (drift). The delay would be longest at short cue-target SOAs. In some ways, this delay corresponds to hypothesized mechanisms in visual

attention. For instance, Sperling & Weichselgartner (1995) suggested that a threshold amount of target information must be collected before identification processes can start, and it is reasonable that this delay would be greatest at short SOAs. In order for this delay to produce strictly-translated RT distributions, it is necessary that the amount of noise accumulated during the delay remain constant. However, the few sequential sampling models that include a variable delay, which has been termed *premature sampling* (Laming, 1968; Rouder, 1996) or equivalently, starting point variability (Ratcliff & Rouder, 1998; Ratcliff et al., 1999), also posit that the system drifts with mean drift rate equal to zero during the delay. This drift would add noise to the process in proportion to the amount of time spent in drift (or the starting point variance), which would show up in differences of σ and τ in the ex-Gaussians.

In order to accommodate the shape constancy in the RT distributions that were found in the present experiments, a diffusion model would need to hold the total accumulated noise to a constant amount. This could be accomplished with a variable initial dwell period in which the integrated noise would be held to 0 or some other constant; i.e., the system would be “on hold” for a variable period of time before information accumulation would start, perhaps waiting for target localization or information of a minimum “packet size”. This constant-noise delay, while allowing the diffusion model to fit the present data, may seem biologically implausible and ad-hoc.

In summary, the same results and implications were obtained for both peripheral (Experiment 1) and central (Experiment 2) cues: Decreases in mean

identification RT as a function of cue-target SOA were accomplished by an x-axis translation of the RT distributions. This similarity across experiments suggests that the two types of cues invoke common mechanisms affecting response time in target identification, but this mechanism does not appear to correspond with simple changes in sensitivity (drift rate) in a diffusion model. In order to accommodate the translated RT distributions, a model based on a diffusion process may be required to include constant-noise (with the degenerate case being zero-noise) variable time delays in the uptake of information. This may seem implausible biologically, but adjusting diffusion model parameters of drift rate, drift rate variability, or boundary (unless precisely coordinated) would have corresponded to changes in the shape of RT distributions as a function of SOA.

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Figure Captions

Figure 1. Order of events in a trial. Experiment 1 used peripheral cues; Experiment 2 used central cues.

Figure 2. Mean correct RT (top) and accuracy (bottom) for valid and invalid trials. Experiment 1 used peripheral cues; Experiment 2 used central cues. Bars represent standard errors.

Figure 3. Means of best-fit ex-Gaussian parameters for Experiment 1, valid trials, correct responses. Bars represent mean standard errors for parameter estimates, computed on individual fits.

Figure 4. Means of best-fit ex-Gaussian parameters for Experiment 2, valid trials, correct responses. Bars represent mean standard errors for parameter estimates, computed on individual fits.

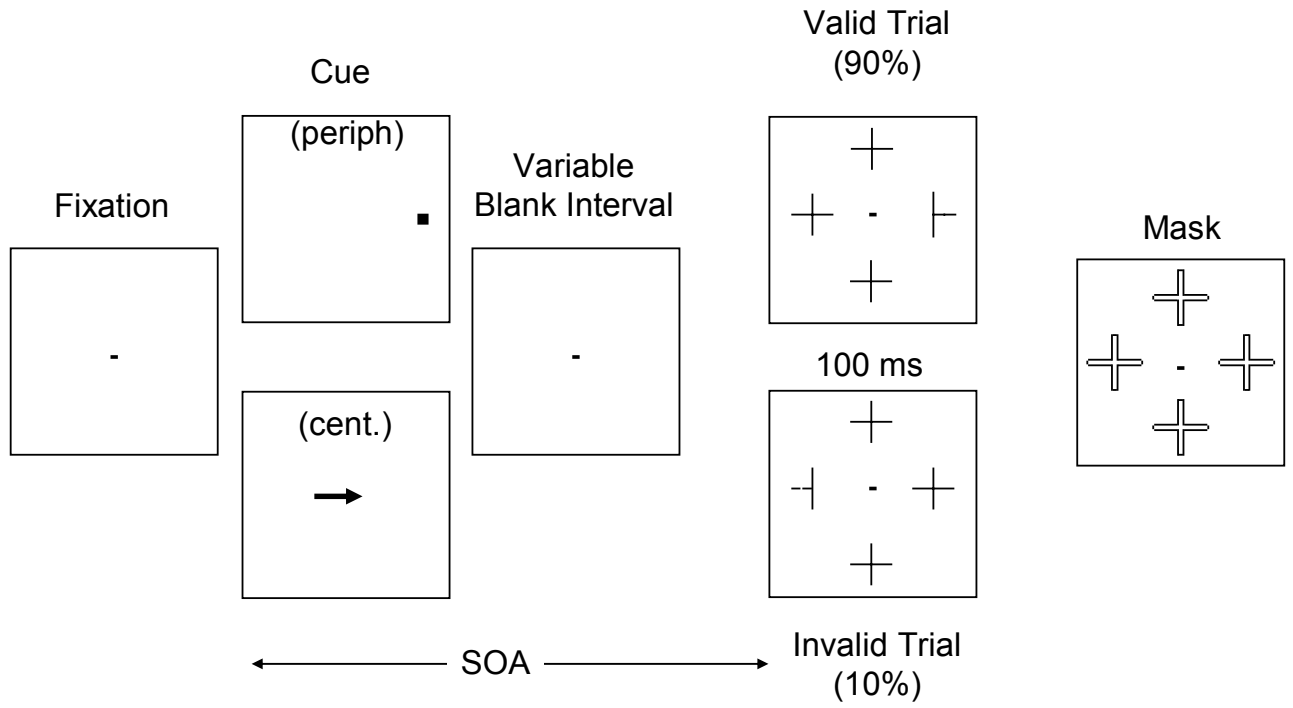


Fig 1

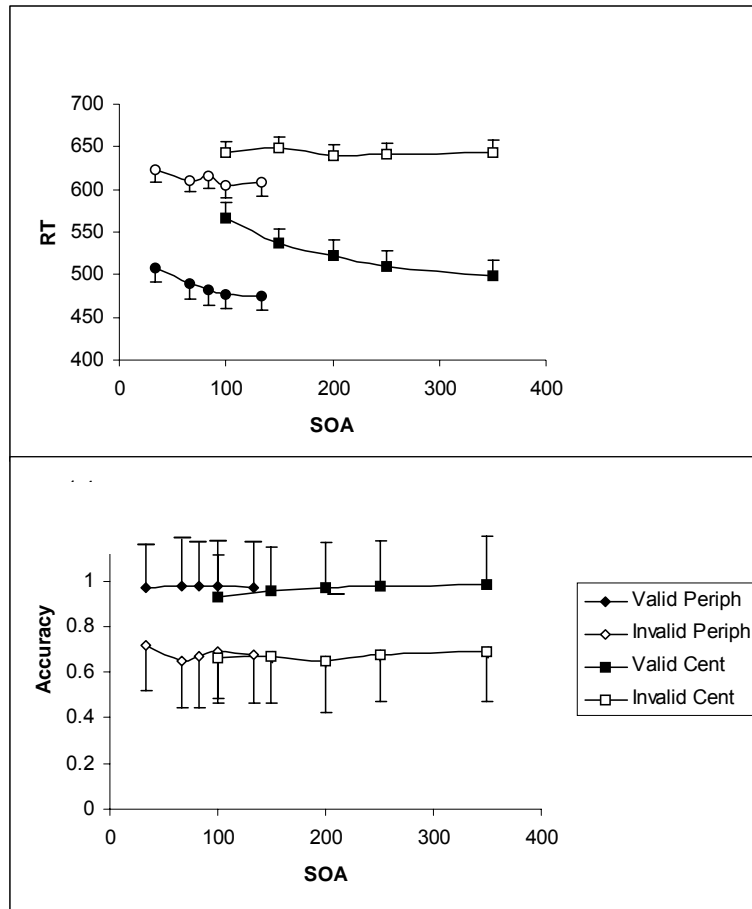


Fig 2

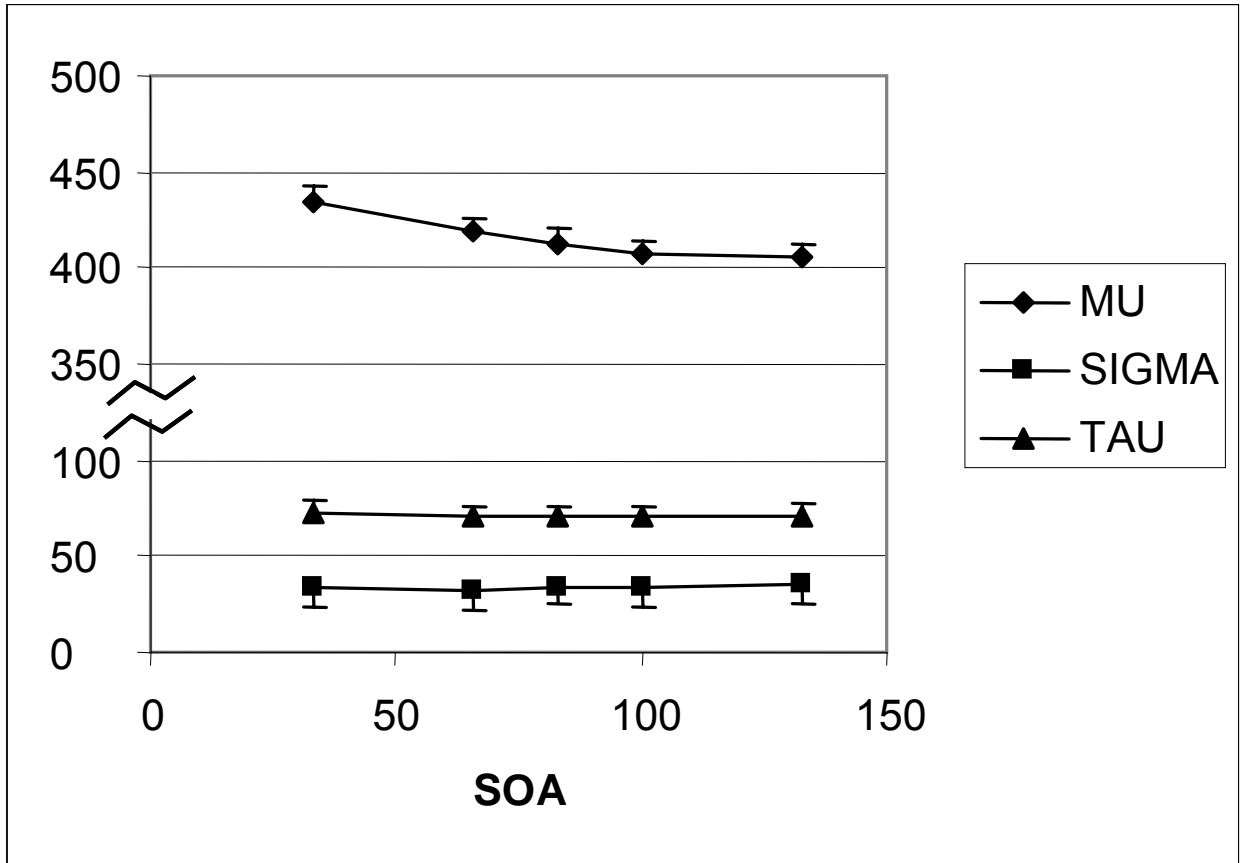


Fig. 3

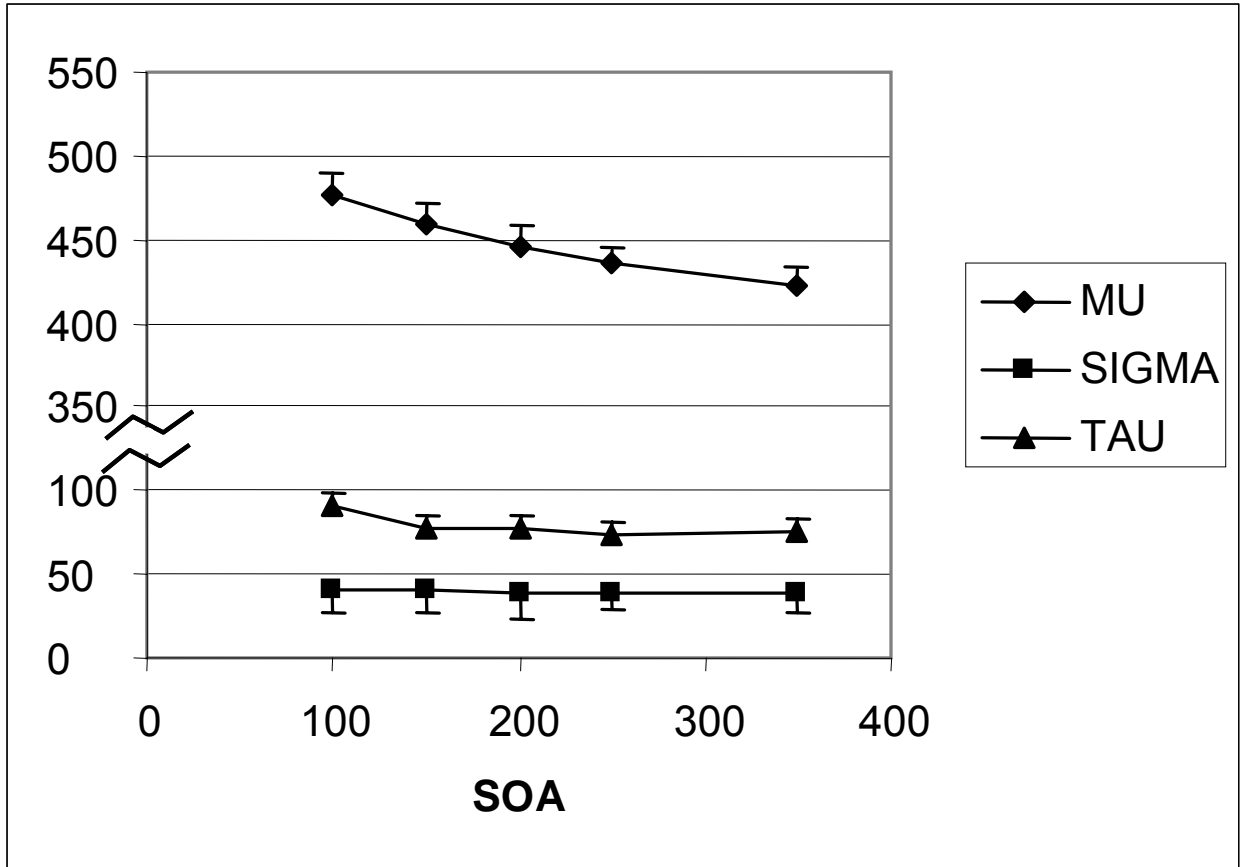


Fig. 4

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