Quantifying the Effects of Spatial Uncertainty in Visual Scanning on Concurrent Task Performance

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Abstract

Much research in visual scanning has adopted a single task experimental paradigm. The characteristics of visual scanning in multi-task situations are largely unknown. This article describes two experiments that were conducted to examine the relation between visual scanning and concurrent activities, to quantify the effects of spatial uncertainty in visual scanning on concurrent performance of multiple tasks, and to address the relation between theories of selective attention and visual scanning and theories of divided attention and multi-task performance. Subjects were required to perform a simple information acquisition task in the first experiment and a complex information integration task in the second experiment. The two types of tasks were performed either alone or concurrently with a tracking task, and involved either spatial or verbal material. The location of the relevant spatial and verbal material was displayed with 4 levels of spatial uncertainty, but with approximately the same expected scanning distance. The results revealed unique characteristics of visual scanning in multi-task performance, demonstrated the strengths and limitations of existing theories, and provided strong support for a queuing network model of human multi-task performance.

Introduction

Visual scanning is one of the most important attention mechanisms of obtaining environmental information. In many visual tasks involving a large field of view, the perceiver has to scan and sample the sources of visual information sequentially in a selective manner if the acuity demands of the information sources are high, since human foveal vision has a limited size of about 2 degrees in visual angle. This requirement for sequential and selective scanning exists in these tasks, no matter whether the nature of visual attention can be best captured as a searchlight (Wachtel, 1967), which functions in a focused state, or as a zoom or variable-power lens (Eriksen and Yeh, 1985; Eriksen and James, 1986), which functions in a continuously adjustable manner with focused state and widely-distributed state as two extremes.

Researchers have devoted a great deal of attention to the sequential and selective nature of visual scanning. Patterns and characteristics of visual scanning have been studied in a large variety of contexts such as reading processes (e.g., McConkie, Underwood, Zola, and Wolverton, 1985), pictorial processing (e.g., Friedman and Liebelt, 1981), infant and developmental mechanisms (e.g., Hainline, 1981), static and dynamic displays (e.g., Moray, 1986), industrial inspection (e.g., Drury, 1990), and internal mental processing such as mental rotation (e.g., Carpenter and Just, 1978). The focus of research has been on identifying the psychological and stimulus-related factors that may affect the temporal and spatial patterns of visual scanning, and on identifying the potential mechanisms that may affect the perceiver's strategies in visual scanning. Much research in this area has adopted a single task experimental paradigm, in which no simultaneous tasks are performed with the task of visual search. The issue of visual scanning in multi-task situations, in which the perceivers are simultaneously engaged in other concurrent activities while scanning sources of visual information, has received little research attention.

In real-world situations visual scanning is often performed simultaneously with other tasks. For example, one characteristic of automobile driving is the need to perform a number of concurrent manual control and decision activities, while selectively and sequentially scanning physically separated sources of information. Thus, a natural and important extension to the current visual scanning research is to systematically examine the characteristics of visual scanning in multi-task environments, and to address the relation between visual scanning and other concurrent activities.

From the perspective of practical applications, a better understanding of visual scanning in multi-task environments will prove to be of great value to human-machine system designers in their analysis of multi-task human-machine interfaces such as driver-vehicle interfaces and cockpit instrument panels. One important research topic in addressing the immediate needs of designers of multi-tasking human-machine systems is to quantify the cost of visual scanning involved in time-sharing between an instrument panel and the forward view of a roadway or other critical environmental information, and to identify the critical factors that may affect this cost (Baron, Kruser, and Huey, 1990; Elkind, Card, Hochberg, and Huey, 1990). Although a substantial amount of data and knowledge have been accumulated in evaluating the cost of scanning in single task situations, it is not clear whether or not these results are readily generalizable to multi-task situations. For example, converging evidence from a large number of single task studies indicates that the time required for a complete eye movement cycle is about 200-250 msec (Bartz, 1962; Dodge and Cline, 1901; Fuchs, 1971; McConkie et al., 1985). However, it remains to be determined how the rate of scanning in dual task situations would compare with this single task result, and how the scanning rate may change as a function of the demands and characteristics of concurrent activities. A major objective of the present study is to address this issue.

From a theoretical perspective, studies of visual scanning in multi-task situations will not only provide unique insights into the nature of visual scanning that cannot be gained through single task studies, but may also provide a natural link in bridging the substantial gap that currently exists between studies of selective attention and studies of di :ed attention in investigations of concurrent performance of multiple tasks. There is an urgent need to address the relation between the serial processing theories of selective attention and the parallel processing theories of divided attention in the context of complex task performance (Liu and Wickens, 1989, 1992).

Scanning and sampling behavior has been regarded as one of the direct indicators of single channel selective information processing, and is an area of research that has enjoyed great success in theoretical analysis and computational modeling through the efforts of single channel theorists (Moray, 1986; Sanders, 1983; Senders, 1964). However, single channel theories have shown no direct consideration of the processes that are concurrently performed with visual scanning. The effects of concurrent processes have been treated as additive factors, with no analysis of the possible differential effects of those processes. Parallel processing theories of divided attention such as the multiple resources theory (Wickens, 1980), in contrast, have shown no direct consideration of selective processes such as visual scanning. A typical strategy of investigators in this research paradigm has been to treat visual scanning as an extraneous factor or to keep the amount of scanning as small and constant as possible. Since the activity of visual scanning itself can only be performed in a selective and sequential fashion, but other concurrent activities of a different nature can be performed simultaneously with the activity of visual scanning, Liu and Wickens (1989, 1992) proposed that studies of visual scanning in multi-task situations may serve as a natural experimental paradigm in addressing the relation between the two schools of theories. Furthermore, based on a review of research findings on the characteristics of visual scanning, they proposed that spatial uncertainty in visual scanning may be a critical factor in analyzing the cost of scanning.

In an experiment designed to address these issues, subjects were required to perform a primary tracking task, which was concurrently performed with a secondary spatial or verbal decision task. The relevant information that was needed to perform the decision tasks was displayed with or without spatial uncertainty. Converging evidence from three of a total of four dependent measures (decision accuracy, tracking performance, and subjective difficulty rating) showed that visual scanning as a spatial exploratory activity produced greater task interference with concurrent spatial tasks than with verbal tasks. Spatial uncertainty in visual scanning was identified to be the crucial factor in producing this differential effect. These results are consistent with the predictions of multiple resource theories of divided attention (Baddeley, 1986; Friedman and Polson, 1981; Wickens, 1980). The common belief of these theories is that there exist multiple parallel processing mechanisms or resources such as spatial and verbal processing codes, and that task interference will occur only to the extent that concurrent tasks compete for common processing resources. Since experimental evidence from a large number of studies has identified visual scanning as a spatial exploratory activity driven by a perceiver's intentions and strategies for the purpose of reducing scanning uncertainty (Fisher et al., 1981; Brogan, 1990; Gale and Johnson, 1984), it is not surprising that visual scanning produced greater task interference with concurrent spatial tasks than with verbal tasks, particularly when spatial uncertainty was involved in scanning. Single channel theories of selective attention, with their common serial processing assumption about human information processing, would have difficulties in explaining these results.

However, an analysis of additive factors on response time data also showed a close fit between the experimental results and the data that would be predicted by single channel theories of selective attention and eye movement data. Response time was longer when spatial uncertainty was involved in visual scanning, and the response time functions were almost identical for both the spatial and the verbal decision tasks. Since scanning uncertainty introduced additional eye movements, which can only be performed sequentially, this result was shown as an evidence of the particular strength of single channel theory in analyzing response time. Thus, the results of the experiment provided support to both the parallel processing theories of divided attention and the serial processing theories of selective attention. The results also indicated that when selective and divided aspects of attention are intertwined with each other, as when visual scanning is simultaneously performed with concurrent tasks of different nature, neither class of theories alone is sufficient to make accurate predictions and provide fully satisfactory explanations (Liu and Wickens, 1989, 1992).

While Liu and Wickens demonstrated the effects of spatial uncertainty in visual scanning on concurrent decision and manual control tasks, spatial uncertainty was manipulated at only two levels, i.e., either the presence or absence of uncertainty regarding the spatial location of the stimulus material. Thus, the data did not provide an empirical basis for quantifying the effects of scanning uncertainty on concurrent activities. Another feature of the experiment was that the discrete response tasks were complex information integration tasks, which imposed simultaneous demands on multiple information processing systems such as running memory, mental rotation or arithmetic processing, and choice response. Due to the complexity of the discrete decision tasks employed, it was difficult to unravel the processes involved and disentangle the effects of various contributing factors. The present study seeks to quantify the effects of scanning uncertainty on concurrent task performance, to provide a much stronger test of the relation among the factors involved in performing these activities, and to further examine the relation between the single channel theories of selective attention and the parallel processing theories of divided attention. Two experiments were conducted to meet these research objectives.

The experiments required the subjects to perform a discrete response task, which was a simple information acquisition task in the first experiment and a complex information integration task in the second experiment. The two tasks were designed in a way such that the information acquisition task is a component of the information integration task in terms of the information processing activities involved. The discrete response tasks in both experiments were performed either alone or concurrently with a tracking task, and involved either spatial or verbal material. The location of the relevant spatial and verbal material was displayed with 4 levels of spatial uncertainty, but with approximately the same expected distance for visual scanning. The purpose of the first experiment was to quantify the effects of scanning uncertainty on the simple task of information acquisition in single and dual task conditions. The second experiment attempts to quantify the effects of scanning uncertainty on the complex task of information integration in single and dual task conditions. Due to the intrinsic relation between the two discrete tasks in their information processing requirements, a more comprehensive view of the role of visual scanning in multi-task environments can be obtained by comparing the results of both experiments.

Experiment 1

Method

Subjects

Twelve right-handed University of Michigan students (six men and six women) were recruited as subjects and paid for their participation in the experiment. All subjects had normal or corrected to normal vision.

Task and Stimuli

Two types of information acquisition tasks were employed in this experiment. Both tasks presented stimuli for three seconds, were force-paced at the same rate of six second stimulus intervals. Both tasks required subjects to make four-alternative responses manually by pressing one of four right-hand keys on a keyboard.

Spatial information acquisition task. The subjects were presented with a sequence of organized arrays of circles, each of which carried a vector emanating from the center of the circle (fig. 1). Upon presentation of each display, the subjects were required to (a) search for the vector that was displayed with a solid line, and (b) make a four-alternative response regarding which quadrant that vector was in. The vectors in other circles were displayed with dashed lines. Visual search was not involved under no-scanning conditions, in which the subjects were informed about the location of the solid line and were instructed to fixate that circle before the start of the trials.

Verbal information acquisition task. The subjects were presented with a sequence of organized arrays of circles, each of which carried a double-digit decimal number at the center of the circle. Upon presentation of each display, the subjects were required to (a) search for the number that was displayed with a slightly greater size than the numbers in the other circles, and (b) make a four-alternative response regarding the value of the displayed number. The four response alternatives correspond to a value of smaller than 0.25, between 0.25 and 0.50, between 0.50 and 0.75, and greater than 0.75, respectively. As in the spatial information acquisition task, visual search was not involved under no-scanning conditions.

Task display and visual scanning. The task display consisted of eight information display circles and a horizontal tracking display (fig. 1). For explanatory purpose, the eight information circles are named circles C1 through C8, respectively, as shown in fig. 1. On a given experimental trial, only one of the eight circles carried the information required to make the spatial or verbal decision, which was either a vector displayed with a solid line or a number displayed with a slightly greater size. The subjects were instructed to use only the information from the relevant circle, while ignoring the other circles. The factor of spatial uncertainty in visual scanning was manipulated at four levels, corresponding to the situations in which the relevant information was equally likely to be in one of 1, 2, 4, or 8 circles, respectively. For explanatory purpose, the four uncertainty conditions are referred to as N=1, N=2, N=4, and N=8, respectively, where N is the number of circles that were equally likely to carry the relevant information. At the lowest uncertainty level (i.e., the N=1 condition), the relevant circle was always the circle C5. Under the N=2 condition, the relevant information was in either circle C3 or circle C7 with equal probability on each trial. Under the N=4 condition, the relevant circle could be any one of the following four circles with equal probability on each trial: C1, C3, C5, or C7. At the highest uncertainty level, i.e., the N=8 condition, the relevant information was in any one of the eight information circles with equal probability. It can be verified through geometric calculation that the expected scanning distances were approximately the same for the four conditions involving different levels of scanning uncertainty.

Before the start of each experimental block, the subjects were always instructed about the signal display structure, i.e., which circle or circles would be relevant in that block. The visual angle subtending the centers of two adjacent circles was about 9 degrees, which was the same as that subtending the center of the tracking display and the center of Circle C1. The subjects were instructed not to make head movements while they were performing the task. The display was selected according to results from previous studies (Liu and Wickens, 1992) and observations from testing pilot subjects to ensure that critical details of the decision stimuli could not be resolved in peripheral vision. Therefore, visual scanning was necessary to accomplish the tasks.

Tracking task. A first-order one-dimensional pursuit tracking task was developed as a simulation of driving down a winding road. Three equally spaced parallel red lines were used to represent the edges and the center of a lane (shown as the three solid lines on the horizontal bar in fig. 1). As a simulation of a curved road, a random function was used to continuously change the lane's position. The subject's position in the lane was represented by a black line (shown as the dashed line on the horizontal bar in fig. 1). The subjects manipulated a computer mouse in the left-right direction with the left hand in order to minimize the error between their own position (the dashed line) and the center of the lane (the center solid line).

Insert fig. 1 about here

Design and Procedure

The experiment employed a 4 X 2 X 2 repeated measures design with level of scanning uncertainty (N=1, 2, 4, 8), decision code (spatial/verbal), and type of task (single or dual task) as three experimental factors. In the single task conditions, the decision tasks were performed alone, whereas in the dual task conditions, they were performed with the concurrent tracking task. The experiment consisted of seven sessions. The first three sessions were devoted to single and dual task training. The last four sessions were experimental sessions. Each session included 21 blocks of 90 seconds each: five no-scanning baseline conditions (spatial or verbal discrete response task performed with or without concurrent tracking task, and the tracking task performed alone) and 16 experimental blocks formed by the combination of the 4 levels of scanning uncertainty X 2 types of decision codes (spatial/verbal) X 2 types of tasks (with or without concurrent tracking task). Subjects made fifteen decisions of the same type during each block. When the tracking task was involved in a given block, subjects performed the tracking task continually and were instructed to give attention priority to tracking performance, which was measured by tracking root mean square error (RMSE). Decision error was measured by the percentage of incorrect responses. Decision response time was measured as the duration between stimulus presentation and subject's decision response. After each block in the experimental sessions, the NASA bipolar workload scale was used to collect the subject's subjective workload experienced in that block. This procedure resulted in a weighted workload rating for the subject in each experimental condition, which was based on the subject's ratings of six subscales and his/her assignment of importance weights to the different subscales. A detailed description of the rationale and implementation of the NASA workload scale is provided by Hart and Staveland (1987). A video camera and a video cassette recorder were used for a subset of four subjects to record their eye movements while they were performing the various tasks. The video camera was installed on top of the display monitor. The tasks were implemented on an Macintosh IIci computer with a 21 inch color monitor, and were conducted in a sound-attenuated experimental chamber.

Results and Discussion

For analysis purpose, the experimental conditions can be classified into four general classes: no-scanning single or dual task conditions, and single or dual task conditions that involved visual scanning. The purpose of the no-scanning single task conditions was to establish the difficulty level of the two decision tasks as a basis for evaluating their effects on performance and workload in other conditions. The no-scanning single and dual task conditions provided the baselines for determining the effects of scanning uncertainty on performance and workload in corresponding single or dual task conditions that involved visual scanning.

No-scanning Single and Dual Task Results

Presented in table 1 are the single task performance and workload measures of the spatial and verbal four-alternative decision tasks when visual scanning was not involved in their performance. Each of the three measures was subjected to an identical univariate F-test. None of the three dependent measures showed a significant difference between the two types of decisions (all p' s > 0.10), indicating that the choice of the two types of decision tasks was successful in equating the performance and difficulty levels of the two tasks in no-scanning single task conditions. This experimental manipulation was important for the analysis and interpretation of the results in other conditions.

Insert table 1 about here

Presented in table 2 are the performance and workload measures of no-scanning baseline dual task conditions. Each of the dual task measures was compared with the corresponding single task data. The result showed that concurrent performance of the tracking task produced a significant workload increment ($F(1,11) = 6.88$, $p < 0.05$), but none of the other three scores showed a significant difference between the single and the dual task conditions. Furthermore, none of the four dual task measures showed a significant difference between the spatial and verbal conditions (all p 's > 0.10).

Insert table 2 about here

Effects of visual scanning: Results of Analysis of Variances

Performance and workload measures of the single and dual task conditions are plotted in fig. 2 as a function of scanning uncertainty (on the abscissa), task type (the two pairs of lines within each panel) and decision code (the two lines within each pairs). The no-scanning single and dual task data are plotted on the ordinate. Data points and lines near the top of each graph always indicate poor performance or high workload. Since the

N=1 condition did not involve scanning uncertainty, each of the N=1 measures was first compared to the corresponding no-scanning data. The result showed that the scanning requirement produced a significant increment in response time ($F(1, 11) = 8.79$, $p < 0.05$) and in workload ($F(1, 11) = 5.31$, $p < 0.05$), and neither of the increments was affected by decision code or task type. Decision error did not show any difference for the two conditions, nor did tracking error (all p's > 0.10).

In order to examine the effects of scanning uncertainty, each of the three decision and workload measures was subjected to an identical 4 (scanning uncertainty) x 2 (task type) x 2 (decision code) x 12 (subject) repeated measures analysis of variance (ANOVAs), whereas tracking performance was subjected to a 4 (scanning uncertainty) x 2 (decision code) x 12 (subject) repeated measures ANOVA. Where appropriate, as will be described, these ANOVAs were broken down further for the examination of two-way interaction effects and simple main effects (Keppel, 1982).

Insert fig. 2 about here

Response time. A significant two-way interaction between scanning uncertainty and decision code was found in the dual task condition ($F(3,11) = 5.37$, $p < 0.05$), but not in the single task condition ($F(3,11) = 1.35$, $p > 0.10$), resulting in a significant three-way interaction between the three variables ($F(3, 11) = 4.22$, $p < 0.05$). Closer inspection of the data suggests that this two-way interaction in the dual-task condition is attributable to the differential behavior of the decision code when scanning uncertainty was at the level of N=8 compared to the other scanning uncertainty conditions. The results of more detailed ANOVAs confirmed this speculation. In 3 x 2 x 2 ANOVAs from which the N=8 condition was removed, neither the two-way interaction nor the three-way interaction was found (all p's > 0.10), but the main effect of scanning uncertainty was not changed by the reanalysis. These results, together with paired comparisons between data at adjacent uncertainty levels within each variable, indicate that in both the single and the dual task conditions, every increase in scanning uncertainty resulted in a significant increase in decision response time (all p's < 0.05 for the 12 paired comparisons). Furthermore, when scanning uncertainty was at the level of N=8, scanning uncertainty produced greater response time increment when tracking was concurrently performed with the spatial task than with the verbal task.

Decision error. As suggested by the data in fig. 2, decision error was not influenced by any of the experimental variables (all p's > 0.10).

Tracking error. As shown in fig. 2, tracking error was greater when scanning uncertainty was at the level of N=8 than at other levels, which were not different among themselves ($F(3,11) = 14.8$, $p < 0.001$, for the data that includes the N=8 condition; $F(2,11) = 1.73$, $p > 0.10$, for the data that does not include the N=8 condition). Tracking performance was not influenced by decision code, nor did this variable interact with scanning uncertainty (all p's > 0.10).

Subjective workload. Every increase in scanning uncertainty resulted in a significant increase in subjective workload (main effect of scanning uncertainty: $F(3, 11) = 21.53$, $p < 0.001$; all p's < 0.05 for the 12 paired comparisons between data at adjacent scanning uncertainty levels within each variable). Subjects also reported higher workload ratings in dual task conditions compared to the corresponding single task conditions (main effect of task type: $F(1, 11) = 33.98$, $p < 0.001$). No indication for any effect of decision code was found, nor was any interaction between the experimental variables (all p's > 0.10).

Effects of visual scanning: Results of Regression Analysis.

Visual inspection of the performance and workload data shown in fig. 2 suggests that increases in scanning demand produced linear increases in response time, but nonlinear increases in tracking performance and subjective workload. The results of the following regression analysis on the data points corresponding to the four scanning uncertainty conditions (i.e., when N=1, 2, 4, and 8) lend support to this speculation.

Response time. For the single task data, averaged across the two decision codes, linear regression provided the best fitting least squares line relating response time (RT) to scanning uncertainty (i.e., the number of relevant circles: N) in the equation form of (RT = 914 + 132N), with an Adjusted Squared Multiple R of 0.985. This result indicates that 98.5% of the total variation in response time could be accounted for by a linear prediction from changes in scanning demand. For the dual task data, the best fitting linear model has the form of (RT = 981 + 148N), with an Adjusted Squared Multiple R of 0.986. The slope of the regression line for the dual task data had a significantly larger value than for the single task data (slope: $t(10) = 2.47$, $p < 0.05$), but the difference between the two intercept values did not reach statistical significance ($t(10) = 1.77$, $p > 0.10$).

Tracking error. While increases in scanning demand produced linear increases in response time, data shown in fig. 2 suggests that tracking performance degraded at an accelerated rate as the demand for eye movement increased. This speculation was confirmed by the results of regression analysis, which indicated that a power function in the form of (RMSE = 0.209 + $0.003N^2$) accounted for 97.7% of the variance in tracking RMSE data, whereas the best fitting linear model in the form of (RMSE = 0.173 + 0.026N) was able to account for 85.2% of the variance.

Workload. Workload increased at a decelerated rate as scanning demands increased, which was a trend different from both response time and tracking error. Power functions in the forms of (Workload = 9.083 + 6.844 $N^{0.5}$) and (Workload = 11.951 + 9.751 $N^{0.5}$) accounted for 96.9% and 94.1% of the variations in workload data in the single and dual task conditions, respectively, whereas the best fitting linear models in the forms of (Workload = 15.041 + 1.716N) and (Workload = 20.582 + 2.407N) accounted for 90.8 % and 83.8% of the variances, respectively. All of the regression coefficients for the dual task data had a significant larger value than the corresponding coefficient for the single task data (all t's < 0.05).

It should be noted here that due to the limited number of data points obtained in the present study, no attempt was made to identify the best fitting exponent of the power functions, or to identify alternative functions that may fit the data better. The regression analysis conducted here is a preliminary attempt to quantitatively characterize the interesting dissociation among the dependent measures observed in the present data, and to suggest a research topic that is worthy of further investigation.

In the current experiment, both the eye movement recording performed on a subset of four of the subjects and subjective report indicate that the relevant stimulus information could not be or was very hard to be determined through peripheral vision. It was apparent that subjects did not attempt to use peripheral vision or head movement to locate the relevant stimulus. The close fit between the observed response time data and the linear model further illustrate this point.

In summary, the results of the first experiment showed that every increase in scanning uncertainty produced a significant increase in response time and in workload, and the increase was faster in the dual task conditions than in the corresponding single task conditions. A two-way interaction between scanning uncertainty and decision code was observed in the dual task response time data, indicating that concurrent performance of the tracking task produced a greater response time increment for the spatial decision task than for the verbal decision task when the demand for visual scanning was high.

It is reasonable to assume that the spatial and the verbal task employed in the present study had the same level of task difficulty, considering the no-scanning baseline single task data that showed the equivalence of all the performance and workload measures for the two tasks. Therefore, the observed difference in the dual task response time data between the spatial and the verbal task when visual scanning was required is most likely attributable to the difference in the processing materials involved in the two tasks. The finding that this differential behavior of decision code emerged only in the dual task when scanning uncertainty reached the level of N=8 indicates that neither the presence of a concurrent task nor the presence of scanning uncertainty is a sufficient condition for this interaction to emerge. An interesting question is to predict the situations in which this interaction will occur and to identify the critical factors that must be considered in making this prediction. Experiment 2 attempts to address this issue.

Experiment 2

The discrete response tasks employed in Experiment 1 were simple information acquisition tasks. In order to accomplish the task, the subjects needed to perform two activities serially: searching for the relevant information, and then making a four-alternative response regarding the location or value of the stimuli. The two serial activities were performed with either the presence or absence of a concurrent tracking task. Experiment 2 extends the scope of study by employing a complex information integration task as the discrete response task, which by itself required the subjects to perform a number of activities concurrently. An interesting question is the effects of the concurrent activities embedded within the discrete task, with either the presence or the absence of a concurrent tracking task, on the subject's scanning behavior and complex task performance.

Method

The method was basically the same as the method of Experiment 1, except for the discrete response task employed. Twelve right-handed University of Michigan students (six men and six women) were recruited as subjects and paid for their participation in the experiment. All subjects had normal or corrected to normal vision. None of the subjects had participated in the first experiment.

<u>Information Integration Task</u>

Two types of information integration tasks were employed in this experiment, involving either spatial or verbal material. Both the spatial and the verbal tasks imposed analogous demands on the respective spatial or verbal working memory systems, by imposing a continuous running memory task with overlapping encoding, storage and retrieval processes. The processing demands of the spatial and verbal decision tasks were equated according to the results from previous studies that employed similar tasks (Liu and Wickens, 1989, 1992; Wickens and Liu, 1988), and on the basis of Experiment 1 and testing pilot subjects. Both tasks presented stimuli for three seconds, were force-paced at the same rate of six second stimulus intervals, had both a four-alternative choice component and a continuous running memory component. Both decision responses were made manually by pressing one of four right-hand keys on a keyboard.

<u>Spatial information integration task</u>. As in Experiment 1, the subjects were presented with a sequence of organized arrays of circles, each of which carried a vector emanating from the center of a circle. However, the integration task required the subjects to make four-alternative responses based on his/her prediction of the future position of the displayed vector. Upon presentation of each display, the subjects were required to (a) search for the vector that was displayed with a solid line, (b) compare that vector's angular position with the memorized position of the previous vector to make a prediction about which quadrant the future position of the vector would be in, and (c) remember the currently displayed vector's position for use in the next judgment. The vectors in other circles were displayed with dashed lines. Visual search was not involved under no-scanning conditions, in which the subjects were informed about the location of the solid line and were instructed to fixate that circle before the start of the trials. The decision rule is: the angle of clockwise rotation between the "past" and the "current" vectors should equal the angle of clockwise rotation between the "current" and the "predicted" vectors.

To accomplish the task then, the subjects need to maintain an analog representation in spatial working memory, while performing a mental rotation (Shepard and Metzler, 1971). The position vectors were generated randomly, with the restriction that the "predicted" position (i.e., the one whose position was to be estimated) never fell in the +/- 15 deg area centered on n*90 deg (n is integer). This constraint was imposed to reduce decision ambiguity in resolving angle differences that were near the boundaries between the quadrants.

Verbal information integration task. This task required the subjects to make four-alternative responses based on his/her calculation of a "predicted" value. The subjects were presented with a sequence of organized arrays of circles, each of which carried a double-digit decimal number at the center of a circle. Upon presentation of each display, the subjects were required to (a) search for the number that was displayed with a slightly greater size than the numbers in the other circles, (b) make four-alternative responses based on his/her calculation of a "predicted" value according to a decision rule, and (c) remember the value of the currently displayed number for use in the next judgment. According to the decision rule, the "predicted" value is always between 0.00 and 1.00, and should be the summation of the "past" and the "current" number. The requirements for visual scanning, and the definition and function of "past", "current' and "predicted" were analogous to those in the spatial information integration task. The four response alternatives corresponded to a "predicted" value of smaller than 0.25, between 0.25 and 0.50, between 0.50 and 0.75, and greater than 0.75, respectively. If the result of summation is greater than 1.00, then the 'predicted' value is the difference between the result of summation and 1.00.

Other aspects of the experimental methods, including task display, visual scanning requirements, the primary tracking task, and the experimental design and procedure, were the same as in Experiment 1.

Results and Discussion

No-scanning Single and Dual Task Results

Presented in table 3 are the single task performance and workload measures of the spatial and verbal four-alternative decision tasks when visual scanning was not involved in their performance. Each of the three measures was subjected to an identical univariate F-test. As in Experiment 1, none of the three dependent measures showed a significant difference between the two types of decisions (all p' s > 0.10), indicating that the choice of the two types of decision tasks was successful in equating the performance and difficulty levels of the two tasks in no-scanning single task conditions.

Insert table 3 about here

Presented in table 4 are the performance and workload measures of no-scanning baseline dual task conditions. Each of the dual task measures was compared with the corresponding single task data. The result showed that concurrent performance of the tracking task produced significant workload and decision response time increments (workload: $F(1, 11) = 17.22$, $p < 0.01$; response time: $F(1, 11) = 8.92$, $p < 0.05$), but did not result in any change in tracking performance and decision accuracy (both p's > 0.10). Furthermore, none of the four dual task measures showed a significant difference between the spatial and verbal conditions (all p's > 0.10).

Insert table 4 about here

Effects of Visual Scanning: Results of Analysis of Variance

As in Experiment 1, performance and workload measures of the single and dual task conditions are plotted in fig. 3 as a function of scanning uncertainty (on the abscissa), task type (the two pairs of lines within each panel) and decision code (the two lines within each pairs). Data points and lines near the top of each graph always indicate poor performance or high workload. A comparison between the N=1 data and the no-scanning data (on the ordinate) showed that the scanning requirement produced a significant increment in response time ($F(1, 11) = 14.33$, $p < 0.01$) and in workload ($F(1, 11) = 6.48$, $p < 0.05$), and neither of the increments was affected by decision code or task type. Decision error did not show any difference for the two conditions, nor did tracking error (all p's > 0.10).

Each of the three decision and workload measures was subjected to an identical 4 (scanning uncertainty) x 2 (task type) x 2 (decision code) x 12 (subject) repeated measures analysis of variance (ANOVAs), whereas tracking performance was subjected to a 4 (scanning uncertainty) x 2 (decision code) x 12 (subject) repeated measures ANOVA. The following important and salient results emerged.

Insert fig. 3 about here

Response time. The same data pattern depicting a significant two-way interaction between scanning uncertainty and decision code was found both in the single task and in the dual task conditions (dual task: $F(3, 11) = 10.47$, $p < 0.01$; single task: $F(3, 11) = 6.04$, $p < 0.05$). Further analysis of the single task data suggests that this two-way interaction is attributable to the differential behavior of the decision code when scanning uncertainty was at the level of N=8 compared to the other three levels of scanning uncertainty. In the 3 x 2 ANOVA of the single task data from which the N=8 condition was removed, this two-way interaction was not found ($F(2, 11) = 2.37$, $p > 0.10$), but the main effect of scanning uncertainty was not changed by the reanalysis ($F(2, 11) = 5.44$, $p < 0.05$). For the dual task data, similar results of reanalysis were observed only in the 2 x

2 ANOVA from which both the N=4 and the N=8 conditions were removed, indicating that this two-way interaction emerged in the dual task condition when scanning uncertainty reached the level of N=4. These results, together with paired comparisons between data at adjacent uncertainty levels within each variable, indicate that in both the single and the dual task conditions, every increase in scanning uncertainty resulted in a significant increase in decision response time (all p's < 0.05 for the 12 paired comparisons). Furthermore, when scanning uncertainty was sufficiently high (N=8 in the single task condition, and N=4 in the dual task condition), scanning uncertainty produced greater response time increments when tracking was concurrently performed with the spatial task than with the verbal task.

Decision error. In the single task conditions, subjects had more decision errors in the N=8 condition than in any of the other three conditions, which were not significantly different among themselves ($F(3, 11) = 4.88$, $p < 0.05$, for the data that includes the N=8 condition; $F(2, 11) = 3.15$, $p > 0.05$, for the data that does not). Furthermore, this error increment under the N=8 condition was greater for the spatial task than for the verbal task ($F(1, 11) = 6.11$, $p < 0.05$), resulting in a significant two-way interaction between decision code and scanning uncertainty ($F(3, 11) = 3.83$, $p < 0.05$). In the dual task conditions, a similar two-way interaction emerged when the level of scanning uncertainty reached the level of N=4 ($F(3, 11) = 8.99$, $p < 0.01$).

Tracking error. Tracking performance showed a significant decrement when scanning uncertainty reached the level of N=4, compared to the N=1 and N=2 conditions ($F(2, 11) = 6.77$, $p < 0.05$), which were not significantly different between themselves ($F(1, 11) = 1.08$, $p > 0.10$). When scanning uncertainty reached the level of N=8, tracking performance showed a further decrement compared to that in the N=4 condition ($F(1, 11) = 35.22$, $p < 0.001$). Furthermore, this decrement was greater for the spatial than for the verbal task ($F(1, 11) = 11.24$, $p < 0.01$), resulting in a significant two-way interaction between scanning uncertainty and decision code ($F(3, 11) = 5.89$, $p < 0.05$).

Subjective workload. In both the single and the dual task conditions, every increase in scanning uncertainty resulted in a significant increase in subjective workload (all p's < 0.05 for the 12 paired comparisons between data points at adjacent scanning uncertainty levels within each variable). Furthermore, when scanning uncertainty was at the level of N=8, subjects reported higher workload when tracking was concurrently performed with the spatial task than with the verbal task ($F(1, 11) = 7.62$, $p < 0.05$).

Effects of Visual Scanning: Results of Regression Analysis.

The dependent measures showed a pattern of dissociation similar to that observed in Experiment 1: increases in scanning demands produced linear increases in response time, but accelerated increases in tracking error and decelerated increases in workload.

Response time. For the single task data, averaged across the two decision codes, linear regression provided the best fitting least squares line relating response time (RT) to scanning uncertainty (i.e., the number of relevant circles: N) in the equation form of ($RT = 1844 + 158N$), with 97.1% of the total variation accounted for by this linear prediction. For the dual task data, the best fitting linear model has the form of ($RT = 1952 + 193N$), with an Adjusted Squared Multiple R of 0.964. Both the slope and the intercept of the regression line for the dual task data had a significantly larger value than for the single task data (slope: $t(10) = 4.66$, $p < 0.01$; intercept: $t(10) = 3.73$, $p < 0.01$).

Tracking error. A power function in the form of ($RMSE = 0.223 + 0.005N^2$) accounted for 98.6% of the variance in tracking RMSE data, whereas the best fitting linear model in the form of ($RMSE = 0.159 + 0.044N$) accounted for 92.8 % of the variance.

Workload. Power functions in the forms of ($Workload = 23.09 + 12.55\ N^{0.5}$) and ($Workload = 28.46 + 18.28N^{0.5}$) accounted for 96.9% and 92.7% of the variations in workload data in the single and dual task conditions, respectively, whereas the best fitting linear models in the forms of (Workload = 36.95 + 2.35N) and (Workload = 42.67 + 5.54N) accounted for 81.6 % and 87.5% of the variances, respectively. All the regression coefficients for the dual task data had a significant larger value than the corresponding coefficient for the single task data (all t's < 0.05).

In summary, several major findings of the second experiment are similar to those of the first experiment: every increase in scanning uncertainty produced a significant increase in response time and in workload; both the slope and the intercept of the regression lines for the dual task data were greater than those for the single task data; and increases in scanning demand produced a linear increase in response time, but an accelerated increase in tracking error and a decelerated increase in workload.

A salient characteristic of the result of Experiment 2 is that it showed more evidence of the interaction between scanning uncertainty and decision code than did Experiment 1. Interestingly, this interaction was found in the single task as well as the dual task data. Since the single task condition in the second experiment required, by itself, concurrent processing of multiple activities, this result has particular significance as an evidence in support of the role of decision code in analyzing scanning costs. The finding that this interaction emerged at lower levels of scanning uncertainty when the decision task was concurrently performed with the tracking task further supports this argument. The implications of the results of the two experiments will be discussed in the following section.

General Discussion

One common characteristic of many everyday tasks is the need to scan and search physically separated sources of information selectively and sequentially, while performing a number of concurrent manual control and decision activities. The purpose of the present study is to examine the characteristics of visual scanning in multi-task environments, to quantify the effects of scanning uncertainty on concurrent task performance, and to address the relation between the single channel serial processing theory of selective attention and the multiple resources parallel processing theory of divided attention in investigations of concurrent performance of complex tasks. The results of the two experiments conducted in the present study provide some inspiring insights into these issues: the data showed close relations between visual scanning and concurrent activities that could not be revealed through single task studies; neither the single channel serial processing theory of selective attention nor the multiple resources parallel processing theory of divided attention could provide fully satisfactory explanations of the results; but the results do point to a simple, unified account of multi-task behavior, which will be discussed in the last section of the paper.

Effects of visual scanning

In both experiments every increase in scanning uncertainty produced a significant increase in response time and in workload. This result is not surprising considering the fact that increases in the spatial uncertainty of the stimulus location introduced additional eye movements and extra scanning efforts. However, the fact that this increase was faster when scanning was concurrently performed with other tasks, such as a tracking or a running memory task in the current study, indicates that concurrent processes may not simply behave as additive factors in their effects on scanning costs. Thus, visual scanning data observed in single task environments may not be readily generalizable to the analysis of scanning costs in multi-task environments.

The two-way interaction between scanning uncertainty and decision code observed in both experiments suggests that analysis of scanning costs in multi-task situations should take into account the nature and the characteristics of the concurrent processing tasks involved. This interaction indicates that increases in scanning demand produced greater performance decrements and workload increments in the spatial task than in the verbal task. However, this interaction emerged only when the level of scanning uncertainty was sufficiently high. Increases in the concurrent task demands tend to lower the "threshold level" for this interaction to emerge.

A common and legitimate concern in interpreting the interaction between processing codes and other experimental factors such as visual scanning is the potential difference in the level of difficulty of the tasks: a task that demonstrates a greater interference with other tasks may happen to be a more difficult task. The present study was successful in addressing this concern. The no-scanning baseline single task data showed an equivalence of all the performance and workload measures for the spatial and the verbal tasks in both experiments. This result provides a strong evidence in support of the interpretation that the observed interaction between decision code and scanning uncertainty is attributable to the difference in the processing materials involved in the two types of tasks.

Dissociation among dependent measures

In both experiments increases in scanning demand produced a linear increase in response time, but an accelerated increase in tracking error and a decelerated increase in subjective workload. This dissociation among dependent measures was reflected in the result of regression analysis: A linear models in the form of $(a + bN)$ could provide a close fit for the response time data, but a power function with an exponent that is greater than 1.0 (i.e., a function in the form of, $a + bN^c$, $c>1$) could provide a better fit of the tracking error data than a linear model, whereas subjective workload seemed to follow a trend that can be better described in the equation form of $(a + bN^c, c<1)$. In the above, "a" and "b" are regression coefficients that have different values for different measures and for different types of tasks. For the present data, power functions in the form of $(a + bN^2)$ and $(a + bN^{0.5})$ provided a better fit of tracking error and workload data, respectively, compared to linear functions in the form of $(a + bN)$.

The use of power functions have appeared extensively in psychophysics since Stevens' classic work (Stevens, 1957). The current study suggests that power functions may also have great potential value in quantifying different aspects of task interference in multi-task performance modeling. Although the number of data points obtained in the present study and the post-hoc nature of the analysis can potentially make the generalization of this finding cumbersome at best, this interesting dissociation does point to an important research topic that is worthy of further investigation. Further research should examine the generalizability of this finding, identify the best fitting exponent of the power functions, or to identify alternative functions that better capture the essence of task interferences. For example, it is possible that tracking performance decrements follow an exponential growth function, or that workload increments can be better described by a logarithmic function. These issues could only be resolved through further empirical research and the development of related theoretical models. A deeper understanding of this issue will also prove to be of great practical significance to some application domains such as aviation and automotive industry.

Implications for theories of selective and divided attention

The results of the current study have significant implications for both the single-channel queuing theoretic models of selective attention and the multiple resources parallel processing models of divided attention. The basic premise of serial competition for processing time adopted by the single channel models of selective attention demonstrated its value in analyzing and predicting some linear functions observed in the current data. However, the models can not satisfactorily explain the differential effects of scanning uncertainty on concurrent spatial or verbal tasks. The multiple resources theory of divided attention (e.g., Wickens, 1980, 1992) demonstrated its strength in predicting and explaining this differential effect, but showed limitations in explaining some other aspects of the data. It is difficult for the theory to explain why the verbal information integration task also produced task interference with the tracking task when scanning was involved, and why this interference was progressively greater when the level of scanning uncertainty increased, although the rate of progression was smaller than that for the spatial integration task. The results of an earlier study showed that visual scanning was not a prerequisite for this interference to occur. In that study, a verbal task produced significant interference with a tracking task when visual scanning was not involved (Liu and Wickens, 1992). A critical difference between that study and the current study is that both the verbal task and the tracking task in that study was harder than the ones employed in the current study.

While these results posed a challenge to both the single channel theories of selective attention and the multiple resources theory of divided attention, they lent support to a queuing network model of human multiple task performance (Liu, 1993), that was proposed recently as a unified theory and an integrated computational model of human multi-task performance. Since it is not the purpose of the present article to fully explicate the model, the following section will discuss this model mainly in the context of explaining the current results. Potential applications of the model in analyzing many important aspects of multi-task performance will be briefly referred to in the following introduction as illustrations.

<u>A queuing network model of multi-task performance</u>

According to this model, human multi-task information processing system is, in many respects, analogous to an industrial production system. In general, this system can be modeled as a network of information processing nodes (called servers), with each node representing a service facility of some kind. Information processing tasks (called customers) may enter the system at some node, traverse from node to node in the system, and depart from some node, not all tasks necessarily entering and leaving at the same nodes (e.g., inputs from different perceptual modalities), or taking the same path once having entered the system. Tasks may return to nodes previously visited (e.g., response feedback), skip some nodes entirely (e.g., skill and automaticity development), and even choose to remain in the system for a long time (e.g., memory and rehearsal). Each node can have a queue formed in front of it, and thus multiple queues may exist simultaneously in the system (e.g., concurrent performance decrement). Some customers may failed to enter a busy system (e.g., tunnel vision and cognitive tunneling behavior), leave a busy system before they have been fully serviced (e.g., performance errors), jockey for position by switching from one queue to another (e.g., cross-talk), or preempt earlier customers if the queue discipline allows this to happen (e.g., the alerting behavior of auditory presentation, and some perceptual dominance phenomena). Multiple queues may improve their joint performance by adopting some coordinated service schemes (e.g. task integration), or lose effective communication in the face of overwhelming information (e.g., confusion and outcome conflict).

This queuing network model provides not only a unified theoretical account, but also an integrated computational model of human multi-task performance. Queuing network theory is a fertile and productive area of mathematical research (Bruell and Balbo, 1980; Cooper, 1981), whose results can be readily transferred to the quantitative modeling of human multi-task performance, based on this proposed close relation between the two areas. For example, the time for a customer to traverse portions of or an entire network is an example of a quantitative index of task performance. One of the indices of task interference is the increase in a customer's waiting time in front of a server, due to the simultaneous service demands of other tasks.

There are fundamental differences between the queuing network model proposed here and the existing queuing theoretic models of selective attention, multiple resources model of divided attention, network models of human performance, and neural network models of cognition. Briefly stated, the basic premise of the queuing theoretic models is that human information processing system is a single channel system, and that information processing tasks form a single queue, waiting to be serviced by the system (Moray, 1986; Senders, 1964). The multiple resources model advocates that two tasks will suffer performance decrements only when they compete for common processing resources, and the model does not address the existence and the role of potential serial processing bottlenecks (Wickens, 1980, 1992). The network models of human performance do not allow queues to form in a network (Schweickert, 1978). A neural network model of cognition relies on a dense mesh of a large number of neuron-level processing units, which only perform primitive computational functions such as summing, thresholding and nonlinear mapping operations (McClelland and Rumelhart, 1986; Zurada, 1992)

A detailed description of the model is presented in Liu (1993). The particular strength of this modeling approach can be illustrated through a simple, three-node queuing network presented in fig. 4 in the context of the present study. This queuing network model has a parallel processing component and a serial processing component. The parallel processing component refers to the parallel operation of a "spatial server" (S) and a "verbal server" (V), analogous to the spatial and verbal processing mechanisms and resources advocated in the multiple resources theory. The serial processing component refers to the serial operation from either S or V to the third server, which can be tentatively referred to as the central server (C). The model assumes that a spatial task must be serviced by the server S, and a verbal task must be serviced by the server V, before they receive the required service of the server C prior to their completion.

Insert fig. 4 about here

It can be seen easily that, in essence, the multiple resources models of divided attention and the single channel theories of selective attention become special cases of this queuing network model. The multiple resources model only considers the parallel processing component, whereas the single channel model only acknowledges the serial processing aspect of this model. However, as mentioned above, neither the single channel model nor the multiple resources model could provide fully satisfactory explanations to the following important findings of the current study: the verbal information integration task interfered with the tracking task only when scanning demand was sufficiently high, and the interference was progressively greater as scanning demands increased, but at a slower rate than the interference between the spatial information integration task and the tracking task. It is reasonable to assume that the tracking task, the spatial integration task, and visual scanning are primarily spatial tasks, whereas the verbal decision task is primarily a verbal task.

As demonstrated below, these results can be readily explained by the current queuing network model, with two assumptions about the model. The two assumptions, by making successful explanations of the results, suggest two important characteristics of human information processing. The first assumption is that the serial processing bottleneck (i.e., the central server) has a capacity that is smaller than the sum of the capacities of the spatial and the verbal server, but greater than the capacity of either of the two servers. That is, $C < S + V$, $C > S$, and $C > V$ (e.g., $C=7$, $S=5$, $V=5$, where C, S, V refer to the capacity of the three server nodes respectively). The second assumption is that the cost of waiting in front of S or V is higher than that in front of C. That is, $W(S) > W(C)$, $W(V) > W(C)$, where W(A) refers to the cost of waiting in front of server A.

The first assumption implies that two tasks will interfere with each other when their total service demand exceeds the capacity of S or V or both servers (similar to the predictions of multiple resource model), or that of C (similar to the predictions of single channel model), <u>or</u> a combination of both cases. One of the implications of the second assumption is that a verbal task will interfere with a spatial task when the sum of their capacity demands is greater than C, and this interference will be progressively greater as the spatial or the verbal demand increases. However, as long as neither S nor V has exceeded its capacity, the rate of progression will be slower than that between two spatial tasks with a total spatial demands greater than S. These predictions are exactly the same as the results observed in the present study.

In the present study, the total service demand of the verbal information integration task and the tracking task exceeded the capacity of C, only when scanning demand was sufficiently high. That is, $(v + t + sL) < C < (v + t + sH)$, $v < V$, $(t + sH) < S$, in which v, t, sL, and sH are the processing demands of the verbal integration task, tracking task, and scanning with low or high levels of uncertainty, respectively. Since the spatial information integration task, the tracking task and scanning all required the service of the spatial server, their total demands exceeded the capacity of S in many cases: the spatial task interfered with the tracking task when scanning demand was at a lower level than that for the verbal task (i.e., $S < (s + t + sL)$, in which s refers to the processing demand of the spatial integration task), suffered a performance decrement in the single task condition when scanning was at a higher level (i.e., $(s + sL) < S < (s + sH)$), and showed faster increase in performance decrement than the verbal task, due to a higher cost of waiting in front of S than in front of C.

The 3-node queuing network, together with the two assumptions, can also explain the earlier finding that a verbal task interfered with a tracking task when scanning was not involved (Liu and Wickens, 1992). The verbal task and the tracking task were more difficult than those in the present study, and thus their total demand exceeded the capacity of C without the presence of the scanning demand (i.e., $C < v + t$). Furthermore, this interference increased when scanning was involved, but with a smaller magnitude than that for a spatial task, as predicted by the model described above.

In summary, the present study provides a quantitative evaluation of the relation between visual scanning and concurrent tasks, and demonstrates the strength of a queuing network model of multi-task performance in integrating the serial processing models of selective attention and the parallel processing models of divided attention in explaining and predicting complex task performance.

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Figure Captions

Fig. 1. A pictorial representation of the task display for the dual task condition showing the horizontal tracking bar and eight information circles.

Fig. 2. Results of Experiment 1: Performance and workload measures as a function of scanning demand, task type and decision code. (Data points and lines near the top of each graph always indicate poor performance or high workload.)

Fig. 3. Results of Experiment 2: Performance and workload measures as a function of scanning demand, task type and decision code. (Data points and lines near the top of each graph always indicate poor performance or high workload.)

Fig. 4. A 3-node queuing network model of multi-task performance that consists of a parallel processing component (S and V) and a serial processing component (S->C and V->C). Information processing tasks involving two different types of information materials are represented in the figure as diamonds and circles. The current results suggest the capacity of C is smaller than the total capacity of S and V, but greater than the capacity of either server; and the cost of waiting in front of S or V is greater than in front of C.

Table 1

Performance and workload measures in no-scanning single task conditions

Measure	Decision Task	
	Spatial	Verbal
Error (in %)	4.2	5.8
Response time (in msec)	802	836
Workload (in raw score)	14.1	12.8

Table 2

Performance and workload measures in no-scanning dual-task conditions

Measure	Decision task	
	Spatial	Verbal
Error (in %)	6.1	4.8
Response time (in msec)	815	846
Workload (in raw score)	19.0	18.3
Tracking (RMSE)	0.222	0.227

Table 3

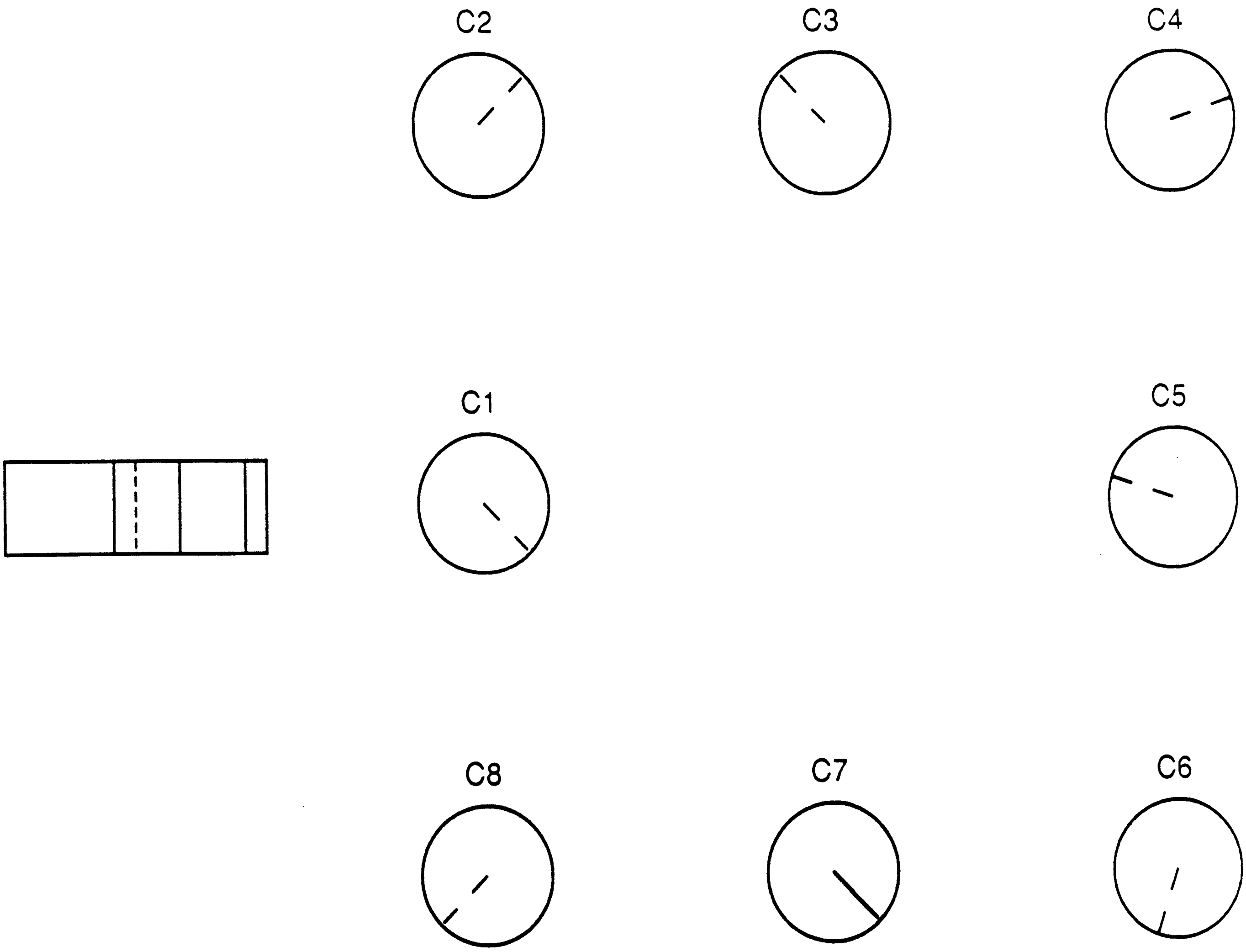
Performance and workload measures in no-scanning single task conditions

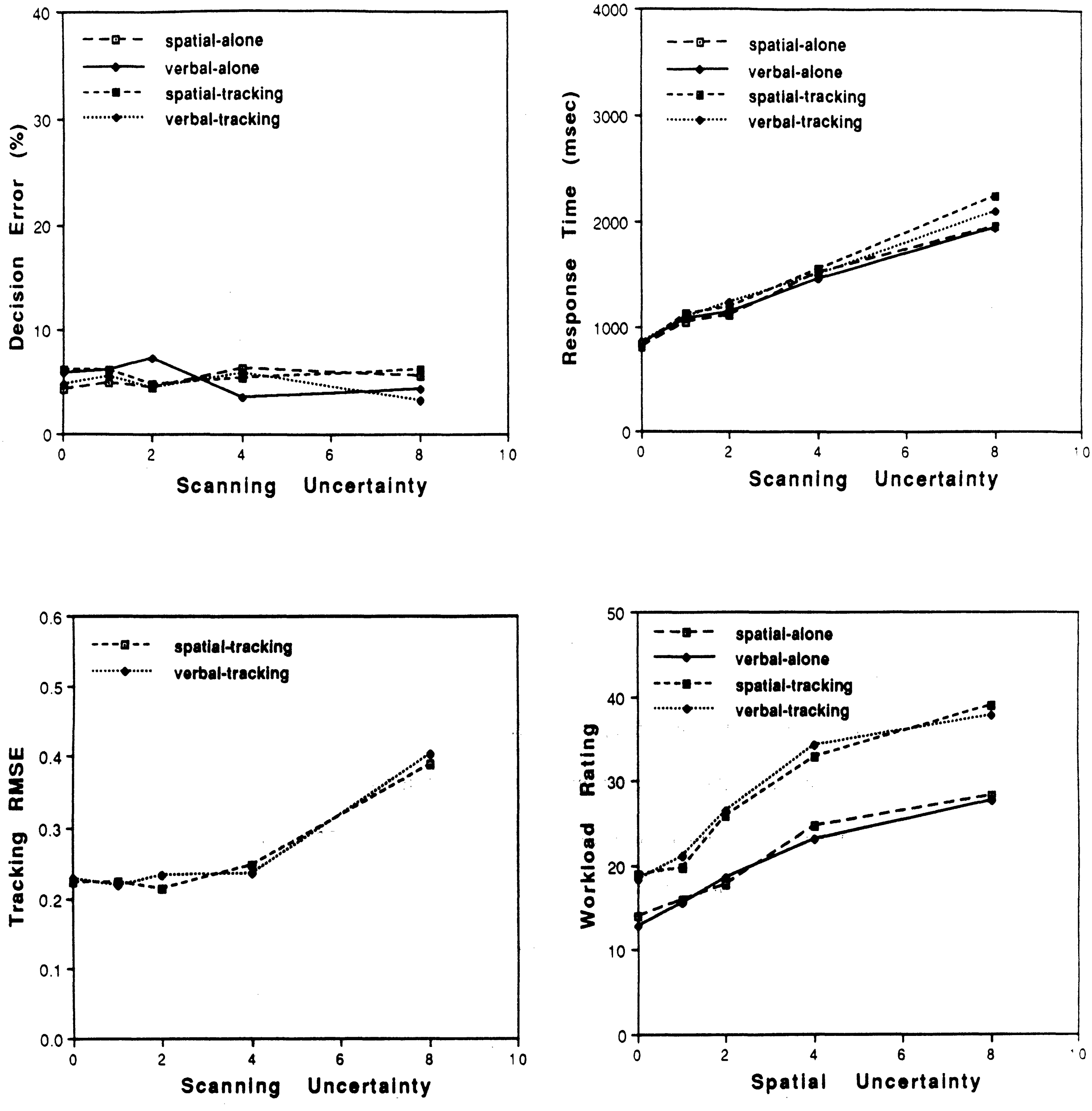
Measure	Decision Task	
	Spatial	Verbal
Error (in % correct)	12.4	9.8
Response time (in msec)	1740	1778
Workload (in raw score)	31.9	33.5

Table 4

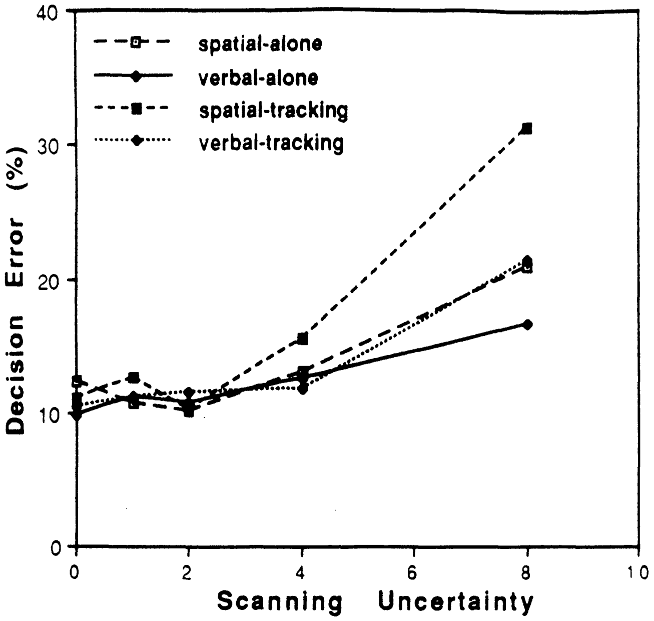
Performance and workload measures in no-scanning dual-task conditions

Measure	Decision task	
	Spatial	Verbal
Error (in %)	11.1	10.4
Response time (in msec)	1797	1827
Workload (in raw score)	38.2	40.6
Tracking error (in RMSE)	0.220	0.228

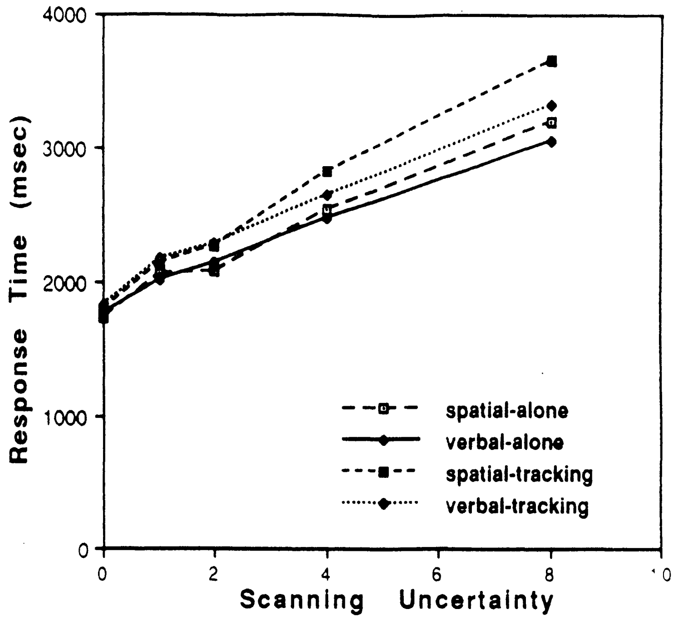

C2
C3
C4
C1
C5
C8
C7
C6



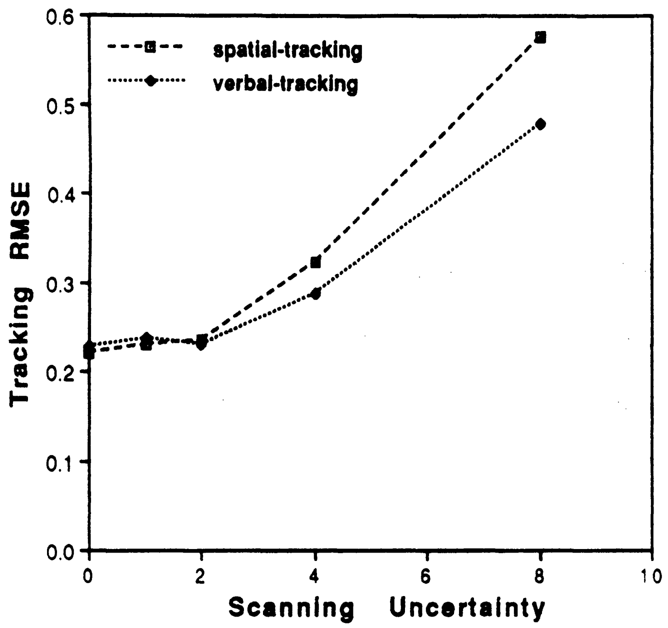
spatial-alone
verbal-alone
spatial-tracking
verbal-tracking
Decision Error (%)
Scanning Uncertainty
Response Time (msec)
Scanning Uncertainty
spatial-tracking
verbal-tracking
Tracking RMSE
Scanning Uncertainty
Workload Rating
Spatial Uncertainty



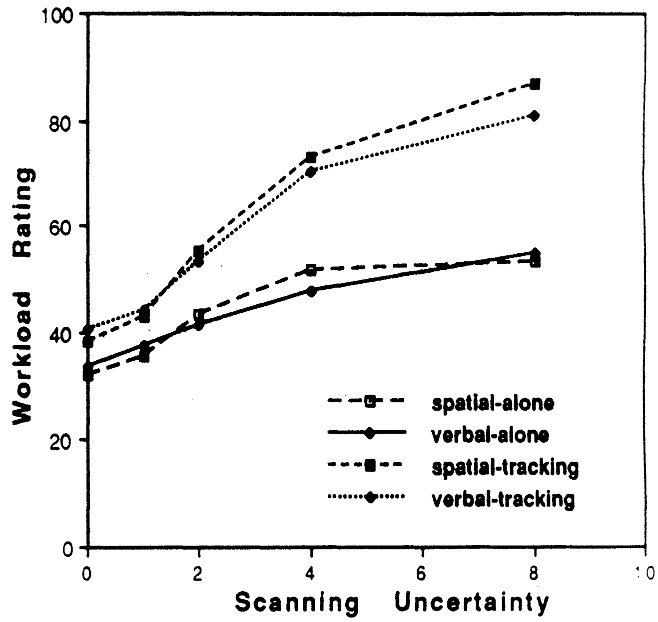
Decision Error (%)
spatial-alone
verbal-alone
spatial-tracking
verbal-tracking
Scanning Uncertainty



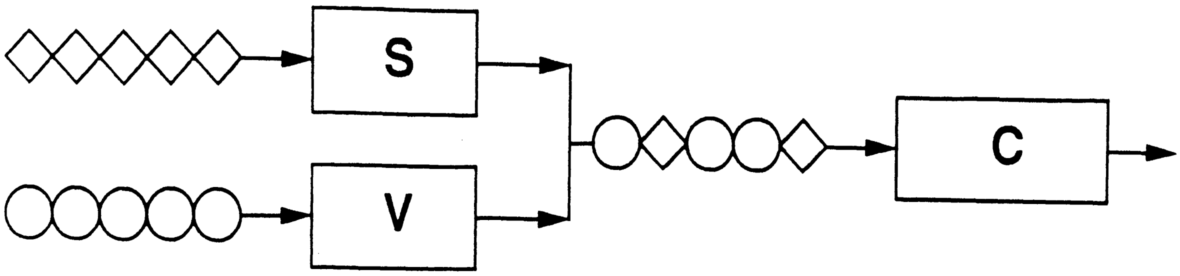
Response Time (msec)
spatial-alone
verbal-alone
spatial-tracking
verbal-tracking
Scanning Uncertainty



Tracking RMSE
spatial-tracking
verbal-tracking
Scanning Uncertainty



Workload Rating
spatial-alone
verbal-alone
spatial-tracking
verbal-tracking
Scanning Uncertainty


S
V
C