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Visual attention allocation and scanning strategies of pilots have enjoyed sustained research effort for decades, resulting in many useful models and better understanding of the relationship between pilots' eye movements and underlying cognitive mechanisms. However, much less research has been done on modeling air traffic controllers' attentional processes and visual performance. Yet, such efforts are becoming increasingly critical in the light of changing tasks and task environments of controllers and increasing amounts of traffic under their responsibility. This paper will consider the SEEV (Salience, Effort, Expectancy, Value) model of visual attention allocation by Wickens and collaborators, which is an extension of Senders' and Carbonell's original model, as it is applied to air traffic control (ATC). The SEEV model integrates a comprehensive set of features influencing visual attention allocation and is thus an attractive candidate for modeling also air traffic controllers' behavior and performance. We discuss many unique characteristics of ATC and focus on three particular challenges to applying the SEEV model to ATC tasks presented in the literature: uncertainty, time pressure and workload.

Introduction

Modeling visual scanning of pilots has long been a topic of interest in aviation research because any semblance of 'optimal scan strategy' might well guide both cockpit layout design as well as pilot training (Wickens et al., 2005). Much progress has been made over the years in determining the relationship between pilots' eye movements and underlying cognitive mechanisms, such as attention. Moray and Rotenberg (1989) find that eye movements are an especially useful tool in inferring underlying information processing mechanisms when the operator is not engaging in an action and that they have been shown to relate to operators' mental model of the situation. However, the aviation task itself is changing such that the responsibilities of the pilots are increasing. New cockpit designs include the Cockpit Display of Traffic Information (CDTI), which changes the pilots' task and undoubtedly will affect what is currently thought of as optimal in terms of scanning strategy (Wickens et al., 2003).

The notable change to the aviation task when systems such as CDTIs are added is an addition of uncertainty to the pilots' task that did not exist in the same sense previously. Without this display, general aviation pilots are alerted to traffic by auditory air traffic control (ATC) communications. Their primary task of aviating the airplane (i.e. maintaining a collection of instrument parameters) contains relatively little uncertainty, especially under normal flight conditions, as the various parameters tend to move in predictable patterns relative to one another. Pilots' secondary tasks of navigating the route and communicating with air traffic controllers contains still less uncertainty. Most of current theories of visual scanning capitalize on the relationships among the flight parameters and assign values to the parameters accordingly. The relative values guide predictions of when pilots look at particular information displays and how much time they spend looking at them. The addition of CDTI and similar tasks simultaneously increases the demand for visual attention (which is already quite high) and creates a potential need for a pilot to modify his or her scan pattern in a strategic fashion, given the uncertainty surrounding the traffic detection task (Wickens et al. 2005). Work continues to be carried out to determine how well models of visual attention allocation that currently exist will transfer to a modified aviation task involving uncertainty (Wickens et al., 2001a, Wickens, et al., 2001b, Wickens et al., 2001c).

A more recent area of interest is modeling the visual scan of air traffic controllers. This area has received relatively less attention than pilot visual scanning, but deserves attention for the same reasons as listed earlier in the case of pilot research (Stein, 1992; Willems et al., 1999; Remington et al., 2000). The task requirements for air traffic controllers are also undergoing change as the number of flights under their control continues to increase and as new automation tools are implemented to aid controllers manage this their increased task load. The ATC task inherently contains uncertainty regarding the location and paths of multiple aircraft. This uncertainty will also increase as a result of improved navigational capabilities of aircraft and implementation of technology and procedures associated with the free flight concept. As controllers' workload increases in terms of the number of aircraft he or she is responsible for and uncertainty of their trajectories under free flight, the importance of a suitable model of visual scanning that can be used to predict and measure controller performance is highlighted. The question of interest is the extent to which research on pilot scanning can be directly applied or modified to describe the ATC task.

This paper reviews existing literature on pilot visual scanning, concentrating on the SEEV model of visual attention allocation, in an effort to evaluate which modeling methods are appropriate to use in measuring and predicting operator performance in the class of tasks described above. Following the literature review, the ATC task is evaluated in terms of its cognitively demanding factors—specifically how this task differs from the demands in typical aviation tasks in aircraft cockpits. Suggestions for which components of existing visual models or modification to these models that may be useful in describing ATC tasks involving uncertainty are offered.

Expected Value Models of Attention

Carbonnell (1968) pioneered work on visual scanning in aviation with his queuing model of visual sampling. The model assumes a pilot wishes to minimize risk, with risk defined as 'a unitary cost times the probability that the display value may, while not being observed, exceed a certain threshold that could lead to some catastrophic result' (Carbonell 1968). In order to minimize risk, a pilot scans instruments in knowledge-guided manner. Each instrument is assigned a value based on the information it displays and a probability of the displayed information exceeding a given threshold, which may in turn lead to a negative outcome. The model acknowledges that the value assigned to each instrument depends on the type of maneuver the pilot is completing. Carbonell, Ward & Senders (1968) performed a validation experiment of the queuing model of visual sampling, which compared the percentage of total fixations allocated to each of a specified group of instruments predicted by the queuing model with obtained percentage of total fixation eye-movement data. Results found validation for the model on a global level, as the predicted percentage of fixations matched the obtained value well for each instrument. This was the first experiment to record both instrument readings and eye movements in a simulated flight context (Carbonell, Ward, & Senders 1968).

The SEEV Model of Visual Attention Allocation

Carbonell's work does a relatively good job predicting behavior, but lacks insight into the underlying psychological mechanisms, such as attention, which would add to the descriptive quality of such a model. Wickens et al. (2001a, 2003) developed and tested a model of attention based on expectancy and value of information that is directly concerned not only with the prediction of eye-movement, but also in describing the nature of the underlying attention mechanism.

In both the model described earlier by Carbonell and the present model proposed by Wickens et al (2001a), the task can be characterized by four features. First, in the type of task these models refer to, the operator's task is to monitor a dynamic system, not search for a single target. Second, the primary emphasis in task is to notice critical events at relatively consistent locations. Third, the dependent variable of interest is typically the proportion of visual attention (scan time), rather than response time. And finally, the challenge is attending to the right information at the right time, not just detecting the right information. Taking all four features collectively, it is clear that the attention being modeled in these sorts of tasks is modulated to some extent by the operator's knowledge of both the system and the situation. The current task of interest—the ATC task—can also be generally characterized by the features above. However, given the uncertainty factor that is inherent in this sort of task, some modifications may need to be made to how the task is conceptualized. For instance, the locations where the operator scans may be less consistent and therefore less easily predicted.

The model Wickens et al. (2001a) proposed expands the scope of Carbonell's "optimal" model, which relies on the parameters of value and expectancy. This type of model is said to be optimal because it relies on the two parameters most related to optimal expected value. The model by Wickens et al. recognizes the mediating effect of the two additional factors of the salience of information and the amount of effort required to access information (or switch attention between displays), in addition to the expectancy and value. Salience can be thought of as the extent to which a piece of information captures attention based on physical qualities of the information display, irrespective of the information value (e.g., display aspects that are brighter and any auditory signal tend to attract attention). Effort is defined as the extent to which a pilot must move his eyes and/or head in order to access information. The more effort required to access information the less likely a pilot is to visually scan that information (Wickens et al. 2004). In theory, optimal scan patterns will be achieved when the parameters of value and expectancy are prioritized. The effects of salience and effort will decrease the optimality of the scan pattern to the extent that they detract a pilot's scan pattern from the optimal one dictated by value and expectancy alone.

This model is unique in that it introduces a many-to-many relationship between tasks and information channels, defined as areas of interest in eye-movement studies (Wickens et al., 2001a). Earlier models, such as Carbonell's (1968) model, assumed a one-to-one relationship between these variables, whereby one particular task value and expectancy were assigned to each information channel. This newer modified model allows for any given information source to be related to any task, and allows for these values to vary, depending on both the overall importance of the task and the relevance of the given information source to completing the task. Overall importance of the task is defined by the commonly accepted hierarchy of 'Aviate, Navigate, Communicate, and Systems Management' (Schutte & Trujillo, 1996). The relevance of any particular information source is determined a priori to an evaluation through methods such as task analysis (Wickens et al. 2001a).

Results of the experiments to validate the attentional expected value models are quite revealing. In general, a model containing just the expectancy and value parameters did very well in predicting scan performance. That is, the salience and effort parameters did not predict performance. Further, those pilots whose visual scans could be modeled better with an optimal expectancy/value model also showed better multitask performance (Wickens, 2004). Reviews of this type of study reveal that performance by operators with higher levels of experience tends to be modeled better by the optimal model as well (Moray, 1986).

Mental Models

An important factor to consider in reviewing pilot visual scanning research is the role of mental models in guiding scan patterns, which may account for observed expertise differences. Such results have interesting implications for when the task requirements change in environments with higher uncertainty such that expectancy and value become less easily defined. On an intuitive level, there are two important components to the pilot's mental model in respect to its role in attention allocation. First, there is knowledge of *where* to look, defined by the pilot's understanding of which information sources are relevant to which tasks. For instance, Wickens et al. (2003) found that pilots rely on two generic sources of information. In relation to the task of aviating the aircraft, they pay attention to the instrument panel, and the relative position of the aircraft to the outside world (if this information is available). With respect to the task of navigation, pilots rely on the instrument panel, maps, navigation equipment and the outside world (again, when available). This component can be thought of as roughly corresponding to the value parameter in the SEEV model. Additionally, knowledge of *when* to look, comprises a mental model. This component represents the pilot's understanding of the interrelationships among the various flight parameters and instrument levels and their effect on flight performance. It can be roughly equated with the expectancy parameter in the SEEV model.

Given this conceptualization, it is expected that expert pilots will demonstrate scan patterns that differ from those of novices. They do, in fact, as Bellenkes, Wickens & Kramer (1997) found: experts generally visited instruments more frequently, whereas novices showed longer dwell times on instruments. Experts also tended to look at information pieces more relevant to the current task dynamics (with relevance determined a priori through task analysis). Experts furthermore showed superior performance in 'minding the store', that is, they had more spare capacity to consciously allocate attention, whereas novices did not have this spare capacity. Finally, experts were more flexible in their scan patterns, showing more variance in the specific patterns they scanned than novices. Experts also showed some adjustment based on the task dynamics. Novices, on the other hand, maintained a more systematic scan, regardless of the underlying task dynamics (Bellenkes, Wickens & Kramer, 1997). Perhaps the most important finding to come out of the study by Bellenkes, Wickens & Kramer (1997) is the evidence that pilots do allocate visual attention based on an underlying mental model of the task dynamics. Further, experts seem to be more adept at utilizing a mental model to guide visual attention allocation. Additional supporting evidence of the mediating effect of expertise on mental model utilization comes from a study by DeMaio et al. (1978). This study found that novices' detection latency of deviations in presented instrument values was more correlated than that of experts, indicating a sequential scan pattern. This finding is important because it illustrates how a model such as SEEV, based on knowledge driven parameters, can be successful in predicting and describing task performance.

A final finding relevant to the use of mental models in visual attention allocation comes from a simulated fault management study by Moray & Rotenberg (1989). This study found a delay in attending to subsequent faults (i.e. faults occurring after the onset of an initial fault), even though the information diagnosing the subsequent fault was scanned fairly quickly after the onset of the fault itself. An inference that may be drawn from this finding is that although a mental model seems to be fairly useful in guiding attention allocation under normal circumstances, it is questionable how useful it may be under non-normal, fault management situations. Or, in the case of the ATC task, this finding might have implications for how well attention allocation can be modeled under conditions of increasing workload.

Adapting SEEV for Use in an ATC Context

In considering how the SEEV model could be adapted for use in an ATC context, there are several aspects of the task that might be considered for how they differ from a pilot context and in so, how they may affect the estimation of the SEEV model parameters. We discuss the possible implications of three such aspects presented in the literature: uncertainty, time pressure and workload.

Uncertainty in ATC

An important difference between pilot visual scanning and visual scanning in ATC is the increased uncertainty inherent in the ATC task. The pilot's task of aviating and the ATC task are similar in that they are both event-driven, requiring actions contingent upon events occurring in the task environment. However, the predictability of certain events occurring based on available information is less structured in the ATC task and there is broader array of possibly relevant information sources to scan. This is in contrast to the pilot's task, where the one fairly uncertain element in flying—traffic detection—is often taken care of for pilots through ATC communications. In thinking about applying the SEEV model to an ATC task with a greater degree of uncertainty, a few points become apparent. While the value of information can still be evaluated to the extent that specific information must be extracted for successful task completion, the expectancy of the relevant events may be more difficult to define due to more information sources and higher variance of information within those sources

Uncertainty can potentially affect the efficacy of both the expectancy and the value parameters of the SEEV model. The expectancy parameter might be thought of as less well calibrated to the extent that the ATC task environment contains many more items to which a controller should allocate attention, so that the familiarity with the distribution of information from any one item might be much less than for items in the pilot's task environment. Attempts to model the ATC task using SEEV should determine the expectancy parameter as objectively as possible and note the extent to which this parameter drives actual behavior. Fortunately, there are several metrics that can be applied to estimation of uncertainty in the traffic environment. These metrics describe many characteristics of controllers' task environment that may contribute to uncertainty, such as distribution or airways and closest points of approach (Kirwan, Scaife, & Kennedy, 2001), variability of aircrafts' altitudes and groundspeeds and number of heading changes (Chatterji & Sridhar, 2001), and many other factors collectively known as dynamic density (e.g., Laudeman et al., 1998). Summaries of these metrics are provided by the Federal Aviation Administration (2000) and Kopardekar and Magyarits (2002). The role of uncertainty in controllers' attention allocation and visual scanning and derivation of the expectancy parameter for the SEEV model from the aforementioned complexity metrics are areas where focused research is long overdue, however.

While the event uncertainty is substantial in ATC and the potential of deriving sufficiently defined, objective expectancy parameters for the use in SEEV from complexity metrics is thus far unproven, certain basic characteristics of bandwidth (event rate) can nevertheless be specified, further facilitating quantification and ordering of expectancy. Thus, for example, fixed locations on the display (e.g., airports, runways, air routes) do not change, nor do fixed items on a data block, like an airplane call sign. Hence their bandwidth is 0. Other items on the data block, such as heading and altitude change only infrequently. Hence their bandwidth, while higher than 0, is less than the location of airplane symbols on the display. Scan data (e.g., Willems et al, 1999) appear to validate this metric. It is important to consider the above examples of bandwidth in the light of controllers' mental models, or 'picture', however. There is a great difference between altitude and route changes commanded by a controller and free flight conditions, where pilots may initiate these chances possibly even without informing the controller about them afterwards. This fact may make models such as SEEV very useful in examining the impact of increasing free flight applications on controller workload and performance.

Value can also be quantified, albeit in a different fashion than that used for flight deck applications. If it is assumed that the most valuable task is to prevent mid-air collisions, and that channels relevant to such collisions are defined by a pair of converging aircraft, then a simple algorithm to compute value is the predicted by a risk factor, inversely related to the distance at the closest point of approach (DCPA; Xu Wickens & Rantanen, 2007). This quantifiable parameter can be easily modified by incorporating the altitude difference (AD) at the CPA. Finally, a third factor influencing value is the time till CPA (TCPA), with increasing value associated with decreasing time. Thus it is possible to generate a Value metric: $V = K – (aDCPA + bAD + c\ TCPA)$, where K is an arbitrary constant, and a, b and c are constants designed to express the differing units (miles, feet, and seconds) in a common framework.

Time Pressure in ATC

In ATC, there exists in some cases a tradeoff between uncertainty and time pressure: as time pressure increases in the sense that less time remains should the controller have to intervene in a conflict situation, for example, uncertainty about the conflict decreases (Averty et al., 2002). Both time pressure and uncertainty present challenges to successful task completion for the air traffic controller. It is perhaps less critical to evaluate the adaptability of the SEEV model with respect to the influence of time pressure than it was in the case of uncertainty because when controllers do experience time pressure, they likely are spending that time performing control actions rather than visually monitoring their environment. Nevertheless, some observations can be made. In cases where viewing a converging pair of aircraft becomes more valuable as time progresses, time pressure creates a need for a mechanism that is able to update the value parameter of information items as time pressure increases. Presumedly the value of certain parameters will increase with time pressure, and others may decrease. Creating a mechanism to dynamically address these value transformations will be necessary to adapt SEEV to the ATC task. Such a mechanism might incorporate both the point of closest passage and the time remaining until the aircrafts arrive at that point (e.g. Value [of an area of interest defined by two aircraft] = K1 [point of closest passage] – K2 [time to closest passage]).

Workload in ATC

Workload in ATC can be thought to be influenced both by the intrinsic nature of the task itself (e.g. uncertainty and time pressure factors that influence the expectancy and value parameters) and by effort created by concurrent task performance demands. In investigating the role of workload in modeling visual attention allocation in the ATC task, we are primarily interested in how workload might modify attention allocation strategies and whether such changes can be captured by the SEEV model. For instance, Wickens et al. (2001c) postulated that workload might influence the weighting of effort parameter. That is, high levels of workload might cause visual scans requiring effort to be less likely to occur because the scan itself will require resources that are heavily demanded by concurrent task processing at that point in time. Time pressure has been shown to be one of the primary drivers of mental workload, (Hendy, 1995; Hendy, Liao, & Milgram, 1997, Hancock & Chignell, 1988; Laudeman & Palmer, 1995). Time pressure may also be defined as the ratio of time required to time available to perform a task (e.g., Hendy, 1995). It is possible that any increased weighting of the effort parameter could be overcome by experienced controllers, however. Work done by Ellis & Stark (1986) provides evidence that pilots monitoring a CDTI may revert to more statistically dependent scan patterns under conditions involving workload because pilots in these conditions have to consciously shift attention from one item to another, rather than simultaneously monitor items. Because this experiment utilized a CDTI, there is reason to believe results may have implications for the related ATC task. Provided air traffic controllers modify their visual scans in a similar manner in response to workload, this may mitigate the impact of the effort parameter in the ATC task under high workload conditions, as this sort of conscious attention allocation should be guided by strategic, knowledge-driven factors (expectancy and value) rather than environmental factors like effort and salience (Wickens et al., 2001b).

Workload may also affect the role of the expectancy parameter in modeling visual attention allocation in the ATC task. Optimally, display items should be sampled with frequencies determined by their bandwidth. There is a general tendency for operators to sample low bandwidth items more frequently than optimal due to working memory constraints (Wickens et al., 2001a). Under conditions of workload in ATC, this tendency might be further enhanced as the prevailing workload degrades working memory capacity. In adapting the SEEV model for use with ATC tasks, workload appears to be one of the most important factors in the determination of the various parameters of the model. Its impact is mediated by time pressure, which is a workload driver and which also affects the effort (time required vs. time available) and expectancy parameters (see the discussion above). The fault management experiment performed by Moray & Rotenberg (1989) showed that participants had a normal chance of fixating on an information source that would signal a subsequent fault following processing of a first fault, but that there was a substantial delay in taking control actions to address the subsequent fault, even after the first fault had been dealt with. The authors refer to this phenomenon as cognitive lock-up, and propose that human operators prefer to deal with faults in a serial fashion. This has implications for how research on mental models can be applied to the ATC task. It appears once the operator is forced to deal with an unexpected event, the robustness of the mental model in guiding his or her scan path may falter.

Conclusion

Research on visual attention allocation in aviation has provided many insights into the relationship between visual scanning and the presumed underlying attention mechanism. Due to changing nature of the aviation domain, it is worthwhile to consider how some of these theories and techniques may be used in evaluating visual attention allocation in tasks containing increased uncertainty and workload. When using the existing research to examine these types of tasks, however, one should carefully consider the relevance of the SEEV model parameters, the possibility of strategies for extending attentional resources and the usefulness of mental models. On the other hand, application of models such as SEEV to new domains such as ATC also forces one to grapple with very important aspects of human performance, such as uncertainty, time pressure, and workload, in a rigorous manner, leading to better understanding of these constructs.

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