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A COMPUTATIONAL MODEL OF ATTENTION/SITUATION AWARENESS

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A computational model of attention and situation awareness (SA) was developed and used to predict pilot errors in the task of taxiing from runway to terminal. The model incorporates a low-level perception/attention module and a higher-level belief-updating module. Attentional scanning is controlled by bottom-up and top-down processes, with the effectiveness of top-down guidance varying as a function of SA. Information sampled by the low-level module is fed forward to the higher-level module for consolidation within a working memory representation of the pilot's situation, with the quality of this representation reflecting the pilot's level of SA. The model was validated by comparing its predictions to the behavior of pilots performing a taxiway simulation. Results indicate that the model successfully predicts the improved performance associated with display augmentations, and provides construct validity regarding the effects of visibility, distraction, and degraded information quality.

INTRODUCTION

As part of an effort to mitigate pilot error in aviation operations, NASA has begun a program to develop computational models of the perceptual-cognitive processes that lead to error. Such models may stand alone, or may be embedded within larger global models of human performance (Tyler et al., 1998; Hart et al., 2001). Their value, *once validated*, is that they may be used early in the development cycle to estimate the effectiveness of error mitigation strategies (Pew & Mavor, 1998).

This paper describes early steps to develop and validate a computational model of attention and situation awareness (A-SA), employed here to predict pilot errors (wrong turns) during taxiway operations on the airport surface. This combination of process (A-SA) and domain (airport surface) was chosen for three reasons. (1) Errors on the airport surface, while generally not catastrophic, are frequent enough to have become a substantial area of concern in aviation safety (Croft 2001, Firoino, 2000). (2) Errors of SA, and particularly those related to a failure to "notice" or perceive critical events, represent a substantial source of aviation mishaps, on the ground and in the air (Jones & Endsley, 1996). (3) Data to allow initial validation of such a model are relatively easy to obtain in a high fidelity simulation because low situation awareness has predictable effects on easy-to-quantify discrete errors (wrong turns) which occur with sufficient frequency (Hooey et al., 2000) that meaningful predictions can be made and tested.

In developing the A-SA model, we were aware of only one other effort to develop a computational model of SA (i.e., in contrast to descriptive models such as Endsley, 1995), and aspects of that model (Shively et al., 1997) provided foundations for the current effort. However, we also attempt to make strong links to basic research on attention, and belief updating.

The A-SA model shown in Figure 1 incorporates two semi-independent components, a perception/ attention module and a cognitive SA-updating module. Information collected by the former module is fed forward to the latter, where it is integrated within a mental representation of the operator's circumstances. Information from this representation is fed back to the perception/attention module to guide future sampling of the environment. The output of the model is a value representing the operator's momentary state of SA, ranging from 0 to 1, where SA reflects the degree of correct awareness about a current situation. The analyst in a particular model application identifies the nature of this situation. The core architecture of model was not designed to incorporate action-related phenomena. However, the current application assumes that to the extent that SA is degraded, pre-existing response tendencies (e.g., guessing), will dominate the selection of action in taxiway navigation, and these guesses, if wrong, will be the source of error.

The model was constructed with three goals in mind: (1) that where possible, quantitative estimates of parameters, or formulas that provide such estimates, be borrowed from existing models of attention and cognition; (2) that the mental operations represented in the model be "cognitively plausible"; (3) that the model predict the effects of *changes* in a task environment meant to mitigate the loss of SA.

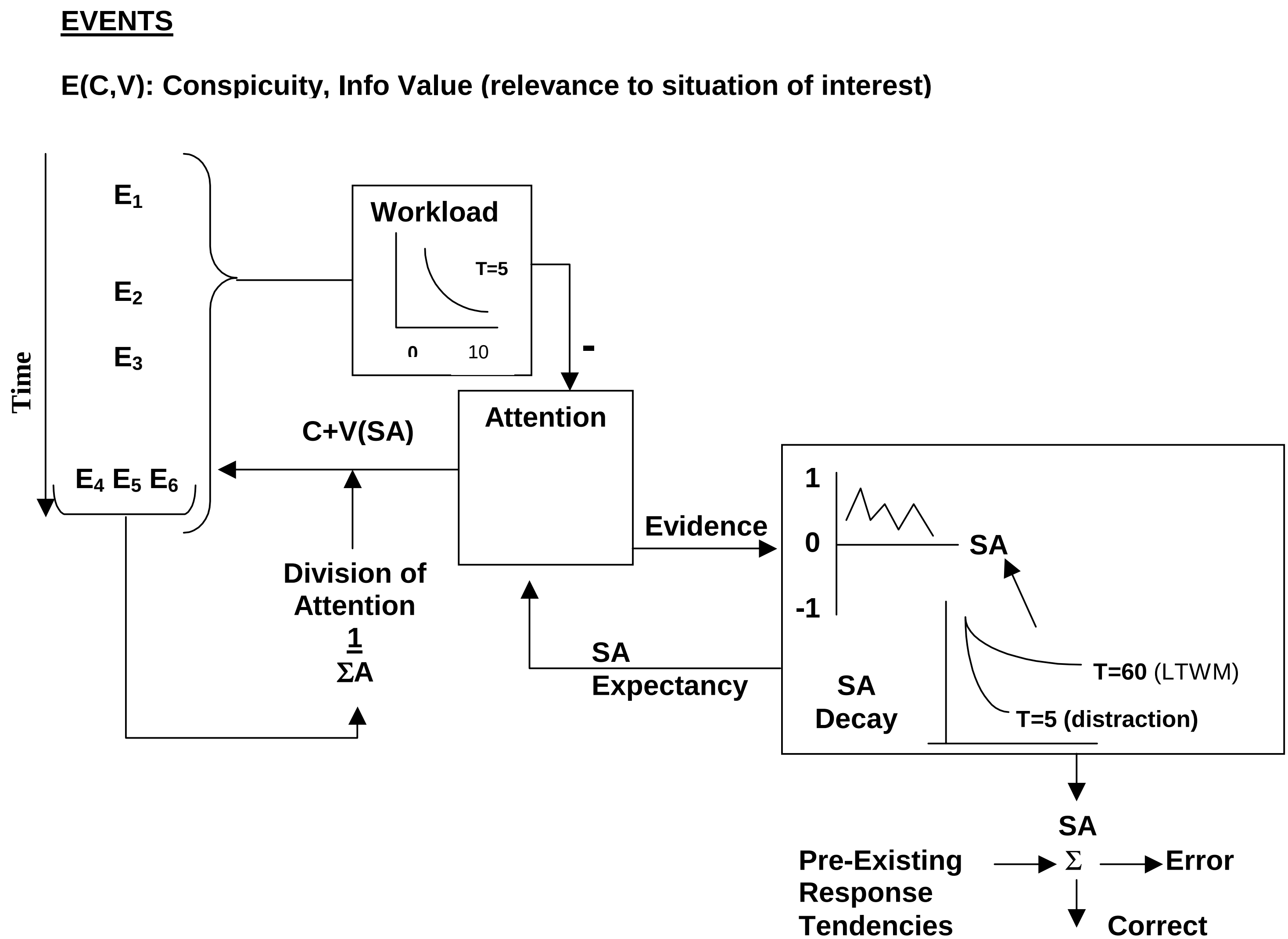

Figure 1. The attention/situation awareness model. A sequence of events (upper left) are attended (center) to a degree that is degraded by workload. Attended events provide evidence for the belief module (box at lower right) a belief that decays over time. The SA belief then contributes to a choice, at the bottom.

In developing the model, we distinguished its general architecture, describing processes that should govern SA in any environment, from the domain-specific details of the particular instantiation of the model. Such details must be tailored by an analyst with knowledge of the domain in question, capable of specifying the knowledge that constitutes SA within that domain, and of identifying the sources of the information which supports this knowledge.

General Architecture

The attention module of the A-SA model is based on Bundesen's (1990) Theory of Visual Attention. In the current model, attention is regarded as a graded resource allocated in varying quantities to objects and events within a scene. The attention allotted to a given item is determined by the item's conspicuity, *C*, and information value, *V*. Conspicuity describes the item's physical perceptibility, ranging from 0 (imperceptible) to 1 (easily noticed). Information value describes the effect of the item on SA, ranging from –1 (highly degrading of SA, e.g., a mislabeled taxiway) to 1 (highly facilitative of SA, e.g., a sign which correctly labels the taxiway on which the pilot is supposed to turn).

The model treats time as occurring in discrete intervals (here, 1 s). Traversing the taxiway, a pilot may encounter any number of objects or events within a given interval. As each stimulus is encountered, it is assigned an attentional weight *W* according to the formula

$$W = C + SA * V$$

An important aspect of this equation is that the contribution of information value to *W* is modulated by SA. Thus, high SA guides attention toward objects and events further conducive to SA and away from items degrading of SA, capturing the influence of top-down factors such as expectancy on evidence seeking (Adams, Tenny & Pew, 1995). A second point of note is that an item with conspicuity of 0—that is, an imperceptible item—may nonetheless have a positive attentional weight as a result of its information value. The result of this is that an item which is imperceptible or even absent from the scene *but which is anticipated and is sought by the pilot* can consume attentional resources.

In the time after an item has been first noticed, its attentional weight declines according to an exponential decay function. A result of this gradual decay is that processing of an item may add to cognitive load even for some time after the item has been passed. Cognitive load in turn constrains attentional scanning as follows. After attentional weights have been calculated for all of the items within a given temporal interval, the amount of attention allotted to a given item is determined by the ratio of that item's attentional weight to the summed attentional weights of all the items within the current interval, and of all previously encountered items:

$$A_i = C_i * (W_i / \sum W)$$

where A_i is the amount of attention allotted item *i*, C_i is the conspicuity of the item, W_i is the attentional weight of the item, and $\sum W$ is the sum of the attentional weights of all the items within the current temporal interval (Levison, Elkind & Ward, 1971), and of the residual attentional weights of all items which were attended earlier. Two aspects of this equation are important. First, by including C_i as a multiplicative term, the equation ensures that conspicuity modulates the amount of attention allotted to an item, independently of its effect on attentional weight. Second, because the term $\sum A$ includes the residual weights of items which were attended earlier, workload from previously attended stimuli is allowed to modulate attentional control. The model thus captures the degrading influence of cognitive load on SA.

The change in SA effected by the items in a given interval is determined by a weighted mean of their information values, with *V* for each item being weighted by the item's attentional allotment. These weighted values are employed to update SA via an anchoring and adjustment process, described by Hogarth and Einhorn (1992), capturing the effects of various cognitive biases (e.g., primacy and recency effects) on belief updating. After SA has been updated in response to new evidence, the model proceeds to the next temporal interval. If additional evidence is encountered, SA is again revised via the processes described above. If no new evidence is encountered, SA is assumed to decline according to an exponential decay function. This decay in the absence of new evidence reflects the fact that SA maintenance is resource-limited. Based upon an evaluation of Ericsson and Kintsch's (1995) model of long term working memory, a mechanism assumed to underlie situation awareness (Wickens, 2000), the time constant for this decay is likely to be relatively large under low-workload conditions. In contrast, because allocation of attention to new items will disrupt rehearsal in working memory, the model assumes a faster decay rate for SA during attentional processing of irrelevant stimuli (which provide no information to build SA) than during the absence of attention demanding stimuli.

Domain-Specific Details

Here we describe details of the model as applied to the taxiway error (wrong turn) problem. In this case, the pilot is uncertain of the direction to take at each choice point encountered during taxi in order to reach the assigned gate. For simplicity, objects/events in the current implementation are generally assigned one of only three information values. An item which gives or reminds the pilot of her/his instructions, or which marks the location at which the pilot is to execute some non-default action, is assigned an information value of 1. An item which meets neither of these criteria but provides the pilot information as to his/her location or orientation along the taxiway is assigned a value of .5. An item which provides no task-relevant information is assigned a value of 0. Auditory events and branches/intersections are assigned a conspicuity of 1, the former because of the intrinsic attention capturing characteristics of the auditory modality (Spence & Driver, 2000), and the latter because they are assumed to obligatorily pass across the pilot's fovea as they are approached. Most additional visual stimuli were assigned a conspicuity of .5. Values of *V* and *C* for some items are reduced in some of the simulations described below, however, to demonstrate effects of ambiguous evidence and low stimulus salience.

SA is assumed to decay with a half life of 60 seconds during times at which no new stimuli are attentively processed. This parameter, somewhat arbitrarily chosen, can be adjusted to modulate the overall level of SA. During processing of irrelevant stimuli, SA is assumed to decay with a half life of five seconds. Similarly, attentional weights are assumed to decay with a five second half life (i.e., the half life of the contents of unrehearsed working memory; Card, Moran, & Newell, 1986) following the initial perception and processing of a stimulus.

SA affects performance in the model by determining the likelihood with which the pilot will behave correctly when faced with a choice between actions. Upon reaching an intersection of multiple pathways, the pilot's probability of recognizing the correct pathway is set to be equal to the current value of SA. If the pilot does not recognize the correct pathway, she/he is assumed to select a path randomly. The probability of a correct choice is thus equal to the probability of the pilot choosing correctly because he/she recognizes the correct choice, plus the probability that the pilot fails to recognize the correct choice as such but guesses it correctly. One effect of this algorithm is that when SA is imperfect, the probability of a correct guess will decline as the number of pathways converging at an intersection increases. The accuracy of navigational behavior at an intersection will therefore vary as a function of intersection complexity, as has been observed in simulation work (Hooey & Foyle, 2001).

Validation

Preliminary validation of the model was accomplished by comparing its predictions to the behavior of commercial pilots performing high-fidelity simulations of landing and taxi-to-gate operations at O'Hare International Airport. Simulations were carried out at the NASA Ames Advanced Concept Flight Simulator (Hooey & Foyle, 2001; Hooey, Foyle, Andre, & Parke, 2000). A video and audio tape of the simulation was used to extract a time line of events during a typical scenario. A subset of events extracted to exercise the model appears in the timeline below:

Time (sec)	Object/Event	Salience	Infor-mation Value
00	Rehearsal of instructions	1.0	1.0
20	Irrelevant discussion	1.0	0.0
30	2-Way Crossing	0.5	0.5
32	Sign	0.5	0.5
35	Sign	0.5	0.5
40	Branch	1.0	0.5
45	Irrelevant Discussion	1.0	0.0
48	3-way crossing	1.0	0.5
48	3-way crossing	1.0	0.5
50	Visually salient traffic	1.0	0.0
52	Visually non-salient traffic	0.5	0.0
58	Point at which pilot should exit	1.0	1.0

Simulation data from two cockpit display conditions were modeled. In the *current operations condition*, pilots were provided Jeppesen charts for navigation. In the *T-NASA condition*, pilots were provided a head-up display and electronic moving-map which marked the cleared taxi-route. Simulation research by Hooey et al., (2000) revealed that the incorporation of such technology reduced the probability of an error on each taxi mission from .22 to essentially 0 (i.e., perfect SA). Effects of the T-NASA system were incorporated within the model by assuming a visual scan of T-NASA displays every four seconds (a value based on the data of Andre & Purcell, 2001). Additional scenarios further exercised the model by manipulating the salience and information value of objects and events. Results of a subset of these modeled scenarios are presented here.

Figure 2 presents modeled SA values in the current operations and T-NASA conditions for the scenario described above. As can be seen, the model successfully captures the improved SA, and consequent elimination of errors, observed by Hooey et al. (2000) in the T-NASA display condition. Predicted values of SA in the T-NASA condition are consistently higher than those in the current operations condition, and are less susceptible decay. The model also captures the degrading effects of distracting objects and events on SA (irrelevant conversation at t = 20 s and t = 45 s, and traffic at t = 50 s and t = 52 s), along with the beneficial effects of informative stimuli (labeled crossings and branches at t = 30 s, t = 40 s, and t = 48 s, signs at t = 32 s and t = 35 s). Changes in SA, furthermore, are manifest as changes (not depicted here) in top-down attentional guidance, indexed by the amount of attention allotted to relevant vs. irrelevant items, and in navigational behavior, indexed by the probability of correct behavior at taxiway intersections.

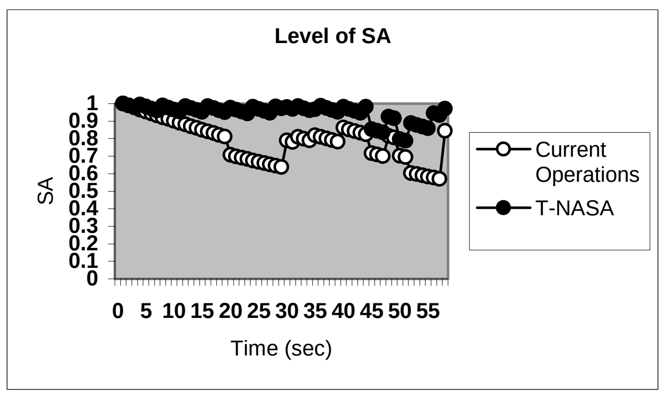

Figure 2.

Figure 3 presents modeled SA values in additional variations of the scenario described above, all assuming current operations displays. Data for the baseline scenario are identical to those of current operations scenario in Figure 2. The low conspicuity condition of models the effects of degraded visibility (e.g., as produced by fog) by halving conspicuity values of all visual stimuli. Similarly, the low information value condition models the consequences of ambiguous stimulus information by halving information values for all visual stimuli. The auditory distractors condition, finally, models effects of irrelevant auditory messages (at times = 12, 15, 27, 37, 55 s). As can be seen, the model predicts the expected effects of all three manipulations. Predicted SA is compromised as a result of degraded stimulus visibility and reduced informativeness, and likewise is reduced by the presence of auditory distractions. Changes in SA in all of the scenarios, finally, again produce changes in top-down attentional guidance and navigational behavior.

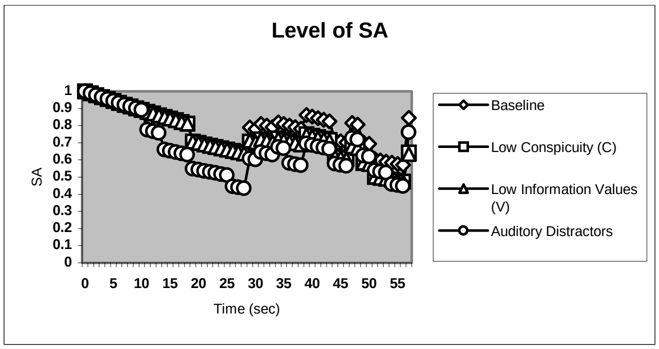

Figure 3.

CONCLUSION

The current "validation" is admittedly preliminary. For example, the actual predictive validation against obtained data is somewhat simplistic. The model predicts a reduction in errors from "some" to "none" when dynamic SA display supports are provided, an effect that was observed. However, it is non-trivial that the SA values throughout the taxi portion of Figure 2 led to a predicted error rate of 24%, a value similar to observed error rate of 22%. Our manipulations in Figure 3 offer construct validity rather than predictive validity, showing simply that SA generated by our model behaves as empirical data would lead us to expect following changes to the environment. It is also the case that our modeling has not provided novel insights about the concept of SA, although we believe that such insights are better provided by experimentation than by model predictions. Nevertheless, the current work is a step toward a comprehensive model of SA, a phenomenon of tremendous importance to the safety of vehicle operators and passengers in high workload environments.

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