Cockpit System Situational Awareness Modeling Tool

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ABSTRACT

This project explored the possibility of predicting pilot situational awareness (SA) using human performance modeling techniques for the purpose of evaluating developing cockpit systems. The Improved Performance Research Integration Tool (IMPRINT) was combined with the Adaptive Control of Thought-Rational (ACT-R) cognitive modeling architecture to produce a tool that can model both the discrete tasks of pilots and the cognitive processes associated with SA. The techniques for using this tool to predict SA were demonstrated using the newly developed Aviation Weather Information (AWIN) system. By providing an SA prediction tool to cockpit system designers, cockpit concepts can be assessed early in the design process while providing a cost-effective complement to the traditional pilot-in-the-loop experiments and data collection techniques.

Keywords: Human Performance Modeling, Situational Awareness, ACT-R, IMPRINT, AWIN

INTRODUCTION

Currently, pilot SA can be measured objectively using existing techniques for current systems or prototypes of future systems. However, these techniques can only be applied to systems mature enough that it is often too late to make fundamental design changes. By providing an SA prediction tool to cockpit system designers, cockpit concepts can be assessed early in the design process while providing a cost-effective complement to the traditional pilot-in-the-loop experiments and data collection techniques. Allowing modeling predictions of SA early in the design also helps designers understand the trade-offs between candidate designs and better explore the design space in response to environmental and operator scenario conditions. Finally, modeling techniques provide insights not only into what went wrong but also into how, leading to direct suggestions on how to alter the design to remedy the problems.

The goal of this work was to determine if the combination of a discrete event simulation tool and a cognitive modeling tool could be used to predict the SA of pilot's during the use of a new cockpit system. We used IMPRINT to execute a weather scenario based on the sequence of weather cues a pilot would encounter while using the AWIN system. ACT-R dynamically simulated the activation levels of each chunk determined by subsymbolic processes such as memory decay, cue priming and rehearsal over the course of the scenario. The pilot's SA was based on the activation levels of the chucks of weather information that determine their availability for cognitive processing (Keller et al 2003).

IMPRINT

IMPRINT is a discrete event simulation tool that consists of a set of automated aids to assist analysts in conducting human performance analyses. It assists a user in estimating the likely performance of a new

system by facilitating the construction of flow models that describe the scenario, the environment, and the goals that must be accomplished. Users build these models by breaking down the goals into a network of functions. Each of the functions is then further broken down into a network consisting of other functions and tasks. Then, a user estimates the time it will take to perform each task and the likelihood that it will be performed accurately. By executing a simulation model multiple times, you can study the range of results that occur. The tool has been used successfully to predict human performance in complex and dynamic operational environments. However, it does not include an embedded model of cognitive or psychological processes. Rather, it relies on the modeler to specify and implement these constructs.

ACT-R

ACT-R is a cognitive architecture that can be used to model a wide range of human cognition. It has been used to model tasks as simple as memory retrieval (Anderson, Bothell, Lebiere & Matessa, 1998) and visual search (Anderson, Matessa & Lebiere, 1997) to tasks as complex as learning physics (Salvucci & Anderson, 2001) and designing psychology experiments (Schunn & Anderson, 1998). It predicts what happens cognitively every few hundred milliseconds in performance of a task. As such, it is situated at a level of aggregation considerably above basic brain processes but considerably below significant tasks like air-traffic control.

The information flow in the ACT-R cognitive architecture is composed of asynchronous modules communicating with a central production module through associated buffers that can hold only a limited amount of information (Figure 1). The perceptual and motor modules extract information from the environment in a plausibly limited manner, e.g. only one item can be attended to at a time, actions and shifts of attention take time, etc. The declarative module holds facts and information in long-term memory. The goal module holds the current context, which is composed of the system's intention together with associated information. The central production system is composed of productions, or condition-action rules, that test the current state of the modules through their associated buffers and requests actions from these modules using the same buffers.

ACT-R also has a subsymbolic level in which continuously varying quantities are processed, often in parallel, to produce much of the qualitative structure of human cognition. These subsymbolic quantities participate in neural-like activation processes that determine the speed and success of access to chunks in declarative memory as well as the conflict resolution among production rules.

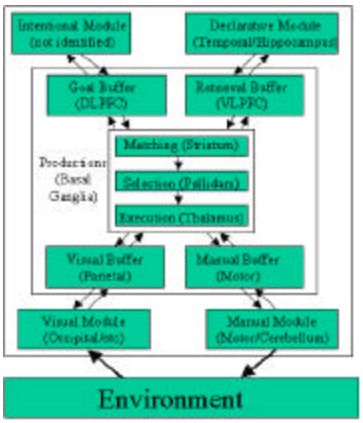

Figure 1. The overall flow of control in ACT-R

Because ACT-R and IMPRINT were targeted at different behavioral levels, they perfectly complement each other. IMPRINT is focused on the task level, how high-level functions break down into

smaller-scale tasks and the logic by which those tasks follow each other to accomplish those functions. ACT-R is targeted at the "atomic" level of thought, the individual cognitive, perceptual and motor acts that take place at the sub-second level. Goals in ACT-R correspond directly to tasks in IMPRINT, providing a natural integration level. Certain tasks in an IMPRINT task network can be implemented as ACT-R models, combining the cognitive accuracy of a cognitive architecture with the tractability and ease of design of task networks.

AWIN

We chose an early prototype of the Aviation Weather Information (AWIN) system as the candidate cockpit system. AWIN is a hand-held tool (Figure 2) that provides weather information to general aviation pilots to support strategic flight planning for hazardous weather avoidance. It presents a graphical map overlaid with NEXRAD mosaic, METAR graphics (showing ceiling and visibility category), as well as textual information. The system gives the user options for how the information is displayed, a range of levels of details through which the user can zoom and an aircraft icon that shows their current position in real time. The tool allows pilots to strategically plan their flight paths in order to avoid bad weather.

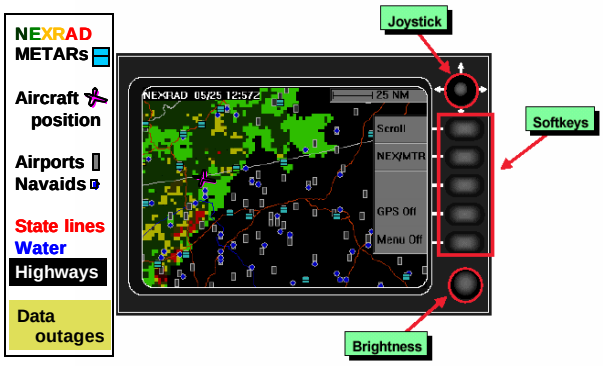

Figure 2. AWIN interface description

METHODS

A recent flight test of AWIN used a prototype system developed by Bendix-King to assess general aviation pilots' weather decision making and included the collection of SA data during the flight tests (NASA website). During the flights, several test subject pilots had access to different types of weather information that included audio weather reports, visual cues and the AWIN system. At specified periods during the flight the pilots were asked to plot the position of the weather cell nearest to their position. In this way, the testers were able to evaluate the weather SA of the pilots across the different types of weather source information.

We created a sequence of weather cues based on data from one of these flights in order to provide a scenario for the model. Table 1 shows the first few events of the scenario timeline. The 'New Nexrad' events represent the periodic updating of the weather maps to the AWIN unit. The 'HIWAS Weather Report' event represents one of the audio weather reports available to the pilots. The 'Position Report' event represents the pilot test task of plotting their exact position based on information from the flight crew. The 'SA Questionnaire' events represent the points during the flight when the test subjects were asked to report their weather SA. Finally, the 'Take off role' event represents the actually beginning of the flight. The full scenario covers approximately 1 hour and includes 12 Nexrad events, 3 audio weather events, 3 position reports and 6 SA questionnaire periods.

Table 1. Weather scenario event list and timeline example

Start time	Interval	Event
18:33:16	0:00:00	New Nexrad 1
18:34:00	0:00:44	Take off role
18:37:17	0:03:17	New Nexrad 2
18:43:17	0:06:00	New Nexrad 3
18:49:30	0:06:13	Position Report 1
18:53:40	0:04:10	SA Questionnaire 1
18:57:48	0:04:08	HIWAS Weather Report
19:01:48	0:04:00	SA Questionnaire 2
19:03:37	0:01:49	New Nexrad 4

Each event includes data relevant to the pilot. The 'Position Report' data included the latitude and longitude of the aircraft for the current time period. Each of the audio weather reports contains the latitude and longitude of locations referenced relative to serious weather. For example, for an audio report indicating that there was a thunderstorm 30 miles north east of Charleston, the event would include the location of the referenced city, the indicated distance and a bearing of 45 degrees. The Nexrad events represent the data available through the AWIN system. It includes the latitude and longitude of the aircraft since the location is given on the AWIN display and the relative distance and bearing to the several of the nearest weather cells.

IMPRINT Model

We used IMPRINT to execute the weather scenario. Figure 3 shows the IMPRINT network diagram for the AWIN weather SA model. The nodes of the diagram are connected by lines that represent the sequence in which the nodes are executed when the model is run. The data from each weather event is stored within the IMPRINT model and is used to either effect the network diagram or is passed to the ACT-R model as weather cues. One entity is generated for each report and is used to reference the associated data. When the model is executed, node 5 schedules all of the report entities that will traverse the network diagram based on the scenario timeline. Each entity in turn will execute one of nodes 8 through 13 depending on what type of event the entity represents. Each of these nodes advances the simulation clock by the amount of time it took for that event to occur. For each entity, node 4 transmits the scenario cue data associated with that entity to the ACT-R model.

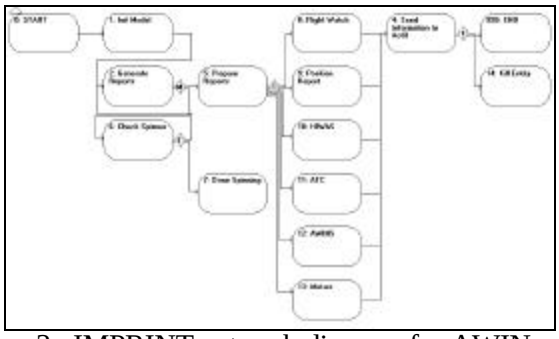

Figure 3. IMPRINT network diagram for AWIN model

ACT-R Model

For the purposes of this project, we focused on SA associated with understanding the situation based on the understanding of the cues commonly referred to as Level 2 SA. As such, the cognitive model is

focused on the tasks of encoding and retrieving spatial weather information. It assumes that the human pilots knew how to process audio report information and how to manipulate the AWIN system to extract the needed weather information. Thus we didn't explicitly model the perceptual/motor processes that would have provided an accurate picture of SA Level 1. According to the position reports, pilots seemed to have an excellent awareness of the current position of the aircraft. Weather patterns, on the other hand, moved slowly and no questions were explicitly asked about projecting their future positions. Thus we didn't try to represent the SA Level 3 expert knowledge that might have been used to perform position corrections.

The ACT-R model is composed of a number of unit tasks consisting of a type of goal, together with the associated production rules to solve that goal. The goals include encoding of weather information and retrieving the location of weather patterns. The first two tasks in the model concern the encoding of spatial weather information. Audio weather information was typically given with reference to a fixed landmark, e.g. "Weather front 60 miles N.N.E. of Wilmington". Therefore, the weather pattern position was encoded in a single chunk as a bearing and distance relative to the stated landmark. Representing visual information, such as that provided by NEXRAD maps, is somewhat more complex. Representational constraints that limit the size of chunks prevent us from representing a map, or even a part of it, as a single chunk. Instead, each weather pattern is encoded using a redundant set of chunks, each representing its position relative to a given landmark. Landmarks are selected to favor those nearer the weather pattern. Each relative position is encoded as bearing and distance from the landmark, with noise added to represent estimation error in encoding (Figure 4).

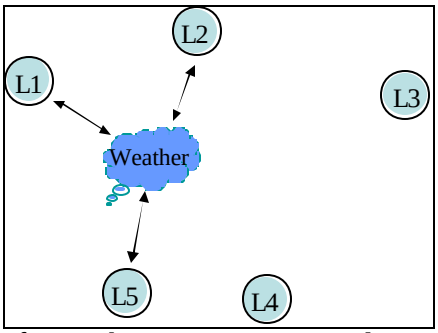

Figure 4. Encoding of a weather pattern position relative to nearby landmarks

RESULTS

The task of answering the SA questionnaire involves retrieving all known weather patterns. For any given pattern, that means retrieving the chunk encoding its position relative to a landmark, then retrieving the chunks encoding the landmark's position as well as the aircraft's current position, and then using those pieces of information to infer the weather pattern's relative position to the aircraft. When all the weather patterns have been retrieved and their relative position to the aircraft determined, the pattern with the shortest distance to the aircraft is matched and returned as the closest one. The SA picture provided could include drawing each weather pattern retrieved or simply the closest one as requested in the SA questionnaire. The probability of retrieving any information about the position of a weather pattern as a function of time elapsed since encoding and of the number of encodings. The probability decreases sharply with time as a function of the decay of activation captured by the base-level learning equation. In addition, multiple model executions generate a measure of the error in recalling the position of a weather pattern as a function of number of encodings for a number of different conditions.

DISCUSSION

The methodology and results demonstrated in this effort provide an effective process for modeling operator SA. The ACT-R cognitive model performs the same task as the human pilots and makes predictions that can be matched directly with human data (latency response, probability recall, magnitude and distribution of positional error, etc). Thus observable performance and situation awareness are a function of the same underlying cognitive and perceptual mechanisms. The same cognitive model can also make workload predictions (Lebiere, 2001), and thus capture possible SA-workload tradeoffs, since more information presented might improve SA at the expense of a higher workload. A quantitative computational model can generate all those performance measures, which can be used to cross-validate the model along multiple scales. The degree of modeling can be adjusted to focus on different levels of SA, e.g. by including a detailed model of the manipulation of the AWIN tool. The impact of design decisions can then be assessed by having the model interact with the same system design used for human pilots.

CONCLUSIONS

The ability to create model-based predictions of SA has a wide range of benefits not only within the cockpit system development community but for the development of any system designed to provide information to human operators in high workload or risk environments. Although additional research and development is required, this work has demonstrated that currently existing human performance modeling tools can be used to predict the SA provided by a cockpit system.

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