Accepted for publication at the *Human Computer Interaction International 2009 Annual Conference*. July 19-24, San Diego, CA

A Computational Implementation of a Human Attention Guiding Mechanism in MIDAS v5

Brian F. Gore[1], Becky L. Hooey[1], Christopher D. Wickens[2] and Shelly Scott-Nash[2],

[1] San Jose State University Research Foundation, NASA Ames Research Center, MS 262-4, Moffett Field, California, USA
[2] Alion Science and Technology, 4949 Pearl East Circle, Suite 300 Boulder, Colorado, USA

{Brian.F.Gore, Becky.L.Hooey}@nasa.gov; {cwickens, sscott-nash}@alionscience.com

Abstract. In complex human-machine systems, the human operator is often required to intervene to detect and solve problems. Given this increased reliance on the human in these critical human-machine systems, there is an increasing need to validly *predict* how operators allocate their visual attention. This paper describes the information-seeking (attention-guiding) model within the Man-machine Integration Design and Analysis System (MIDAS) v5 software - a predictive model that uses the Salience, Effort, Expectancy and Value (SEEV) of an area of interest to guide a person's attention. The paper highlights the differences between using a probabilistic fixation approach and the SEEV approach in MIDAS to drive attention.

Keywords: Human Performance Modeling, Modeling Attention, MIDAS v5, SEEV.

1 Introduction

There is a need for increased realism in human performance models (HPMs) of extreme and potentially hazardous environments. As the fidelity and realism of the HPMs improve, so too does the need for integrating and using complex human cognitive and attention models. HPMs exist that incorporate basic human vision and attention models to drive how and when a human will respond to events in specific environment contexts. Implementing these models computationally has typically taken the form of scripting a sequence of visual fixations points and some apply a probabilistic distribution [1,2]. Few, if any, HPM-attention models today operate in a closed-loop fashion using information from the environment to drive where the operator is going to look next. As automation and advanced technologies are introduced into current operational environments, there is an increasing need to validly *predict* how and when a human will detect environmental events. This paper summarizes the augmentations to the information-seeking (attention-guiding) model within the Man-machine Integration Design and Analysis System (MIDAS) v5 software from a probabilistic approach to a predictive model that uses four parameters (Salience, Effort, Expectancy and Value; SEEV) to guide an operator's attention [3].

1.1 Man-machine Integration Design and Analysis System (MIDAS)

The Man-machine Integration Design and Analysis System (MIDAS) is a dynamic, integrated human performance modeling and simulation environment that facilitates the design, visualization, and computational evaluation of complex man-machine system concepts in simulated operational environments [4,5]. MIDAS combines graphical equipment prototyping, dynamic simulation, and human performance modeling to reduce design cycle time, support quantitative predictions of human-system effectiveness, and improve the design of crew stations and their associated operating procedures. HPMs like MIDAS provide a flexible and economical way to manipulate aspects of the operator, automation, and task-environment for simulation analyses [4,5,6]. MIDAS can suggest the nature of likely pilot errors, as well as highlight precursor conditions to error such as high levels of memory demand, mounting time pressure and workload, attentional tunneling or distraction, and deteriorating situation awareness (SA).

MIDAS links a virtual human, comprised of a physical anthropometric character, to a computational cognitive structure that represents human capabilities and limitations. The cognitive component is comprised of a perceptual mechanism (visual and auditory), memory (short term memory, long term working memory, and long term memory), a decision maker and a response selection architectural component. The complex interplay among bottom-up and top-down processes enables the emergence of unforeseen, and non-programmed behaviors [7].

MIDAS is unique as it can be used as a cognitive modeling tool that allows the user to obtain both predictions and quantitative output measures of various elements of human performance, such as workload and SA, and as a tool for analyzing the effectiveness of crewstation designs from a human factors perspective [4]. This analysis can help point out fundamental design issues early in the design lifecycle, prior to the use of hardware simulators and human-in-the-loop experiments. In both cases, MIDAS provides an easy to use and cost effective means to conduct experiments that explore "what-if" questions about domains of interest. MIDAS v5 has a graphical user interface that does not require advanced programming skills to use. Other features include dynamic visual representations of the simulation environment, support for multiple and interacting human operators, several HPM outputs (including timelines, task lists, workload, and SA), performance influencing factors (such as error predictive performance, fatigue and gravitational effects on performance), libraries of basic human operator procedures (how-to knowledge) and geometries for building scenarios graphically (that leverage heavily from Siemens' Jack™ software) [8]. [1]

---

[1] Additional MIDAS information in [4,5] and http://hsi.arc.nasa.gov/groups/midas/

™ Jack™ is maintained by Siemens PLM Solutions

1.2 MIDAS Attention and Perception Model

MIDAS represents *attention* as a series of basic human primitive behaviors that carry with them an associated workload level determined from empirical research [9,10,11]. Actions are triggered by information that flows from the environment, through a perception model, to a selection-architecture (that includes a representation of human attention loads), to a task network representation of the procedures that then feeds back into the environment. Actions carried out by the MIDAS operator impact the performance of the model in a closed-loop fashion.

MIDAS represents *perception* as a series of stages that information must pass through in order to be processed. The perception model includes visual and auditory information. Visual perception in MIDAS depends on two factors – the amount of time the observer dwells on an object and the perceptibility of the observed object. The perception model computes the perceptibility of each object that falls into the operator's field of view based on properties of the observed object, the visual angle of the object and environmental factors. In the current implementation of MIDAS, perception is a three-stage, time-based perception model (undetected, detected, comprehended) for objects inside the workstation (e.g., an aircraft cockpit) and a four-stage, time-based perception model (undetected, detected, recognized, identified) for objects outside the workstation (e.g., taxiway signs on an airport surface). The model computes the upper level of detection (i.e., undetectable, detectable, recognizable, identifiable for external objects) that can be achieved by the average unaided eye if the observer dwells on it for a requisite amount of time. For example, in a low-visibility environment, the presence of an aircraft on the airport surface may be 'detectable' but the aircraft company logo on the tail might not be 'recognizable' or 'identifiable' even if he/she dwells on it for a long time.

1.3 MIDAS Probabilistic Scanning Model

MIDAS uses a probabilistic scan pattern to drive the perception model. In the current version, probabilistic scan behaviors drive the eyeball towards a particular area of interest (AOI) based on a combination of the model analysts' understanding of the operators scan pattern and the analysts' selection of a statistical distribution of fixation times (i.e. gamma, lognormal, linear, etc) characteristic of the specific environmental context. This approach requires a known scan pattern (in many cases this requires access to eye-movement data from a human-in-the-loop simulation). Models that use probabilities to drive the scan behavior require extensive model development time in order to represent context. An aviation example from a recently completed MIDAS v5 model (for a scenario description see [12]) will illustrate the manner that the information is input into the MIDAS architecture. The modeled pilots scan the displays and out the windows according to a probability matrix, as presented in Table 1. The probabilities were developed and verified by an experienced commercial pilot Subject Matter Expert (SME). The matrix assigns to the Captain (CA) and First Officer (FO) a probability of attending to information sources (shown in rows) for each of eight scenario contexts or phases of flight (shown in columns).

Table 1. Visual fixation probability matrix in a model of pilot performance (see [12])

Captain's fixation probabilities by context (phase of flight)

	Context							
Displays	descent	approach	land	rollout	exit runway	after land check	taxi to gate	arrive at gate
Primary Flight Display	0.20	0.30		0.10	0.10			
Nav Display/Elect Moving Map	0.20	0.30		0.10	0.20	0.20	0.30	0.10
left window	0.05	0.05		0.10	0.20	0.20	0.20	0.30
left-front window	0.05	0.10	0.90	0.50	0.20	0.20	0.20	0.30
right-front window	0.05	0.05	0.10	0.10	0.10	0.20	0.20	0.20
right window	0.05				0.10	0.10	0.10	0.10
Eng. Indicating & Crew Alerting System	0.10	0.05		0.10	0.10	0.05		
Mode Control Panel	0.10	0.05				0.05		
Jepp chart	0.10	0.10						
Control Display Unit	0.10							
Total	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

First Officer's fixation probabilities by context (phase of flight)

	Context							
Displays	descent	approach	land	rollout	exit runway	after land check	taxi to gate	arrive at gate
Primary Flight Display	0.10	0.10	0.30	0.40	0.20	0.10		
Nav Display/Elect Moving Map	0.20	0.10	0.20	0.20	0.20	0.10	0.25	0.10
left window	0.10	0.10	0.10		0.10		0.10	0.10
left-front window	0.10	0.10	0.10	0.10	0.10	0.10	0.20	0.10
right-front window	0.10	0.10	0.10	0.10	0.20	0.20	0.20	0.30
right window	0.10	0.10	0.10		0.10	0.20	0.15	0.40
Eng. Indicating & Crew Alerting System	0.10	0.10	0.10	0.20	0.10	0.20	0.10	
Mode Control Panel	0.05	0.10				0.10		
Jepp chart	0.10	0.10						
Control Display Unit	0.05	0.10						
Total	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

1.4 MIDAS Implementation of the Probability Matrix.

Within the model, the probability of visual fixation (location) is context specific as illustrated in Fig. 1. For example, during 'after land checks', the Captain is primarily scanning the electronic moving map (EMM) and out the window (OTW), while his/her secondary scanning is towards the Engine Indicating and Crew Alerting System (EICAS). The First Officer (FO) is primarily scanning the EICAS and OTW. The Primary Flight Display (PFD) and EMM are secondary. Probabilities are defined in the node to the right of the high level task (e.g. "descent(1_68)").

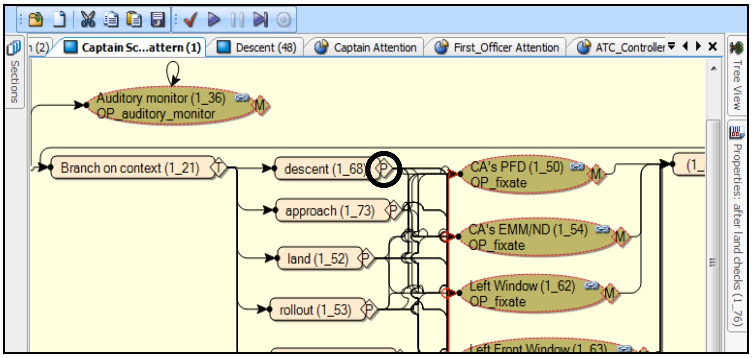

Fig. 1. MIDAS implementation of the probabilistic scan pattern – P decision node (circled) is where the analyst enters the context-specific probabilistic values from probability matrix

This probabilistic approach effectively drives attention when the scan behavior is known but is less suitable when an analyst is interested in *predicting* the scan pattern given the context of the information content in the modeled world. To address this limitation and to improve the cross-domain generalizability of the MIDAS perception and attention model, MIDAS was augmented to include the validated *S*alience, *E*ffort, *E*xpectancy, *V*alue (SEEV) model of visual attention [13] as will be described next.

1.5 The Salience, Effort, Expectancy, Value (SEEV) Model

The SEEV model began as a conceptual model to predict how visual attention is guided in dynamic large-scale environments [13]. SEEV estimates the probability of attending, P(AOI), to an AOI in visual space, as a linear weighted combination of four components (salience, effort, expectancy, and value) as per the following equation:

$$P(AOI) = s*S - ef*EF + ex*EX + v*V. \tag{1}$$

Coefficients in the uppercase describe the properties of a display or environment, while those in lower case describe the weight assigned to those properties in the control of an operator's attention [14]. Specifically, the allocation of attention in dynamic environments is driven by the bottom-up capture of *Salient (S)* events (e.g., a flashing warning on the instrument panel) and inhibited by the *Effort (E)* required to move attention (e.g., a pilot will be less likely to scan an instrument located at an overhead panel, head down, or to the side where head rotation is required, than to an instrument located directly ahead on a head-up display (HUD). The SEEV model also predicts that attention is driven by the *Expectancy (EX)* of seeing a *Valuable (V)* event at certain locations in the environment.

A computational version of this model drives the eyeballs around an environment, such as the dynamic cockpit, according to the four SEEV parameters. For example, the simulated eyeball following the model will fixate more frequently on areas with a high bandwidth (and hence a high expectancy for change), as well as areas that support high-value tasks, like maintaining stable flight [15].[2] SEEV has been under development since 2001 and has been extensively validated with empirical human-in-the-loop data from different domains [3,16].

The integration of the SEEV model into MIDAS allows dynamic scanning behaviors by calculating the probability that the operator's eye will move to a particular AOI given the tasks the operator is engaged in within the multitask context. It also better addresses allocation of attention in dynamic environments such as flight and driving tasks. A description of the implementation of the SEEV model into the MIDAS software follows.

2 Augmenting the MIDAS Visual Scan Mechanism with SEEV

In MIDAS, Effort, Expectancy, and Value are assigned values between 0 and 1, while Salience is left unconstrained. As such, Effort, Expectancy, and Value drive the

[2] The SEEV conceptual model has been refined to include a "to-be-noticed event" [15,16,17].

human operator's eye around the displays. However, if a salient event occurs, then P(AOI) may be offset by the display exhibiting the salient event until the display location of the salient event has been fixated and detected. In order to integrate SEEV into MIDAS, provisions were made for the analysts to estimate values for each of the four parameters. Each will be discussed in turn.

Salience. In MIDAS, salience is associated with an **event**, not a display or object. An example of salience could be a proximity indicator on the navigation display that flashes when another aircraft comes too close. That is, for example, a cockpit display becomes salient when it is presenting an alert, but otherwise, is not salient. In addition, salience could include the loudness of an utterance (but not the content), the flash rate of an alert, and the color of an indicator (i.e., red to indicate a failure). In MIDAS, the time between the onset of the salient event and the time at which perception exceeds "Undetected" is reported [15,16,17].

The analyst must assess the salience of an event and provide a weight from 1 to 4. To aid this process, and in an attempt to establish a consistent set of rules to be applied across models, simple heuristics were developed: 1 = change with no luminance increase, 2 = change with luminance increase, 3 = change in position and luminance increase, 4 = repeated onsets (flashing). Fig. 2 below shows how an analyst sets the salience of an event in the MIDAS software.

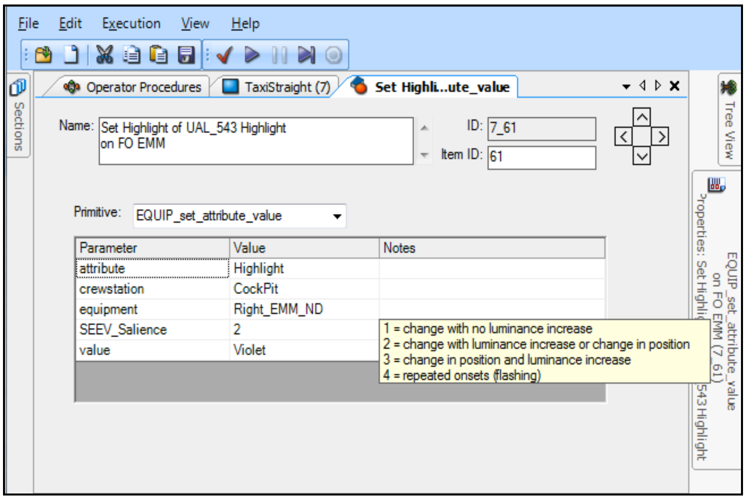

Fig. 2. Salience heuristics are provided to guide model development

Effort. Effort refers to the work that is required to sample the information (distance to the AOI). Effort is the only inhibitory factor in the SEEV equation and impacts the likelihood of traveling from one AOI to another. Since MIDAS knows the location of all displays and objects in the environment, the model can calculate Effort empirically. In MIDAS, an Effort rating between 0 and 1 is calculated for each AOI relative to the currently fixated AOI and is based on the angular difference. Any AOI that is 90 degrees or more from the current AOI is set to the maximum (1.0). The visual angle to any AOI that is less than 90 degrees is divided by 90 degrees.

Expectancy. Expectancy, also called bandwidth, is described as the event frequency along a channel (location). This parameter is based on the assumption that if a channel has a high event rate, people will sample this channel more frequently than if the event rate is lower [14]. An example is the frequent oscillation of attitude of a light plane when encountering turbulence. The pilot expects the horizon line on the attitude indicator to change frequently and therefore monitors it closely. In contrast, the pilot expects the altimeter during a controlled descent to descend at a constant rate and therefore has a low expectation of seeing changes in descent rate. Thus, when the rate of change is constant, the bandwidth is zero. In SEEV applications, bandwidth (event rate) is always used as a proxy for expectancy. In MIDAS, Expectancy is implemented as a *SEEV primitive* (Fig. 3). Different expectancy values on a given display can be set for each context, procedure and operator. The context of events that precede the onset of a given signal will influence the likelihood that operators will bring their attention into the areas that are infrequently sampled.

Expectancy for each AOI is set by the user to 'none', 'low', 'moderate' or 'high'. When used in the SEEV equation, Expectancy is converted to 0, .333, .666 and 1.0 respectively. Drilling down on the SEEV Expectancy primitive in the task network reveals the setting as shown in Fig. 3.

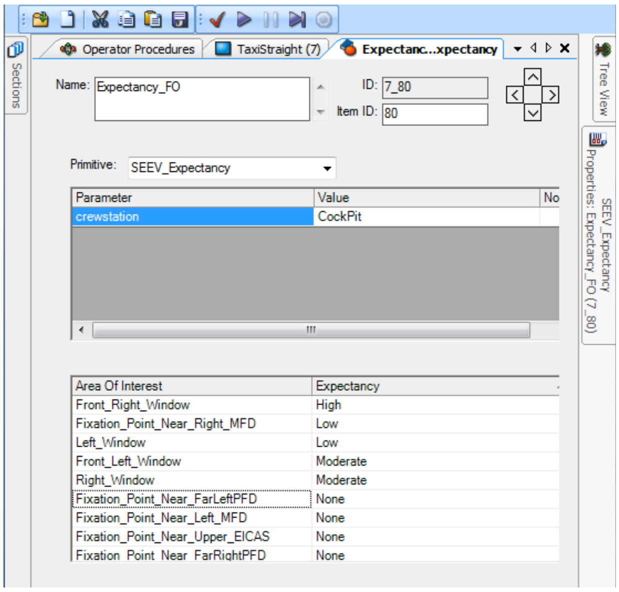

Fig. 3. An example of setting expectancy for First Officer

Value. The level of Value denotes the importance of attending to an event or task or the cost of missing it. For example, information that is used to prevent stalling the aircraft (airspeed, attitude, angle-of-attack), is clearly more important than navigational information, such as waypoint location. The sum of the product of the task value and the relevance of each display to the task is used to compute the value (importance) of the display [14] as illustrated in Table 2. Before the SEEV calculation is run, the task set importance is normalized between 0 and 1 (as shown by the values in Table 2) by computing the sum of all the importance values and then dividing each importance by the sum. It can be seen that an increased weight is given to the front window when avoiding collision relative to maintaining speed and heading.

Table 2. Task value computation to determine display importance per context

		Importance of AOI to task			
Task	Task Value	Front Window	Left Window	Near PFD	Near ND
Avoid collision	.8	.6	.4	0	0
Maintain speed/ heading	.2	.1	.1	.4	.4
Value of AOI		=(.8*.6)+(.2*.1) =.5	=(.8*.4)+(.2*.1) =.34	=(.8*.0)+(.2*.4) =.08	=(.8*.0)+(.2*.4) =.08

In MIDAS, Value is implemented using SEEV primitives in order to bracket sets of primitives belonging to the most relevant task. The SEEV calculation considers all tasks that are active until they are explicitly ended by a SEEV end task primitive. For each task, an overall importance is set by the user. The user can indicate a relevance of none, low, moderate and high for each AOI. Just as with Expectancy, these are converted to 0, .333, .666, and 1. In addition, the user can specify none, low, moderate and high importance rating for the entire task. In Fig. 4, monitoring out the window (Front Right Window) is of high importance to the task bracketed by the "Monitoring OTW during land – FO" task set.

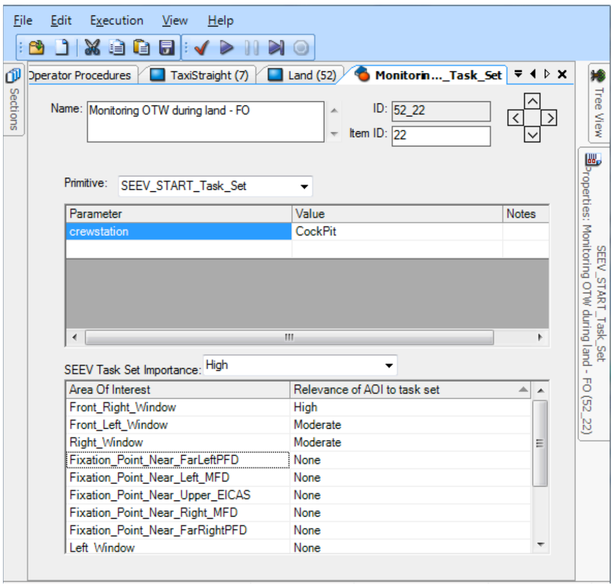

Fig. 4. Example of assigning the value of AOIs to a task

Discussion

Few computational models operate in a closed-loop manner when it comes to seeking information within the environmental context. For a HPM to produce valid output, it must accurately model visual attention. Two attention-guiding mechanisms within MIDAS were presented: Probabilistic fixations and the SEEV approach. Probabilistic scan behaviors drive the eyeball towards a particular AOI based on a known scan pattern and a statistical distribution of fixation times. Models that use probabilities to drive the scan behavior are suitable if the analyst wants to replicate a known scan pattern but are less suitable when an analyst is interested in *predicting* the scan pattern given the context of information in the environment. Further, the probabilistic approach is often limited in that it does not consider dynamic changes to the environment and to the task. The SEEV method overcomes those limitations by breaking down relevant flight deck display features to four parameters (Salience, Effort, Expectancy, and Value). This approach to modeling attention is more consistent with actual human behavior and has previously been validated with empirical human-in-the-loop data (see [14,16]). The SEEV model is also less prone to error introduced by the modeler/analyst, as it does not require adjustment of fixation probabilities each time the task or environment is changed, as the probabilistic method does.

Conclusion

Incorrectly defining visual scanning behavior and the manner that humans seek information when interacting in a system context can result in devastating outcomes and system inefficiencies if model results are to be relied upon for system design and evaluation purposes. The improved predictive capability of information-seeking behavior that resulted from the implementation of the validated SEEV model leaves MIDAS better suited to predict performance in complex human-machine systems.

References

1. Landy, M.S.: Vision and attention for Air MIDAS (NASA Final Report NCC2-5472). New York University, Moffett Field, CA (2002)
2. Corker, K.M., Gore, B.F., Guneratne, E., Jadhav, A., & Verma, S.: Coordination of Air MIDAS Safety Development Human Error Modeling: NASA Aviation Safety Program Integration of Air MIDAS Human Visual Model Requirement and Validation of Human Performance Model for Assessment of Safety Risk Reduction through the implementation of SVS technologies (Interim Report NCC2-1563): San Jose State University (2003)
3. Wickens, C. D., & McCarley, J. M.: Applied Attention Theory. Taylor and Francis/CRC Press Boca Raton (2008)
4. Gore, B.F.: Chapter 32: Human Performance: Evaluating the Cognitive Aspects. In: V. Duffy (ed.), Handbook of Digital Human Modeling, Taylor and Francis/CRC Press, NJ (2008)

5. Gore, B.F., Hooey, B.L., Foyle, D.C., & Scott-Nash, S.: Meeting the Challenge of Cognitive Human Performance Model Interpretability Though Transparency: MIDAS V5.X. In: The 2nd International Conference On Applied Human Factors And Ergonomics, July 14-17, Las Vegas, Nevada (2008)
6. Hooey, B.L. & Foyle, D.C.: Advancing the State of the Art of Human Performance Models to Improve Aviation Safety. In: D.C. Foyle and B. L. Hooey (Eds) Human Performance Modeling in Aviation. Taylor & Francis/CRC Press, Boca Raton (2008)
7. Gore, B.F. & Smith, J.D.: Risk Assessment and Human Performance Modeling: The Need for an Integrated Approach. In K.A. Malek (ed.) International Journal of Human Factors of Modeling and Simulation, 1(1), 119-139 (2006)
8. Badler, N.I., Phillips, C.B. & Webber, B.L.: Simulating Humans: Computer Graphics, Animation, and Control. Oxford: Oxford University Press (1993)
9. McCracken, J.H. & Aldrich, T.B.: Analysis of Selected LHX Mission Functions: Implications for Operator Workload and System Automation Goals (Technical note ASI 479-024-84(b)). Anacapa Sciences, Inc. (1984)
10. Hamilton, D.B. Bierbaum, C.R. & Fulford, L.A.: Task Analysis/Workload (TAWL) User's Guide Version 4.0. U.S. Army Research Institute, Aviation Research and Development *Activity*, Fort Rucker, AL: Anacapa Sciences, Inc. (1990)
11. Mitchell, D. K.: Mental Workload and ARL Workload Modeling Tools. ARL-TN-161. Aberdeen Proving Ground, M.D., Army Research Laboratory (2000)
12. Hooey, B.L., Gore, B.F., Scott-Nash, S., Wickens, C.D., Small, R., & Foyle, D.C.: Developing the Coordinated Situation Awareness Toolkit (CSATK): Situation Awareness Model Augmentation and Application. In: HCSL Technical Report (HCSL-08-01) NASA Ames, Moffett Field, CA (2008)
13. Wickens, C. D., Goh, J., Helleberg, J, Horrey, W., & Talleur, D. A.: Attentional Models of Multi-Task Pilot Performance using Advanced Display Technology. In: Human Factors, 45(3), 360-380 (2003)
14. Wickens, C. D., McCarley, J. S., Alexander, A., Thomas, L., Ambinder, M., & Zheng, S.: Attention-Situation Awareness (A-SA) Model of Pilot Error. In: D. Foyle, & B. L. Hooey (Eds.) Human Performance Modeling in Aviation. Taylor and Francis/CRC Press Boca Raton (2008)
15. Wickens, C.D., Hooey, B.L., Sebok, A., Hutchins, S., Koenecke, C., Bzostek, J., Gore, B.F., & Salud, E.: Identifying Black Swans in NextGen: Predicting Human Performance in Off-Nominal Conditions. Review in progress: for the 53rd Annual Human Factors and Ergonomics Society General Meeting, San Antonio, TX, October 19-23, (2009)
16. Gore, B.F., Hooey, B.L., Salud, E., Wickens, C.D., Sebok, A., Hutchins, S., Koenecke, C., & Bzostek, J.: Identification Of Nextgen Air Traffic Control and Pilot Performance Parameters for Human Performance Model Development in the Transitional Airspace. In: NASA Final Report. ROA 2006 NRA # NNX08AE87A, SJSU, San Jose (2009)
17. McCarley, J. Wickens, C.D., Steelman, K., & Sebok, A.: Control of Attention: Modeling the Effects of Stimulus Characteristics, Task Demands, and Individual Differences. NASA Final Report, ROA 2007, NRA NNX07AV97A (in prep)

Acknowledgments.

The SEEV model integration into MIDAS v5 is the result of NASA's Aviation Safety Program's Integrated Intelligent Flight Deck Technologies (IIFTD), System Design & Analysis project. The reported modeling effort was coordinated by Dr. David C. Foyle (NASA Ames Research Center). The opinions expressed in this paper are those of the authors and do not reflect the opinions of NASA, the Federal government, Alion Science and Technology, or SJSU.