



2004

Vigilance Performance Modeled As A Complex Adaptive System With Listener Event Graph Objects (LEGOs)

Wellbrink, Joerg C.G



Calhoun is a project of the Dudley Knox Library at NPS, furthering the precepts and goals of open government and government transparency. All information contained herein has been approved for release by the NPS Public Affairs Officer.

**Dudley Knox Library / Naval Postgraduate School
411 Dyer Road / 1 University Circle
Monterey, California USA 93943**

VIGILANCE PERFORMANCE MODELED AS A COMPLEX ADAPTIVE SYSTEM WITH LISTENER EVENT GRAPH OBJECTS (LEGOS)

Joerg C.G Wellbrink

Federal Office of the Bundeswehr
for Information Management
and Information Technology
Ferdinand Sauerbruch Strasse 1
56073 Koblenz GERMANY

Arnold H. Buss

The MOVES Institute
Naval Postgraduate School
700 Dyer Road
Monterey, CA 93943, U.S.A.

ABSTRACT

There has been an increasing need to incorporate human performance in simulation models. Situations in which human performance is subject to degradation over time, such as vigilance tasks, are not represented. This article describes a computational model for vigilance performance embedded in a new cognitive framework that utilizes recent advances in system neuroscience, evolutionary psychology and complexity theory. The Reduced Human Performance Model (RHPM) captures human errors in monitoring tasks to a greater degree than previous attempts. RHPM is implemented as a discrete event simulation using Listener Event Graph Objects (LEGOS). The model captures leading vigilance theories and can be used as a tool to improve existing vigilance theories and to improve current monitoring procedures minimizing errors that could lead to catastrophic outcomes.

1 INTRODUCTION

The surprise attacks of September 11, 2001, generated a need for more sophisticated models for the detection of potential threats. A prerequisite of such models is the ability to simulate reduced human performance realistically. Realistic human performance should include the very human traits of imperfect perception, imperfect cognitive processing, and imperfect behavior. Imperfect or lowered performance caused by lack of information, lack of perception, or lack of cognitive resources, is termed “reduced human performance” and takes a variety of forms, which simulated entities must portray, if they are to be realistic.

An unexpected event is called a surprise, and surprises are more likely to occur when performance is reduced. Thus surprises may be seen as a by-product of reduced human performance. A sophisticated cognitive model should generate surprises and unexpected outcomes as part of its portrayal of complex problem domains.

Current cognitive models often lack flexibility and realism; they struggle with modeling individual behavior and generating a reasonable range of behavior (Tenney et al. 2003). This research has hypothesized that reduced human performance, specifically vigilance performance, can be best modeled as a complex adaptive system implemented (Wellbrink 2003). The next sections explain in more detail human information processing, vigilance performance, and design and validation issues for the computational model.

2 HUMAN INFORMATION PROCESSING

Cognitive models or architectures try to model the human information process as realistic as possible. The two predominant theories for cognitive architectures are symbolism (essentially producing ruled-based architectures) and connectionism (neural networks). In 1998 Richard Pew and others discussed strengths and weaknesses of the resulting cognitive architectures in a National Research Council report (Pew and Mavor 1998). The conclusion was rather sobering: “Even the best of them [cognitive models] assume ideal human behavior according to doctrine that will be carried out literally, and rarely take account of the vagaries of human performance capacities.” (Pew and Mavor 1998, p.4).

There is a broad agreement that the human stage processing model for the human information process is well suited as a framework for current and future cognitive architectures. The next figure shows this model.

Figure 1 shows the different stages for the human information processing. A stimulus is stored in the short-term sensory store (STSS) for a few seconds (visual stimulus about 1 second, auditory stimulus about 5 sec; echoic memory). If it is not perceived within this timeframe, it is not a perception. Perceptions are sometimes matched with patterns, likely stored in long-term memory. This is the encoding stage.

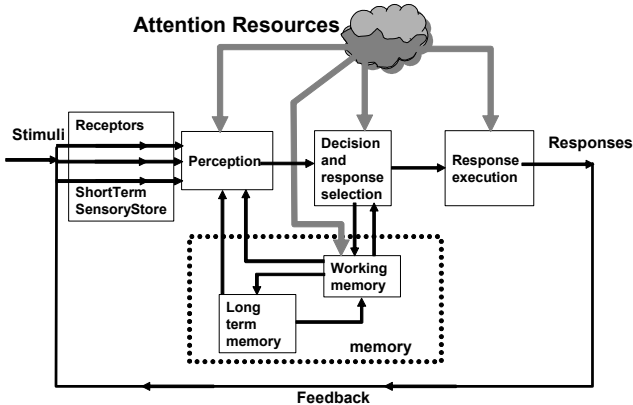


Figure 1: Stage Model of Human Information Processing (Wickens, 1992)

Next, during the central processing stage, the perception is forwarded to the decision- and response-selection system, which uses the working memory to determine whether an action should be initiated. The last stage is the response-execution stage, which leads either to a vocal or manual response to the perceived stimuli (Wickens 1992).

Pew and Mavor (1998) modified this model slightly to show the elements that should be included in an integrative architecture. They left out the STSS and connected the perception to long-term memory via working memory. However, a major alteration to the original stage model is the fact that Pew did not show the attentive resources that are central to modeling reduced performance.

The attentional resources are imperative when modeling reduced human performance caused by a lack of attentional resources. There are several theories and models on how humans use their cognitive resources. We favored Wickens' multiple resource model which suggests that cognitive resources can be divided into modalities and codes in different stages of the information process.

Figure 2 is an adaptation of the better known cube that can be seen in many textbooks (Wickens 1992, Matthews et al. 2000, Wickens 2004). It assumes that humans have two main attentional resource pools: one for the perceptual and central-processing phase, and one for the response-selection and execution phase. These resources can be divided into verbal and spatial, or, respectively, vocal and manual. The structure indicates a hierarchical system. The system is adaptive since humans can focus their attention (selective attention) filtering information to a certain extent in context. Thus, humans adapt cognitive resource consciously or sub-consciously (or both) to a changing environment. We envisioned implementing this model by using reactive agents that compete for resources and also supply energy to others. We also expected that the nonlinear interactions between the attentive resources would have different effects on the information processing stages, which eventually result in interesting human-like emergent behavior.

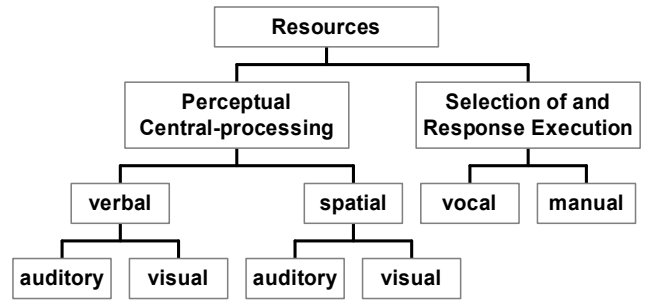


Figure 2: Multiple Resource Model (Wickens, 1992)

A major design decision was using discrete event simulation to model human information processing. The stage processing model lends itself to this approach because it is conceivable that individual pieces of information start and finish a stage within the process. They are then forwarded to the next stage. A rather informal argument for the use of discrete event simulation would be that people do not usually interrupt an action in a periodic fixed interval. Rather, it appears to be natural that they react continually to changes in their environment, which favors an event-driven approach. The next section shows essential design features and explains the use of LEGOs

3 REDUCED HUMAN PERFORMANCE MODEL (RHPM)

RHPM is based on the assumption that reduced human performance can be modeled as a complex adaptive system. Complex adaptive systems have some interesting features that are very similar to human behavior like the non linear interaction of autonomous agents. Human performance data often show curvilinear relationships between stressors (like heat) and the performance. Multi agent systems are ideal to implement such systems. RHPM is composed of several separate multi-agent systems (see modules 4, 5, and 6 in Figure 3).

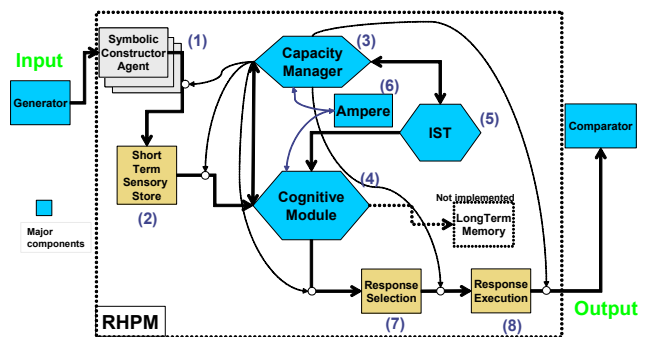


Figure 3: RHPM Modules

RHPM uses the information stage processing as a blueprint with one addition. It adds a module to allow for individual differences (Individual States and Traits (IST)

module). The Capacity Manager component is an implementation of Wickens MRM where resource agents and working agents compete for cognitive resources. The Meta Agent inside this manager distributes resources to the different stages. The Cognitive Module represents the processing stage. It consists of several reactive agents that perform specific tasks on perceptions. Symbolic Constructor Agents (1) encode knowledge and store it into the STSS (2). The Cognitive Module (4) selects information to process and once it recognizes the percept it informs the Response Selection Agent (7) about this percept. This agent has to decide on an appropriate action and forwards this action to the Response Execution (8). This process depends on available resource for speed and accuracy. The Ampere module (6) computes changes in resource flows whereas the Capacity Manager (5) consists of several reactive agents competing for resources and taking actions to receive the desired amount of resources.

All these software components are loosely coupled using the listener pattern. This pattern and its use are explained in greater detail in Buss and Sanchez (2002) and Buss (1996). The use of listener pattern enables us to create parallel actions within the model of the human information process. Figure 4 shows RHPM's data flow

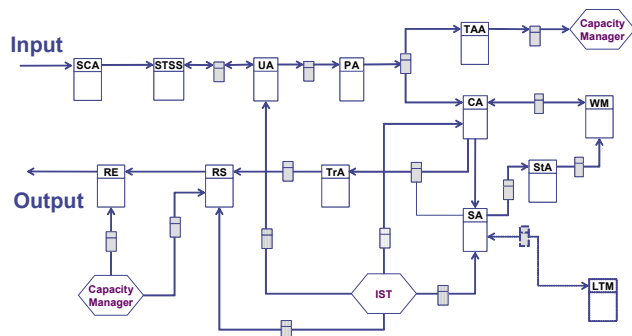


Figure 4: Data Flow RHPM

Figure 4 shows how information is processed within RHPM. The Symbolic Constructor Agent SCA encodes information and sends out a message containing pre-conscious information. The STSS listens to the SCA storing the information into its queue. Only if the UpdateAgent (UA) sends a signal asking whether or not there are any stored pieces of information. STSS sends out a message by itself. The little grey boxes indicate special software objects that we called routers. They are used as “in-between listener objects” and serve several purposes. They enable us to use the same type of listener object listening only to specific messages. They are also used to split information to allow parallel actions. The UpdateAgent (UA) works on the now conscious percept. When it finishes its task the listening router object relays the information to the PerceptAgent (PA). PerceptAgent codifies the information such that the Capacity Manager knows which agents should dis-

tribute resource to this task. Parallel to that action the Comparison Agent (CA) looks into Working Memory (WM) whether or not the percept is recognized information. Depending on the outcome a new search in Long Term Memory (LTM) is initiated via the Search Agent (SA). In any case the Storage Agent (StA) pushes the perceived information into Working Memory. Next the Transmit Agent works on the perception. Once it is done the listener object relays this new information to the Response Selection Agent from where it will go to the Response Execution Agent. This data flow is managed by the inherent message system of the listener pattern. It is possible to establish and cancel connections between agents during runtime giving us a robust and fast mean to have agents communicate with each other. The components can also be exchanged without the need of re-compiling the entire system. The only pre-requisite is that the executive class connects the new component with the associated router.

4 VALIDATING A COMPUTATIONAL MODEL OF VIGILANCE

Vigilance or sustained attention is a cognitive function that occurs in almost every monitoring task (auditory, visual). Wickens defines vigilance: “Vigilance is a state of readiness to detect and respond to certain specified small changes occurring at random time intervals in the environment (Wickens 1992)”.

Unfortunately, humans are not well suited for this kind of task. Monitoring tasks belong to high workload tasks and there is evidence that within the first 30 minutes of a monitoring task the loss of efficiency is pronounced. This phenomenon is known as vigilance decrement. Vigilance research started in the early 1930s and was established by Mackworth's work on naval recruits. Mackworth was tasked to research the question why so many enemy submarines that were on the radar screen of radar operators still remained undetected. He studied the phenomenon of the vigilance decrement in laboratory settings.

Figure 5 (adapted from Mackworth, 1950) shows the results of Mackworth clock test. It was used to establish the increase in misses and the increase in reaction time. Subjects watched a clock's watch hand for two hours. Whenever the watch hand jumped two instead of one second the subjects had to report it. Within the first 30 minutes the decrement in hit rate was most pronounced. After that the decrement leveled off and stayed at an almost constant level (Mackworth 1950). There are many factors that influence vigilance performance.

Figure 6 summarizes the findings of several researchers (Davies and Tune 1970, Davies and Parasuraman 1982, Warm 1984, Matthews et al. 2000). It shows the main factors that influence vigilance performance. It also shows a sample of the different measures of performance (MOP). There are three main factors that impact vigilance perform-

Mackworth: Clock Test 1948
Research on Radar Operators

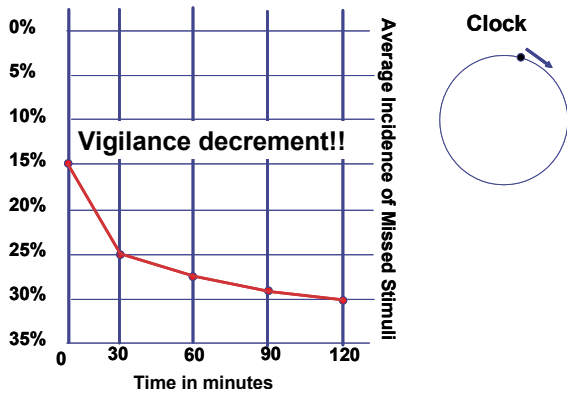


Figure 5: Mackworth’s Clock Experiment and Results

ance: Task factor, environmental factor and subjective factor. These factors are determined by their identified variables (i.e. the environmental factor is determined by the stress level). Vigilance performance can be measured in reaction times, correct detection, and commission errors (false alarms).

Vigilance Performance Factors

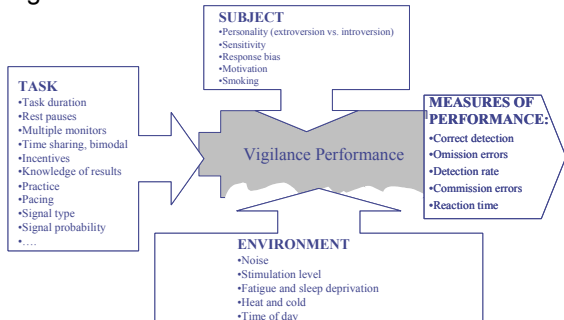


Figure 6: Vigilance Performance Factors

We conducted four experiments (low workload, high workload, low high low (LHL) high low high (HLH)) to collect data on vigilance performance. Hits, false alarms and reaction times were measured in 10 minute intervals. Two sets of data were used to calibrate RHPM’s rules and parameters with the help of genetic algorithm. The fitness function’s value was computed as the sum of squared error difference between model and human behavior for all measures of performance.

Then the model was exposed to two scenarios (namely LHL and HLH) with the computed parameter set up. The results are very encouraging as the match between human data and RHPM data was very close. RHPM differed in 4 out of 36 measures and these differences can be explained by looking at obvious limitations of vigilance theories. There was no statistical evidence for a difference between 32 of 36 measures.

RHPM is a stochastic model and still has more potential to increase its range of behavior. However, it already showed variability close to human subjects.

Figure 7 shows a comparison of the MOPs’ standard deviations of RHPM and human subjects in the LHL condition. Human data is more dispersed, however the differences especially in misses are small.

Standard Deviation LHL		
	FalseAlarm RHPM	FalseAlarm Human
10	1.21	2.04
20	1.29	2.76
30	1.32	2.72
	Misses RHPM	Misses Human
10	1.38	2.30
20	1.33	1.75
30	1.88	1.92

Figure 7: Standard Deviation Comparison

5 CONCLUSIONS

The validation run results of RHPM match our expectations. The model showed reliable behavior during “normal” simulation runs. It also generated insights into applying theories to the phenomenon (e.g. the importance of the detectability of a signal). RHPM could be validated against two previously unseen scenarios. RHPM can also demonstrate the pitfalls of certain theories. For example: it is well known, that an increase in signal probability leads to an improvement of the miss and false alarm rate. Signal detection theory does not address this phenomenon. Consequently, RHPM increases the miss rate instead of decreasing it. However, by looking at the design of the model and how different modules work with each other, there are possible solutions on how to improve the model performance. These improvements could potentially reflect improvements in the theories. Its open architecture, using LEGOs, facilitates improvement at any time.

RHPM can certainly generate surprises by simply missing signals or giving false alarms too often. The surprise factor can be increased by changing certain parameters. One example is the probability of a slip. The response selection agent passes the decision (e.g. SayYes) to the Response-Execution agent. The response execution then depends on how busy this agent is. It can conduct an omission error by having the information fade away or simply by a slip saying “No” instead of a “Yes” with a given probability. This probability can be linked to the stress level to indicate an increase in error rates with increasing stress.

RHPM can help to gain more insights into the phenomenon of vigilance decrement and more generally into human performance degradation. Implementing multi agent system with discrete event simulation proofed as a viable alternative to the often used time step method and there are many advantages that we did not discuss. Modeling reduced human performance as a complex adaptive system appears to be a step in the right direction.

REFERENCES

- Buss, A. 1996. Modeling with Event Graphs. In *Proceedings of the 1996 Winter Simulation Conference*, ed. J. Charnes and D. Morrice, 153-160. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.
- Buss, A. and P. Sanchez. 2002. Building Complex Models with LEGOs (Listener Event Graph Objects). In *Proceedings of the 2002 Winter Simulation Conference*, ed. E. Yücesan, C.-H. Chen, J. L. Snowdon, and J. M. Charnes, 732-737. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers.
- Davies, D. and R. Parasuraman. 1982. *The Psychology of Vigilance*. New York: Academic Press.
- Davies, D. and G. S. Tune. 1970. *Human Vigilance Performance*. London, United Kingdom Trinity Press.
- Mackworth, N. H. 1950. *Researches on the measurement of human performance*. London, United Kingdom: HMSO., Medical Research Council.
- Matthews, G., D. Davies, S. Westerman,, and R. Stammers. 2000. *Human Performance Cognition, Stress and Individual Differences*. East Sussex, United Kingdom: Taylor & Francis Group.
- Pew, R. W. and A. S. Mavor. 1998. *Modeling Human and Organizational Behavior: Application to Military Simulation*. Washington D.C: National Academy of Science.
- Tenney, Y.J., D.E. Diller, R.W. Pew, K. Godfrey, and S. Deutsch. 2003. The AMBR Project: A Case-Study in Human Performance Model Comparison, In *Proceedings of the 12th Conference on Computer Generated Forces and Behavior Representation*, Scottsdale, AZ.
- Warm, J. 1984. *Sustained Attention in Human Performance*. New York: John Wiley & Sons.
- Wellbrink, J. 2003. Modeling Reduced Human Performance as a Complex Adaptive System. Modeling, Virtual Environments and Simulation (MOVES) Institute. Monterey, California: Naval Postgraduate School.
- Wickens, C. 1992. *Engineering Psychology and Human Performance*. New York: Harper Collins.
- Wickens, C. 2004. Multiple Resource Time Sharing Mode .In *Handbook of Human Factors and Ergonomics Methods*, ed. Stanton, N., A. Hedge, K. Brookhuis, E. Salas and H.W. Hendrick. London, United Kingdom: CRC Press.

AUTHOR BIOGRAPHIES

JOERG WELLBRINK is a German Army officer who completed the modeling, virtual environments and simulation (MOVES) Ph.D. program at the MOVES Institute of the Naval Postgraduate School (NPS) in Monterey, California, in September 2003. He received his M.S. in electrical engineering from the German Armed Forces University, Munich, in 1985 and in 1998 received his M.S. in operations research at the Naval Postgraduate School. His research covers artificial-life techniques, human-performance modeling, cognitive modeling, and complexity theory. He currently works as a modeling and simulation scientist for the Federal Office of the Bundeswehr for Information Management and Information Technology.

ARNOLD H. BUSS is a Research Assistant Professor in the MOVES Institute at the Naval Postgraduate School, where he has been teaching and doing research in Discrete Event Simulation and military applications since 1994. His e-mail is <abuss@nps.edu> .