Modeling Attention Allocation in a Complex Dual Task with and without Auditory Cues

Brian McClimens and Derek Brock

Naval Research Laboratory, 4555 Overlook Ave. S.W.,
Washington, DC 20375 USA
{brian.mcclimens,derek.brock}@nrl.navy.mil

Abstract. Navy watchstanding operations increasingly involve information-saturated environments in which operators must attend to more than one critical task display at a time [1]. In response, the Navy is pursuing a model-based understanding of human performance in multitask settings. Empirical studies with a complex dual task and related cognitive modeling work in the authors' lab suggest that auditory cueing is an effective strategy for mediating operators' attention [2,3,4]. Characterizing the effects of widely separated displays on performance and effort is an important ancillary concern, and a series of cognitive models developed with the EPIC cognitive architecture [5] is used for this purpose. These cognitive models verify a key finding from an empirical study; namely, time spent on the primary, relatively stateless, tracking task is regulated by state information retained from the secondary, radar task. These findings suggest that in multitask settings, operators use relatively simple state information about a task they are about to leave to gauge how long they can attend to other matters before they must return.

Keywords: Cognitive modeling, EPIC architecture, head-tracking, urgency, multitasking.

1 Introduction

Auditory display research at the Naval Research Laboratory (NRL) is motivated primarily by the U.S. Navy's need to improve efficiency in the Combat Information Center aboard ships, reducing required manpower. Research at NRL has shown that the use of auditory cueing can dramatically improve operator performance in information-saturated environments [2,3,4]. In order to better exploit the benefits of auditory cueing for the purpose of attention management, a good understanding of the underlying mechanisms driving attention switching in both cued and uncued settings is needed. This paper furthers the understanding of these mechanisms by presenting cognitive models of a method utilizing situational awareness to trigger attention switches in environments with and without external prompting, and evaluating these models using head-tracking data collected in a human subjects study.

C. Stephanidis (Ed.): Posters, Part I, HCII 2011, CCIS 173, pp. 317–321, 2011.

2 Background

The Dual Task. The dual task environment that provides the foundation for the models explored in this paper was developed at NRL in the early 1990s [6]. This dual task consists of a tracking task, in which subjects are asked to follow the movements of a target object on the primary display with a joystick, and a radar task, in which subjects make a series of rule-based classifications of objects that appear on a secondary screen.

The tracking task is a continuous task where performance is directly related to attention. Movement of the target is slow enough that subjects are capable of tracking well when attending to the task, but rapid enough that performance falls off abruptly when the subjects attend to the radar task.

The radar task is a more complex episodic task, requiring subjects to respond to individual classification events (sixty-five events over a thirteen minute scenario). Objects of three different types, referred to collectively as blips, appear near the top of the screen and travel towards the bottom of the screen over the course of about twenty seconds. Based on the speed and trajectory of these blips, subjects are asked to classify them as either hostile or neutral according to separate rules for each of the three blip types. Subjects are not permitted to enter their response until blips are approximately halfway down the screen at which point a blip will change color (and in some conditions an auditory alert will be presented), signifying that a response is needed. Blips may turn red, indicating that they are hostile; blue, indicating neutrality; or yellow, in which case subjects must rely on the rules alone to determine threat level.

In the Dual Task configuration addressed by this modeling effort, the two tasks were presented to subjects on different monitors separated by a ninety-degree arc. Two features of this setup are of critical importance. First, the separation angle is wide enough that subjects attending to one task do not have visual information from the other task available in their peripheral vision. Second, the cost for switching between tasks is significantly higher than it would be if the two tasks were on the same screen. Thus, rapid interleaving of the two tasks is not as feasible as in many other modeled multitasking environments.

EPIC. The EPIC cognitive architecture [5] has been used to build several models of this dual task in the past [3,7,8]. The models in this paper are an extension of previous modeling work at NRL, and again use the EPIC architecture. These models also make use of a custom-designed encoder for the hostility property of blips on the radar screen, and a timing mechanism that regulates the amount of time spent on the tracking task between attendances to the radar task.

Human Data. The design of this model relies on data collected in a human subjects study conducted at NRL [4]. Subjects wore a head-tracking device mounted on top of a set of headphones while performing the dual task in four conditions: one with no auditory cues to aid in their task, and three conditions that varied the type of sounds presented and the manner in which they were presented to subjects. This head tracking data allowed for analyses concerning the number of attention switches, response times to auditory cues, and the amount of time spent on any given instance of the tracking or radar tasks. A key finding from this study, shown in Figure 1, was the negative correlation between the time spent on the tracking task and the number of blips onscreen when subjects turned from the radar task to the tracking task. This correlation implies that subjects incorporate state information from the radar in their strategies for managing time spent on the tracking task.

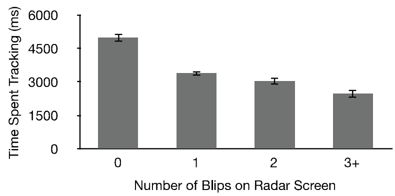

Fig. 1. Emprical data from [4]. The number of blips onscreen when a subject leaves the radar task to attend to the tracking task has a strong impact on the amount of time spent tracking before returning to the radar task. Error bars show the standard error of the mean (s.e.m.).

Upon completion of the four conditions, subjects were presented with a simpler version of the radar task. Blips were presented one at a time, and subjects were permitted to respond at any time; they did not wait for blips to become active. Each subject responded to 72 blips with auditory cues and 72 blips without auditory cues. This task provided a measure of classification and response times for situations in which no distractions were present.

3 Modeling

Base Model. All models were run under two conditions: one that made use of auditory cues to signify when a blip on the radar task became active, and one that used no auditory cues. Each of the models was run using four thirteen-minute scenario files that were used to drive the radar task in the human subjects study. A timing mechanism developed by Taatgen [9], and implemented in EPIC by Hornof [8] was used to determine the amount of time spent on the tracking task between episodes of executing the radar task. This timer adds a certain level of non-determinism to the model, so each condition-scenario pair was run ten times, and all recorded measures are averages of those model runs.

Two elements of note in the base model’s strategy were influenced by information collected in the human subjects study. First, the classification of blips on the radar screen begins before they have become active. During the dual task, subjects spent less time on the radar screen after a blip had become active than it took them to classify a blip in the simpler single-blip task performed at the end of the experiment. This suggests that subjects began the classification process prior to a blip becoming active. Second, the model classifies blips in stages, with classification taking place over multiple attendances to the radar task. The duration of subjects’ attendances to the radar task rarely exceeded 1500ms. Because blip classification and response were determined to take longer than this, it was concluded that subjects must classify blips over multiple attendances to the radar task. A custom encoder created in EPIC ensures that the model attends to blips for a 1000ms period, followed by a separate 565ms inspection period before the hostility of a blip is available to the model.

Modeling Urgency. When subjects looked away from the radar task to attend to the tracking task, the amount of time spent on tracking was inversely proportional to the number of blips on the radar screen. This is likely due to a sense of urgency that increased with the amount of activity on the radar task. We hypothesized that subjects used state information from the radar task to facilitate intelligently-timed attention switches, allowing subjects to spend more time on tracking when the radar task did not require attention, and to return to the radar task in a timely fashion when blips required a response. Such a strategy should improve performance in both tasks.

In order to test this hypothesis, our models were run in each of three modes. All models used the strategies described above in the Base Model section. The first model, referred to as mono-urgency, would spend approximately 2700ms on the tracking task each time it attended to it, regardless of the number of blips on the radar task. The dual-urgency model used two different durations on the tracking task: approximately 2450ms when there was a blip on the radar task, and 5915ms when there were no blips on the radar screen. A third, multi-urgency model made use of 5915ms, 2980ms, 2450ms, and 2000ms durations for tracking sessions beginning with zero, one, two, or at least three blips onscreen, respectively. All of these durations were based on data observed in the human subject study. In the sound condition, models used the same numbers to guide their tracking durations, except that if the model had already classified all blips on the radar task, it would wait for an auditory cue signifying that a blip had become active to return to the radar task.

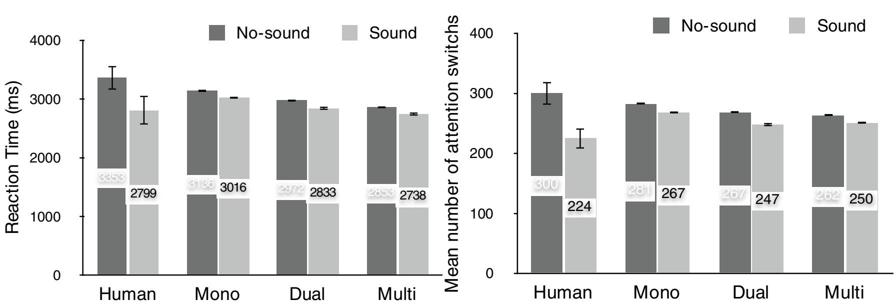

Fig. 2. Reaction times (left) and the number of attention switches (right) decreased as the model used more state information from the radar task. Note that error bars, which show the s.e.m., are present for the various models' measures. The variance is too small to see at this scale.

4 Results and Conclusion

Model performance was evaluated on reaction times in the radar task, the percentage of time spent on the tracking task and the number of attention switches between the two tasks. The models' reaction times in the radar task decreased as more information from the radar task was used to regulate time spent on the tracking task, as shown in Figure 2. In the no-sound condition, the models' mean reaction times were 3156ms, 2972ms and 2852ms for mono-, dual- and multi-urgency models respectively. In the sound condition, reaction times were 3016ms, 2833ms and 2738ms. The percentage of time spent on the tracking task remained relatively even, with mono-, dual- and multi-urgency models spending 64.9, 64.9, and 65.1 percent of their time on tracking in the no-sound condition, and 66.0, 66.3 and 66.0 percent of their time on tracking in the sound conditions. The number of attention switches decreased in the dual- and multi-urgency models, with 282, 273.2 and 282.4 attention switches in the no-sound condition and 284.4, 276.8 and 280.4 attention switches in the sound condition for mono-, dual- and multi-urgency models, respectively.

The human performance data suggests that subjects employ a strategy utilizing state information from the radar task to govern time spent on the tracking task, and data from the models suggests that this type of strategy can indeed be beneficial to the radar task without negatively affecting performance in the tracking task. However, the models fail to sufficiently capture the performance differences found in the sound and no-sound conditions, and further work must be done to ensure that a strategy utilizing state information from the radar task can be effectively applied in models that are more faithful to human performance in both of these conditions.

References

1. Hearn, J., Mills, J.H.: Finding the knowledge edge. CHIPS Magazine 13(3), 17–20 (2005)
2. Brock, D., Ballas, J.A., Stroup, J.L., McClimens, B.: The design of mixed-use, virtual auditory displays: Recent findings with a dual-task paradigm. In: Proceedings of the 10th International Conference on Auditory Display, Sydney, Australia (2004)
3. Brock, D., McClimens, B., Hornof, A., Halvorson, T.: Cognitive models of the effect of audio cueing on attentional shifts in a complex multimodal dual-display dual-task. In: 28th Annual Meeting of the Cognitive Science Society (2006)
4. Brock, D., McClimens, B., McCurry, M.: Virtual auditory cueing revisited. In: Proceedings of the 16th International Conference on Auditory Display, Washington, DC (2010)
5. Kieras, D., Meyer, D.: An overview of the EPIC architecture for cognition and performance with application to human-computer interaction. Human Computer Interaction 12, 391–438 (1997)
6. Ballas, J.A., Heitmeyer, C.L., Perez, M.A.: Evaluating two aspects of direct manipulation in advanced cockpits. In: Proceedings of ACM CHI 1992: Conference on Human Factors in Computing Systems, pp. 127–134 (1992)
7. Kieras, D.E., Ballas, J., Meyer, D.E.: Computational Models for the Effects of Localized Sound Cuing in a Complex Dual Task (EPIC Report No. 13). University of Michigan, Department of Electrical Engineering and Computer Science, Ann Arbor, Michigan (2001)
8. Hornof, A.J., Yunfeng, Z.: Task-Constrained Interleaving of Perceptual and Motor Processes in a Time-Critical Dual Task as Revealed Through Eye Tracking. In: Proceedings of ICCM 2010: The 10th International Conference on Cognitive Modeling (2010)
9. Taatgen, N.A., van Rijn, H., Anderson, J.R.: An integrated theory of prospective time interval estimation: The role of cognition, attention, and learning. Psychological Review 114(3), 577–598 (2007)