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Time Pressure, Memory, and Task Knowledge Facilitate the Opportunism Heuristic in Dynamic Tasks

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There are a variety of strategies that operators can utilize when performing a dynamic task, yet operator strategies are typically studied in a well-controlled environment that prevents the possibility of these strategies from interacting or competing with one another. In this study we investigated operator strategy use in a dynamic supervisory control task. We identified four possible strategies that the operator may use: scanning, opportunism, task knowledge, and memory. In order to determine the impact of time pressure on strategy use, we manipulated the speed of the vehicles. We found that as time pressure increased, operators shifted from a scanning strategy to a heuristic opportunistic strategy. We also found that when operators used task knowledge and memory they were more likely to be opportunistic.

INTRODUCTION

One of the differences between experimental psychology and human factors is the complexity of the tasks typically explored in each. In experimental psychology, the tasks are frequently simple, with very few possible strategies available to the participant. Experimental psychologists keep the number of possible strategies to a bare minimum in order to maintain experimental control. In human factors, the tasks are typically quite complex with multiple strategies available to the operator throughout performance. These strategies increase the ecological validity of the experiment at the cost of control (internal validity). Our goal in this paper is to show how, in a dynamic task, different strategies can emerge from a mix of perception, memory, and task requirements, each understood in terms of the results of experimental psychology research.

In a dynamic task an operator must switch between understanding the situation and executing sub-tasks. There is a tension between understanding and task-execution in that as a task is executed, the operator loses some comprehension of both the global situation and the specific state of non-focal entities in the world (Breslow, Gartenberg, McCurry, & Trafton, *submitted*; Crandall, Goodrich, Olsen, & Nielsen, 2005; Cummings & Mitchell, 2008). This tension is heightened when time pressure is high. We propose four high-level strategies that operators can perform in a dynamic task in order to decide what to act on next. These strategies are not the only possible strategies, but they seem to account for most of the observed strategies in dynamic tasks. The strategies we focus on are scanning, opportunism, task knowledge, and memory.

After an operator finishes executing a task in a dynamic environment, the optimal strategy (given unlimited time) is to perceptually scan the entire environment. Of course dynamic tasks do not allow unlimited time, but nevertheless some scanning of the environment must occur. The amount of scanning that occurs is typically not complete (Wolfe, Horowitz, and Kenner, 2005), though it is informative to the operator. Specifically, when under time pressure or when responses are biased, the operator is less likely to consider alternatives (Ben Zur & Breznitz, 1981; Wolfe et al., 2005). Thus, operators are likely to perform less visual search when they are under increased time pressure.

Satisficing is a decision strategy that operators can use instead of performing an exhaustive search, which is especially prevalent under time pressure (Payne, Bettman, & Johnson, 1988). When operators satisfice they stop searching when they have reached a "good enough" point (Simon, 1955). For most tasks, people rarely optimize, deciding instead to satisfice due to diminishing returns. Unfortunately, most decision-making algorithms do not consider that humans satisfice (Cummings, Clare, & Hart, 2010; Goodrich, Stirling, & Frost, 1998). In this paper, the satisficing strategy we focus on is opportunism, i.e., terminating search with the first relevant object found.

A third strategy that operators may employ in dynamic tasks is to utilize task knowledge. Task knowledge is learned from previous experience with a task. A comprehensive survey of task knowledge is beyond the scope of this paper, but for this report, task knowledge refers to learning regularities in the environment to guide action. One mechanism that has been implicated in task knowledge is probability matching (for a review, see Vulkan, 2000). According to one model of probability matching, it arises from a heuristic whereby responses are made according to the evaluation of observed outcome probabilities (Sugrue, Corrado, & Newsome, 2004). Otto, Taylor, & Markman (2011) found that probability matching increased with higher working memory load, suggesting that under time pressure operators may increase their use of probability matching.

Finally, operators can use memory to guide their actions. The memory for goals model (Altmann & Trafton, 2002; Trafton, Altmann, & Ratwani, 2011) suggests that people create episodic traces as they execute tasks. These episodic traces can then be recalled and used to help future activities and actions. For example, Gartenberg, McCurry, and Trafton (2011) found that in a dynamic supervisory control task operators reacquired situation awareness (SA) by looking at parts of the environment that they had previously looked at. Gartenberg et al. (2011) interpreted this as reactivating the previous episodic trace for the purpose of SA reacquisition (SAR). Additionally, Dattel, Vogt, Fratzola, Dever, Stefonetti, et al. (2011) found that operators preferentially attended to relevant cues to acquire SA. Therefore, operators should preferentially use memory to look at relevant cues.

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Most of the strategies previously discussed are studied independently in laboratory situations. However, in real-world dynamic tasks, these strategies might interact with one another. We investigated the role of scanning, opportunism, task knowledge, and memory in a dynamic task under differing degrees of time pressure.

We predicted that participants would scan less of the environment and be more opportunistic under increasing time pressure due to the cost of acting slowly in a real world dynamic task. A result of being opportunistic is that participants will adopt a sub-optimal strategy of not scanning every object before making a decision on what to act on next.

A nuanced prediction involves the role that task knowledge and memory will play in promoting opportunistic behavior, independent of increased time pressure. If an opportunistic strategy is adopted, then task knowledge and memory are tools that the operator can use to fulfill their objective, such that, opportunism will increase when operators use task knowledge and memory to guide their perceptions.

METHOD

Participants

Fifty-one George Mason University undergraduate students participated for course credit. All participation was voluntary. There were sixteen males and thirty females who participated in the study. The average age of participants was 20.4 years old with a standard deviation of 2.7 years. Participants were asked to rate how often they played video games on a scale of 1 (never), 2 (sometimes), or 3 (a lot). The average amount of video game play was 2.1 with a standard deviation of 0.6. All participants had normal or corrected-to-normal vision.

Data for two participants were eliminated due to experimenter error. Three additional participants were eliminated because their eye movements could not be adequately captured. In total, forty-six participants were analyzed. We manipulated time pressure by doubling the speed of the vehicles across three conditions. There were fourteen participants in the slow condition, sixteen in the medium condition, and sixteen in the fast condition.

Materials

The supervisory control simulation was the Research Environment for Supervisory Control of Heterogeneous Unmanned Vehicles (RESCHU) (Boussemart & Cummings, 2008). The task involved navigating homogenous unmanned aerial vehicles (UAVs) in a dynamic environment.

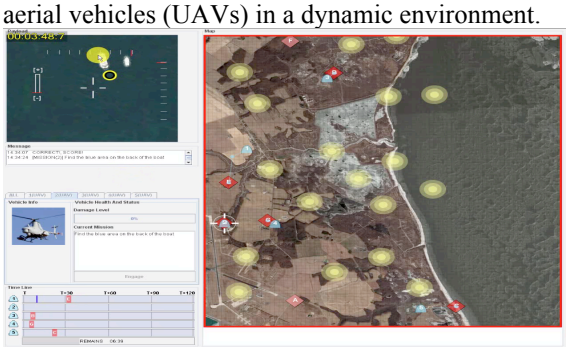

Figure 1. *Supervisory control simulation*

The simulation consisted of three main sections: a map window, a payload window, and a status window (see Figure 1). The map area displayed UAVs (blue half ovals), targets (red diamonds), which UAVs should be directed to, and hazards (yellow circles), which should be avoided. The payload window (top left) displayed a visual search screen where the participant was instructed to identify an object as part of a payload operation (described later). The status window (bottom left) depicted a timeline of when the UAVs would reach important events, which included waypoints and the target of the UAV.

The task began with five UAVs moving at a fixed speed. The speeds doubled between conditions, such that the vehicles moved at 2.5 pixels / second in the slow speed condition, 5.0 pixels / second in the medium speed condition, and 10.0 pixels / second in the fast speed condition. The UAVs continued to move at this fixed speed throughout the duration of the task.

Eighteen hazard areas moved randomly every four-seconds, with the constraint that the hazards could not appear closer than 3° of visual angle (about 50 pixels) away from any UAV. If the UAV passed through a hazard, damage occurred. Damage was indicated as a bar in the status window. The appearance of targets and hazards on the simulation map were randomized with the constraint that targets and hazards could be no closer than 3° of visual angle from each other. This assured that targets and hazards could not co-occur in the same space. There were always 7 targets present on the map.

The operator's goal was to direct UAVs to target areas, while avoiding hazard areas. To avoid a hazard area the operator could assign the UAV to a different target or the operator could assign specific waypoints to the UAV. At the start of the simulation the UAVs were randomly assigned to targets. Once the UAV reached the target destination, the target flashed red until it was engaged. When the UAV arrived at the target the participant could right click on the vehicle and engage it, bringing up the payload visualization.

During the payload, the vehicles in the map task continued to move toward their corresponding target. After identifying the object in the payload task, the UAV's mission was completed. Completion of the payload ranged between 1.8 – 37.0 seconds, with a mean of 5.5 seconds and standard deviation of 2.9 seconds. After completing the mission, the UAV was randomly assigned to a new target that did not have any other UAV assigned to it.

The simulation is a complex task with multiple events occurring in parallel. Each simulation had unique characteristics with randomly generated trajectories, locations, and objectives. More than one UAV could be waiting at a target for engagement, multiple UAVs could be on a path to a hazardous area, and it was left to the participant's discretion to act on any one of the five vehicles.

Design and Procedure

The experiment was a between groups design. Participants were assigned to either the slow speed, medium speed, or fast speed using the Latin squared randomization technique. The dependent variables were related to the patterns of eye fixations directly after participants completed a vehicle

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engagement and were required to complete the payload task.

Prior to beginning, all groups completed an interactive tutorial that explained all aspects of the simulation. Participants learned about the objective of the simulation, which was to prevent as much damage as possible and engage as many vehicles as possible. Additionally, participants learned how to control the UAVs (assigning targets, changing targets, assigning waypoints) and to engage a target (by right clicking on the target and pressing the engage pop-up window). The tutorial lasted approximately ten minutes.

Then the participants began a practice session where they were exposed to the task for which they were assigned. During this practice session the participant was instructed to interact with the task until the experimenter felt that they understood the task and could complete each sub-activity.

After completing the practice session, participants were seated approximately 66cm from the computer monitor and were calibrated on the eye tracker. Participants then began a 10-minute simulation. Participants were reminded to maximize their score by engaging as many targets as possible and preventing as much damage as possible. When the simulation ended, participants received feedback on how many vehicles they engaged and vehicle damage. Participants were re-calibrated and were run in a second 10-minute session. Participants were run in the same condition for both sessions and both sessions were combined in the analysis.

Measures

Keystroke and mouse data were collected for each participant. Eye data were collected using an SMI eye tracker operating at 250hz. A fixation was defined as a minimum of fifteen eye samples within 50 pixels (approximately 3° of visual angle) of each other, calculated in Euclidian distance.

Segmenting the task into intervals of interest. One way to analyze a dynamic continuous task is by distinguishing between interaction time intervals -- where participants make actions, and wait time intervals (i.e. monitoring intervals) -- where participants monitor the screen and decide what to do next (Crandall, et al., 2005; Altmann & Trafton, 2004). The monitoring interval of particular interest was the instance of time after the mission complete (after completing the payload) because this interval represented an interval where the participant was vulnerable to errors due to the task break causing a reduction in SA (Altmann et al., 2004; Gartenberg et al., 2011). On average the participant completed 48.5 missions across the two 10 minute sessions, resulting in an average of 48.5 monitoring intervals analyzed per participant.

Categorizing 'vehicle cluster' fixations. Fixations were categorized based on their object of focus. There were a total of five UAVs on the screen, each having a different target, and possibly hazards associated with it. A vehicle, the vehicle's relevant hazard(s), and the vehicle's relevant target were classified as a 'vehicle cluster.' Since there were a total of five vehicles, there were five respective vehicle clusters. A fixation on an object was categorized by the object's vehicle cluster.

RESULTS AND DISCUSSION

All analyses were conducted on the monitoring interval of time after a mission completion and before the next action. Consistent with the hypothesis that increased time pressure would result in less scanning, there was a difference in the number of vehicle cluster fixations based on the speed of the vehicles, $F(1, 44) = 22.38$, $p < .05$, $\eta^2 = .51$. Using the Benjamini Hachberg correction method it was found that there were more vehicle cluster fixations in the slow speed condition ($M = 2.97$, $SD = 0.42$) than the medium speed condition ($M = 2.58$, $SD = 0.53$), $p < .05$, and more vehicle cluster fixations in the medium speed condition than the fast speed condition ($M = 2.23$, $SD = 0.32$), $p < .05$. Interestingly, when returning to an environment after an interruption where the states of the five vehicles have changed, participants only looked at between 2-3 vehicle clusters. This demonstrates that participants use sub-optimal strategies because in a dynamically changing environment it would be necessary to look at every object in order to ensure that the next decision is optimal.

Opportunism (i.e. satisficing) was defined as terminating scanning after finding a vehicle that was on a path to a hazard and then proceeded by acting on that vehicle without looking at any other vehicles that might possibly need attention more urgently. As expected, participants were more opportunistic under higher time pressure, $F(1, 44) = 21.77$, $p < .05$, $\eta^2 = .49$. Using the Benjamini Hachberg correction method it was found that there was a lower percentage of opportunistic behavior in the slow speed condition ($M = 22.82\%$, $SD = 7.13\%$) than the medium speed condition ($M = 32.44\%$, $SD = 10.62\%$), $p < .05$, and a marginal increase in opportunistic behavior between the medium speed condition and the fast speed condition ($M = 38.26\%$, $SD = 8.83\%$), $p = .10$ (see Figure 2a). This suggested that participants use an opportunistic strategy in response to increased time pressure in order to reduce the number of objects looked at before making a decision.

We were also interested in task knowledge and memory, particularly, if the use of task knowledge and memory resulted in increased opportunism. To examine this, we collapsed across the speed conditions and explored whether participants were more likely to be opportunistic when task knowledge and memory were used.

We measured task knowledge by determining the percentage of time that participant's first fixation after the mission completion was on the payload vehicle. This involved task knowledge because after a vehicle completed the payload mission (i.e. the payload vehicle) it had a high likelihood of being automatically reassigned to a target that resulted in its path intersecting with a hazardous area (41.8% of the time), thus needing attention. Participants responded to this, as evidenced by a greater likelihood of the first fixation after completing the payload being on the payload vehicle ($M = 41.90\%$, $SD = 13.86\%$) than chance would predict ($M = 20\%$), $t(45) = 10.72$, $p < .05$, $d = 2.21$. What is more, participants were engaged in probability matching because the percentage of time that the first fixation was on the payload vehicle (41.9%) was very close to how often the payload vehicle needed attention (41.8%).

In further support of the hypothesis that task knowledge increases opportunism, the strategy of opportunism increased

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when the participant looked at the payload vehicle first and the payload vehicle needed attention (M = 48.81%, SD = 7.31%), as compared to when the participant first looked at a non-payload vehicle that needed attention (M = 33.11%, SD = 6.49%), $t(44) = 3.16$, $p < .05$, $d = 2.27$ (see Figure 2b). This suggested that task knowledge is used to decrease the amount of perceptual activity required to take an action and that task knowledge results in increase opportunism.

Memory can also be used to increase the likelihood of attending to a vehicle that needs help. One memory strategy involves preferentially attending to vehicles that were previously looked at and needed help before the payload subtask, while disregarding vehicles that did not need help. If participants use a memory strategy, then previously looked at vehicles that were safe and did not need help will be looked at less than previously looked at vehicles that needed help since they were heading towards a hazardous area. Consistent with the use of memory, if the participant looked at a vehicle that needed attention before the payload interruption, they were more likely to look at it after the payload than chance would predict (M = 19.02% relative to chance, SD = 7.29%), yet if they had looked at a vehicle that was safe and did not need attention they were less likely to look at the vehicle than chance would predict (M = -5.62% relative to chance, SD = 2.78%), $t(45) = 6.05$, $p < .05$, $d = 4.47$ (see Figure 2c). This suggested that memory guides attention towards vehicles that need help and away from safe vehicles that do not need help.

One of our research questions related to whether memory affects the use of opportunism in a dynamic task. To test this we ran a two-way within-groups ANOVA measuring opportunism based on whether or not the first fixation had a memory trace and the type of memory trace, i.e., a trace of a safe vehicle or a trace of a vehicle that needed attention. If participants are more likely to be opportunistic when they look at a vehicle that they previously seen and that needs attention, this suggests that memory also impacts opportunism. There was only a marginal main effect of memory trace on opportunism, $F(1, 30) = 3.09$, $p = .09$, $\eta^2 = .10$, but there was a significant main effect of object type on opportunism, $F(1, 30) = 11.60$, $p < .05$, $\eta^2 = .89$. Moreover, in support of our hypothesis, there was an interaction between memory trace and type of object (safe vs. needing attention), $F(1, 30) = 4.57$, $p < .05$, $\eta^2 = .15$. Moreover, the Benjamini Hachberg correction method showed that memory for relevant objects that needed attention results in increased opportunism: fixating first on a relevant vehicle with a memory trace resulted in more opportunism than when the first fixation was on a remembered safe vehicle ($p < .05$), or when the first fixation was on a safe vehicle that had not been previously fixated ($p < .05$). Additionally, there was marginally more opportunism when the first fixation was on a relevant vehicle that had been previously fixated than when the first fixation was on a relevant vehicle that had not been previously fixated ($p = .08$). Participants were also more opportunistic when they did not have a memory of a safe object than when they did have a memory of a safe object ($p < .05$) (see Figure 2d). These findings supported our nuanced hypothesis that memory for relevant objects increase opportunism in a dynamic task.

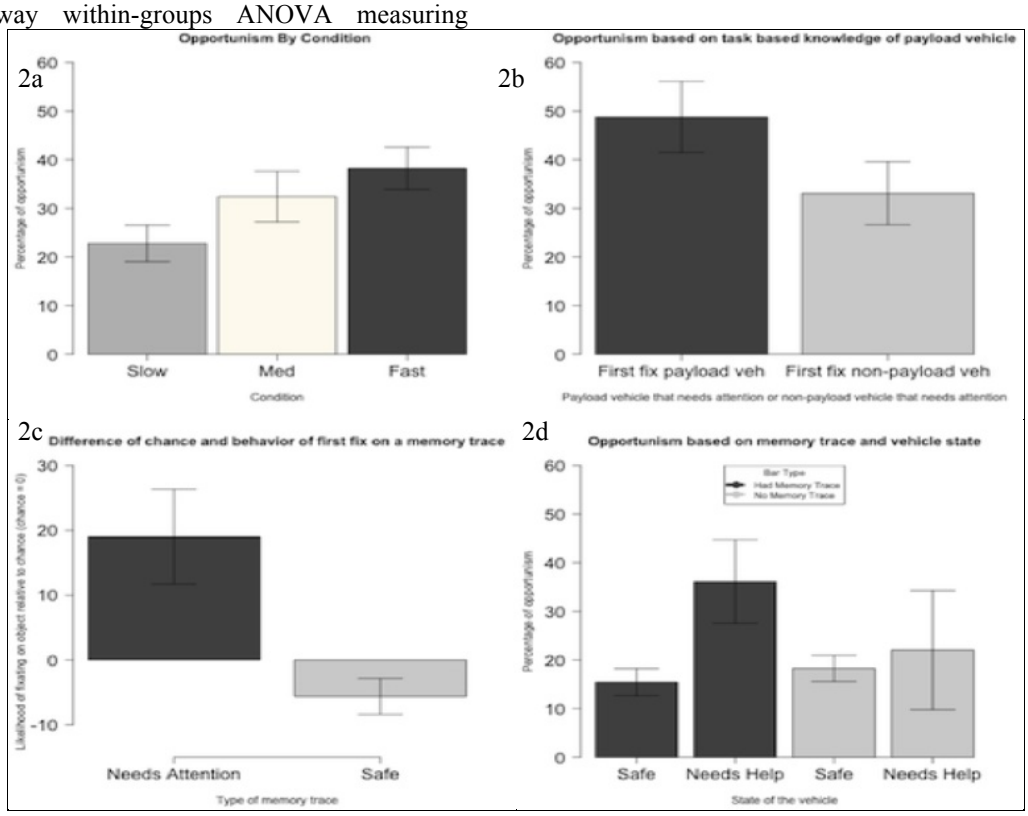

Figure 2. *2a) Percentage of opportunism in the three vehicle speed conditions. 2b) Percentage of opportunism when using task based knowledge. 2c) Use of memory based on the difference between chance of first looking at a vehicle that needs attention and the behavior. 2d) Percentage of opportunism when using memory. Error bars are 95% confidence intervals*

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CONCLUSION

In this study we were interested in the strategies that participants use when engaged in a dynamic time pressured task. As predicted from previous research on non-optimal decision-making and visual search (Ben Zur et al., 1981; Wolfe et al., 2005), after an interruption participants do not exhaustively look at every object before making a decision to act. Additionally, time pressure results in a reduction in scanning and an increase in opportunism.

Task knowledge and memory were strategies that were also found to guide participant's perceptions and actions. Task knowledge was demonstrated by the use of probability matching, where the payload vehicle had a 41.8% probability of needing attention and participants looked at the payload vehicle first 41.9% of the time. As predicted, memory, and in particular, memory for relevant events, was found to guide perceptions, such that participants were more likely to look at relevant objects that were previously looked at than would be predicted by chance. These findings add to previous research related to the process of situation awareness reacquisition (SAR) (Gartenberg, et al., 2011) and support the application of the Memory for Goals model in dynamic tasks.

Our nuanced hypothesis on the effect of task knowledge and memory on opportunism was also supported. When participants used task knowledge and memory for relevant objects they were more likely to follow an opportunistic strategy. One explanation for this is that task knowledge and memory increase memory activation, which induces the operator to preferentially look at and act on activated objects.

Overall, these findings suggest that operators use a combination of optimal strategies in dynamic tasks and that specific strategies interact with one another to facilitate opportunism.

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