Modeling Short-term Fatigue Decrements in the Successive/Simultaneous Discrimination Task

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Abstract

Previous research using goal-directed computational models has demonstrated that microlapses, or brief disruptions in effortful cognitive processing, are related to decreases in vigilance as a function of time-on-task in the psychomotor vigilance test (PVT) (Veksler and Gunzelmann, 2018). We extended these computational accounts of fatigue to model performance in two vigilance tasks that differ with respect to demands on working memory, i.e., successive vs. simultaneous discrimination (Davies and Parasuraman, 1982). While task performance was not affected by working memory demands, simulations show that fatigue moderators successfully capture decreases in vigilance over time. Additionally, participants showed greater individual differences in model parameters related to task performance, but not in the effects of fatigue across time. These results highlight the importance of fatigue moderators in computational accounts of vigilance tasks.

Keywords: ACT-R; fatigue; vigilance; microlapse

Introduction

The ability to direct and sustain attention over prolonged periods of time is essential to normal functioning in adults. Specifically, the ability to sustain conscious processing of a particular set of stimuli for periods longer than 10 s, or "vigilant attention" (VA; Robertson and Garavan, 2004; Robertson and O'Connell, 2010; Langner and Eickhoff, 2013), is directly linked to performance on continuous detection tasks such as the psychomotor vigilance test (PVT), where participants are asked to respond immediately upon presentation of a stimulus (Dinges and Powell, 1985). The PVT has traditionally been used to demonstrate decreases in VA under conditions of fatigue, where increases in degree of sleep loss are positively associated with response errors and latency (Doran et al., 2001; Dorrian and Dinges, 2004; Gunzelmann et al., 2009b). While most studies examine changes in PVT performance over the course of multiple days (typically coupled with sleep deprivation), researchers have also detected and modeled vigilance decrements over the course of single experiment sessions (e.g., 30-min tasks; Veksler and Gunzelmann, 2018). These methods successfully simulate the effects of fatigue on a few brief vigilance tasks, such as the PVT and the Mackworth Clock Task (Mackworth, 1948); however, it is unclear whether these methods can account for vigilance decrements in other related tasks.

In this paper, we describe a computational account of performance on two vigilance tasks in which participants are asked to view stimuli comprised of pairs of vertical lines and respond when the stimuli meet certain criteria. Our primary goals were to a) examine differences in processing and performance between successive and simultaneous discrimination tasks, b) determine whether computational accounts of fatigue provide a better fit to observed data compared to baseline models, and c) examine differences in parameter estimates across tasks and individuals.

Accounts of Vigilance Decrements

Theoretical accounts of VA share the idea that attention modulates performance on vigilance tasks, but differ on the exact mechanism. Underload accounts argue that vigilance decrements stem from "drifts" of attention away from the task, motivated by the monotony of the task (e.g., Robertson et al., 1997; Smallwood and Schooler, 2006). Overload accounts, however, argue the opposite: The taxing nature of vigilance tasks induces fatigue, resulting in "lapses" of attention that negatively affect performance as a function of time-on-task (c.f. Warm and Dember, 1998). Most computational accounts of fatigue are inspired by overload hypotheses of VA and treat alertness as a resource that is exhausted with fatigue and replenished with rest (Gunzelmann et al., 2009a). Specifically, performance on simple vigilance tasks, such as the PVT, has been conceptualized as a balance between fatigue and compensation, where individuals offset decrements by changing response behavior, such as lowering the requirements needed to initiate a response. This performance is additionally affected by small lapses in attention, termed *microlapses*, which are positively related to fatigue and time-on-task (Gunzelmann et al., 2009b; Veksler and Gunzelmann, 2018).

Simultaneous vs. Successive Discrimination

An important topic in vigilance research is understanding how fatigue affects the different cognitive processes that support task performance. This is especially true for the role of working memory (WM) capacity, which has been shown to be strongly correlated to lapses in vigilance (Unsworth et al., 2010) and, more specifically, to PVT performance (Unsworth et al., 2021). One method for understanding the link between WM and vigilance is by contrasting performance on *simultaneous* versus *successive* discrimination tasks (Davies and Parasuraman, 1982; Caggiano and Parasuraman, 2004). In simultaneous discrimination tasks, all of the information that is needed to correctly classify a target item is included in the

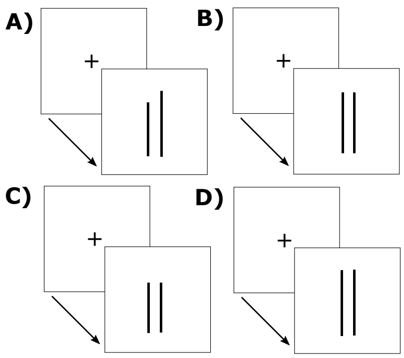


Figure 1: Examples of target trials during the lines task. In the Simultaneous condition, targets were either pairs of lines with different (A) or identical (B) lengths. In the Successive condition, targets were either pairs of lines that were both short (C) or both long (D).

trial. During successive discrimination tasks, however, the response requirements are such that the stimuli presented during a trial must be compared to a template of the target item held in WM. The WM requirements of successive discrimination tasks make them particularly sensitive to the effects of fatigue, where task performance declines more rapidly across trials compared to performance in a comparable simultaneous discrimination task (See et al., 1995; although also see Gartenberg et al., 2018).

The Current Study

We manipulated simultaneous vs. successive discrimination in the current study using a task in which participants are asked to view pairs of lines that are centrally-located on a computer screen (Figure 1). During each trial, participants were shown pairs of black vertical lines for 150 ms following a variable interstimulus interval (between 1.3 and 1.7 sec). The lengths of the two lines (either 14.6 or 18 mm) were randomly chosen during each trial. In the Simultaneous condition, participants were asked to respond only when both lines were the same length or different lengths. In the Successive condition, participants were asked to respond only if both lines matched and were of a particular size (short or long). Here, template-matching is not needed in the Simultaneous condition, as observers need only to determine differences between lines in order to provide a response. In the Successive condition, however, a template of either two "short" or two "long" lines is needed for a comparison. We modeled performance in both of these tasks to better understand differences in performance due to WM capacity and fatigue.

Methods

Behavioral

The models were based on data collected from 24 young adult volunteers ($M_{age} = 21.17$, $SD_{age} = 2.23$) recruited through the University of Dayton Research Institute and surrounding area. Participants were asked to complete two experiment sessions lasting 2 hr each, where part of the study was to complete the successive or simultaneous discrimination tasks on separate days. We counterbalanced the order in which participants completed these tasks to mitigate the influence of one discrimination task over the other. The discrimination tasks each consisted of 100 practice trials (which are excluded from the statistical analyses reported in this paper) and 1,600 test trials, and took approximately 45 min to complete. All participants gave written informed consent in accordance with the Declaration of Helsinki and were compensated for their participation.

	Description	Bounds	BM?	Fixed?
υ	Initial utility value	[0.0, ∞]	Yes	No
τ	Initial utility threshold	[0.0, ∞]	Yes	No
λ	Microlapse penalty	[0.98]	No	Yes
ρ	Utility ToT penalty	[-1.0, 0.0]	No	No
κ	Threshold ToT penalty	[-1.0, 0.0]	No	No
γ	Conflict resolution time	[0.05]	Yes	Yes

Table 1: Parameters of the ACT-R lines models with indications as to whether they are a) included in the baseline model (BM) and b) if they are fixed values or freely estimated. "ToT" = "time-on-task".

Computational

We developed the model using the Adaptive Control of Thought-Rational, or ACT-R (Anderson et al., 2004), cognitive architecture, with inspiration from previous models of the PVT (Gunzelmann et al., 2009b; Walsh et al., 2017; Veksler and Gunzelmann, 2018). ACT-R models behavior as emerging from a series of if/then rules that govern which actions (or "productions") are selected in a given situation, which itself is governed by a central cognitive system. The productions that are selected are a function of a) the amount of activation and noise for any given production (i.e., *utility values)* and b) the minimum activation required for a production to be selected (i.e., *utility threshold*). The strength of any given production can change as a function of baseline activation, the number of times a production is selected, and the match between the outside environment and production specifications. Here, utility values and thresholds will be determined by parameters related to fatigue. Table 1 briefly lists the critical parameters we use in our models, descriptions of the parameters, and the specific simulations that they are included in.

For the tasks in the current study, the production rules can be divided into four stages for any given trial:

- **Pre-attentive**: Prior to stimulus onset (i.e., lines appearing on the screen), participants must withhold a response as they anticipate a signal. Here, the model selects the *Wait* production to fire continuously until another production is selected, such as when lines appear on the screen. Under conditions of fatigue, however, the model may select and fire the *Respond* production, even in the absence of a valid stimulus. This simulates false start responses when no lines are presented on the screen.

- **Attentive**: Immediately upon detecting a visual stimulus, the model will fire the *Attend* production, which represents the relatively automatic process of attending to and harvesting information about a visual cue. Similar to the preattentive stage, the model can erroneously choose the *Respond* production immediately after the *Attend* production, which simulates false start responses that are quicker than conscious processing.

- **Decision**: After moving attention to a visual cue, participants must decide whether the stimulus meets the response criteria (*Match* production) or not (*Mismatch* production). For the simultaneous discrimination task, the model is able to make this determination using only the stimuli presented on the screen. For the successive discrimination task, however, the model is required to compare test stimuli to a template held in WM, which requires more time and effort, i.e., about 50 ms extra. In either case, if the *Match* production is selected, then participants prepare to give a keyboard response; otherwise, the model will select the *Wait* production in anticipation of the next trial. Incorrect responses, which increase under conditions of fatigue, occur when a) the *Mismatch* production is selected given a target stimulus ("Miss") and b) when the *Match* production is selected given a non-target stimulus ("False Alarm").

- **Response**: When the model has decided to respond, it fires the *Respond* production, which simulates the physical act of pressing the "j" key on a keyboard. Consistent with Fitt's Law (Fitts, 1954), the model takes approximately 300 ms to execute the movement at the beginning of the experiment and becomes quicker as a function of practice throughout the task.

Additionally, the model can fire the *Microlapse* production, which is a brief interruption in model processing (50 ms). Microlapses occur when there are no productions with activations that exceed the production selection threshold and increase as a function of fatigue, simulating lapses in VA during continuous response tasks (Gunzelmann et al., 2009b).

In our full model, fatigue penalizes both the utility values (U) of these target productions and the threshold of the selection mechanism that controls which production is executed (UT). Specifically, utility values at a given time t are a function of both time-on-task and occurrence of microlapses, such that:

$$U(t) = \upsilon \times [\lambda^{N_{ml}} \times (1+t)^{\rho}], \quad (1)$$

where υ is the initial utility value, λ is a penalty for microlapses, N_{ml} is the number of microlapses that have occurred in a given cycle, ρ is a time-on-task penalty specific to utility values, and t is the amount of time (in minutes) spent in the task.

Model	Cond	υ	τ	ρ	κ	-2LL
Baseline	Sim.	1.17	0.56	-	-	1546.88
	Succ.	1.90	0.35	-	-	2016.71
Fatigue	Sim.	1.43	0.81	-0.18	-0.21	1374.88
	Succ.	2.03	1.02	-0.24	-0.20	1497.86

Table 2: Best-fitting parameters and associated fit for models fit to all data.

The production selection threshold is affected much in the same way; however, only time-on-task, and not the occurrence of microlapses, has a direct effect on τ:

$$UT(t) = \tau \times (1+t)^{\kappa}, \quad (2)$$

where τ is the initial utility threshold value, κ is the time-on-task penalty specific to the utility threshold and, t is the amount of time spent on the task (scaled to minutes).

We fit the observed experiment data from both tasks to two models: One without fatigue moderators ("Baseline Model") and one with fatigue moderators ("Fatigue Model"). In both models, we freely estimated the starting utility values (υ) and utility thresholds (τ). In the Fatigue Model, we additionally estimated the time-on-task penalties for utility values (ρ) and the utility threshold (κ). We fixed the conflict resolution time (γ) and microlapse penalty (λ) parameters to 50 ms and 0.98, respectively[1], although only γ is present in both Baseline and Fatigue models. The models were fit using maximum likelihood estimation and approximate Bayesian computation with differential evolution (Turner and Sederberg, 2012) against the joint log-likelihoods of the observed vs. simulated reaction times (RTs) (log-normal distribution), hit rates (Binomial distribution), and false alarm rates (Binomial distribution). All models were developed using the Julia language (Bezanson et al., 2017) and fit using the `Optim.jl` (Mogensen and Riseth, 2018) and `DifferentialEvolutionMCMC.jl` (2022) packages.

Results

Here, we present only a few analyses regarding the behavioral data before discussing model fit indices. The results of the experiment are described in more detail elsewhere (c.f. Morris et al., 2022).

Behavioral

We conducted a 2 (Condition: Simultaneous [Sim] vs. Successive [Succ]) x 4 (Block: 4 blocks of 400 trials) within-subjects ANOVA, with Greenhouse-Geisser corrections on degrees of freedom where assumptions of sphericity were violated. For RTs, there was only a main effect of Block, $F(1.56,31.13) = 6.95$, $p < 0.05$, reflecting a significant increase between Block 1, $M = 0.58$, $SE = 0.02$, and Block 2,

[1]We did not freely estimate these values because these values have strong precedence in the extant literature (c.f. Veksler and Gunzelmann, 2018) and because early simulations indicated that model fit was not affected by these parameters.

Cond.	υ	τ	ρ	κ	-2LL
Sim.	3.63 (0.40)	1.74 (0.31)	-0.21 (0.02)	-0.20 (0.02)	1525.61 (95.81)
Succ.	3.62 (0.38)	1.53 (0.39)	-0.23 (0.02)	-0.20 (0.01)	1580.08 (103.00)

Table 3: Means and standard errors of the mean (in parentheses) of the best-fitting parameters and associated fit for individual participants.

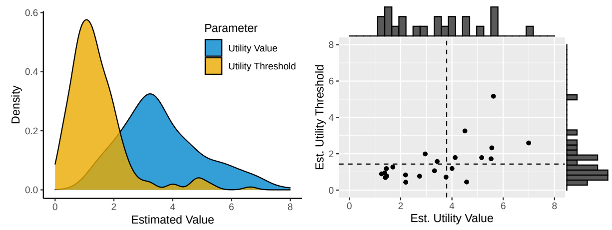
M = 0.63, SE = 0.02, $p < 0.05$. RTs in Block 3, M = 0.64, SE = 0.02, and 4, M = 0.63, SE = 0.02, did not significantly differ from each other, $ps < 0.05$. A similar pattern emerged for accuracy, where there was also a main effect of Block, $F(1.59,31.73) = 3.83$, $p = 0.02$. A partial interaction contrast indicates that accuracy was significantly higher for Block 1, $M = 0.91$, $SE = 0.01$, compared to all other blocks, Ms = 0.89, SEs = 0.01, $\chi^2(1) = 6473.10$. $p < 0.05$. There were no significant main effects of Condition, nor were there any significant interactions between Condition and Block, $ps > 0.05$.

Computational

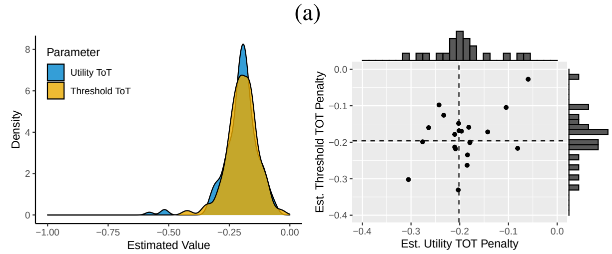
We first fit the aggregated experiment data to the separate Baseline and Fatigue models. For both experiment conditions, the models with fatigue penalties (Sim: -2LL = 1374.88, BIC = 1417.27; Succ: -2LL = 1497.86, BIC = 1540.25) fit the observed data better than the Baseline models (Sim: -2LL = 1546.88, BIC = 1568.07; Succ: -2LL = 2016.71, BIC = 2037.90). Table 2 lists the separate parameters that were recovered from this process.

Given the better fit, we also estimated model parameters separately for each participant, but only using the Fatigue model of task performance (Table 3). For both the Simultaneous and Successive conditions (Figure 3), the estimated initial utility values varied greatly across participants (M_{sim} = 3.63, SE_{sim} = 0.40, M_{succ} = 3.62, SE_{succ} = 0.38), while the corresponding initial utility thresholds were lower and were less varied (M_{sim} = 1.74, SE_{sim} = 0.31, M_{succ} = 1.53, SE_{succ} = 0.39). Interestingly, estimates for both the utility value (M_{sim} = -0.21, SE_{sim} = 0.02, M_{succ} = -0.23, SE_{succ} = 0.02) and utility threshold (M_{sim} = -0.20, SE_{sim} = 0.02, M_{succ} = -0.20, SE_{succ} = 0.01) time-on-task penalty parameters were similar and exhibited little variation. These estimates did not differ significantly between the two experiment conditions, $ps > 0.05$.

As expected, the initial utility value and threshold estimates were correlated, r = 0.77, $t(43)$ = 8.01, $p < 0.05$, reflecting the need for productions to exceed the selection threshold. Initial utility values were significantly correlated with utility time-on-task, r = -0.42, $t(43)$ = -3.03, $p < 0.05$, and threshold time-on-task, r = 0.40, $t(43)$ = 2.84, $p < 0.05$, parameter estimates. Similarly, the initial threshold values were also significantly correlated with utility time-on-task, r = -0.70, $t(43)$ = -6.34, $p < 0.05$, and threshold time-on-task, r = 0.32, $t(43)$ = 2.19, $p < 0.05$, parameter estimates. The

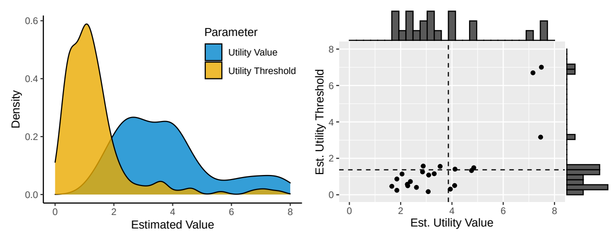


(a)

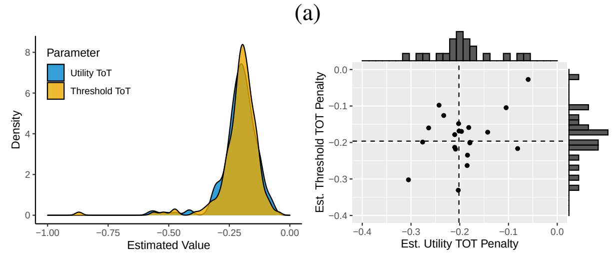


(b)

Figure 2: Parameter estimates across participants for the initial utility and threshold values (a) as well as the utility and threshold time-on-task penalties (b) for the Simultaneous condition.



(a)



(b)

Figure 3: Parameter estimates across participants for the initial utility and threshold values (a) as well as the utility and threshold time-on-task penalties (b) for the Successive condition.

two time-on-task parameters were not significantly related to each other, r = 0.02, $t(43)$ = 0.10, p = 0.92.

Conclusions

These simulations support previous computational accounts of fatigue mechanisms (e.g., Gunzelmann et al., 2009b, 2015) and suggest that accounting for the effects of fatigue in a brief vigilance task provides a better fit to observed experiment data compared to models that do not account for fatigue, regardless of the WM requirements in the experiment task, i.e., Simultaneous vs. Successive conditions. They also suggest that penalties to both production utility values and production selection thresholds as a function of duration (Veksler and Gunzelmann, 2018) provide an accurate account of the decreases in response accuracy and increases in RTs in ACT-R models of the discrimination vigilance tasks. The parameters recovered from model-fitting indicate that while there are individual differences in factors related to general model performance, i.e., initial production utility values and production selection thresholds, this is not the case for parameters that describe decrements as a function of time-on-task, where all estimates for both the utility value and threshold penalty parameters showed little variation from -0.2.

The lack of differences between the two conditions in both behavioral and computational analyses contradict a resource-depletion hypothesis of vigilance decrements (Caggiano and Parasuraman, 2004), where the additional WM requirements of the Successive lines task were expected to result in greater decreases in performance. The results are consistent, however, with a general resource-control theory of vigilance (Thomson et al., 2015), where greater decreases in vigilance are expected for tasks that are more difficult, but not for those that increase task engagement. In this particular task, requiring participants to hold a template of the target stimuli configured in WM might not have been sufficiently taxing in order to replicate the results of previous simultaneous/successive research (Parasuraman and Mouloua, 1987; Caggiano and Parasuraman, 2004). Alternatively, the Successive condition might have been sufficiently taxing, but also engaging enough to offset average differences in performance. Another possibility is that the stimuli used in the task (based on Parasuraman and Mouloua, 1987) were more taxing than previous speeded discrimination tasks, resulting in similar performance outcomes in both tasks. Regardless, the improvement in fit between the Baseline and Fatigue models implicates a performance decrement due to time-on-task, consistent with both theoretical and computational accounts of vigilance. Overall, these models extend previous accounts of fatigue and highlight the importance of accounting for decrements in brief vigilance tasks.

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