Modeling the Workload Capacity of Visual Multitasking

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Abstract

We utilize the capacity coefficient to characterize the workload capacity of visual multitasking. The capacity coefficient compares cognitive work completed on multiple information sources against a baseline parallel model prediction. Capacity coefficient results subsume standard mean response time (RT) dual-task findings while providing a description of workload effects on the whole RT distribution. This yields a theoretically-grounded characterization that can inform computational and process models of multitasking.

Keywords: Workload Capacity; Multitasking; Multi-Attribute Task Battery; Human Information Processing; Dual-Task

Introduction

We seek to provide a better mathematical characterization of cognitive performance during multitasking, the simultaneous execution of more than one task within the same experimental environment. Often, characterizations of multitasking performance are limited to assessments of dual task decrements, wherein mean response time (RT) or accuracy are compared across only two tasks. Increased workload is inferred when an RT increase and/or accuracy decrease is observed when switching from a single task to the dual-task environment. These performance metrics may be further correlated with subjective workload ratings. While these measures do give some indication of participants' experiences of workload, they do not provide strong insight into the cognitive mechanisms supporting multitasking behaviors or the mechanistic reasons for changes in performance under changing workload demands.

We report on an effort to utilize human information processing modeling to provide qualitative and quantitative characterization of the cognitive mechanisms engaged in multitasking. In particular, we focus on changes in workload capacity, the efficiency with which the system responds to the changing number of tasks in a dynamic environment.

Modified Multi-Attribute Task Battery

To study multitasking, we utilize a web-browser implementation of the modified Multi-Attribute Task Battery (mMATB; Cline, Arendt, Geiselman, & Blaha, 2014), developed in the JavaScript D3 library (Bostock, Ogievetsky, & Heer, 2011). The mMATB consists of four possible visual decision making tasks: Tracking, Monitoring, Communication, Resource Management. In our implementation, all aspects of the workload can be manipulated: entire tasks (quadrants) can be turned on or off, the rate of alerting events can be varied as can the probability of simultaneous alerting events, and the speeds at which the moving parts of the displays move can be adjusted. We will focus herein on manipulations of the total number of tasks to be performed simultaneously.

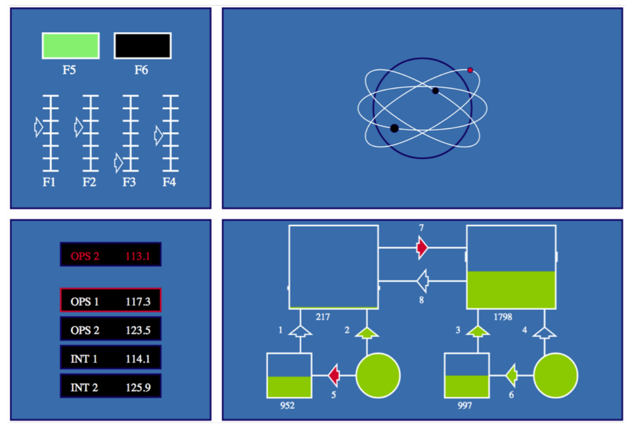

Figure 1: The browser-based modified Multi-Attribute Task Battery (mMATB) used in the present study. The four visual tasks are (clockwise from upper left): Monitoring, Tracking, Resource Management, Communications.

Figure 1 shows the mMATB environment. The Tracking Task, contained in the upper right, entails physically tracking three colored circles moving continuously along individual ellipsoid trajectories. High performance on this task requires continual mouse motion and attention to switching targets.

Both the Monitoring Task (upper left) and the Communications Tasks (lower left) require keypress responses to alert events. In the Monitoring Task, the participant's task is to provide the appropriate response if a parameter is out of its normal state. In the Communications Task, participants must adjust a channel to a new value upon target cuing.

The lower right quadrant contains a Resource Management Task which requires only strategic attention to gates (switched by keypress) in order to maintain fuel levels within a predetermined range for two schematic resource tanks.

The mMATB, thus, demands a division of visual attention and motor activity across the four tasks. During multitasking, participants are instructed to emphasize accuracy in the Tracking Task as their primary task, and to respond to all other alerts appropriately. RTs are collected to cued events; response choices are collected for all interactions.

The Capacity Coefficient

Workload capacity is defined as the ability of the cognitive information processing mechanisms to respond to changes in cognitive load. This is usually interpreted as changes in the number of items that need to be processed within a task. Capacity is assessed with RT data, in order to make inferences about information processing speeds. Qualitatively, the possible capacity classes are unlimited, super, and limited capacity, corresponding to processing speeds remaining steady, increasing, or decreasing, respectively.

Our primary measure of workload capacity is the capacity coefficient (Houpt, Blaha, McIntire, Havig, & Townsend, 2014). This is a ratio measure which compares the observed participant's RTs during multitasking to a model-based prediction about multitasking speed. The baseline RT model is an unlimited capacity independent parallel model (UCIP). We utilize the capacity coefficient for ST-ST responses (Blaha, 2010):

$$C(t) = \frac{K_k(t)}{K_{k,\mathcal{C}}(t)}. \tag{1}$$

In Equation 1, the numerator gives the cumulative reversed hazard function for individual target channel k when processed alone; this is the UCIP model prediction. The denominator is the cumulative reversed hazard function for target channel k when additional tasks (set $\mathcal{C}$) are performed.

Figure 2 illustrates $C(t)$ results for one typical participant in both dual-task multitasking (upper plot) and four-task multitasking (lower plot). Relative to the UCIP baseline at $C(t) = 1$, the data indicate that while while all conditions showed mean RT dual-task decrements, the functional data are more nuanced. Under dual-task conditions, performance in the tracking task improved, showing super capacity $C(t) > 1$ for most times, but falling to limited capacity $C(t) < 1$ when the number of tasks increased to four. Thus, additional task demands have the potential to improve tracking performance.

Detection performance in the monitoring task, on the other hand, was limited capacity in both the dual task and four-task multitasking conditions. Communication task detection was also limited capacity in the four-task condition. This indicates that division of attention across multiple tasks slows alert detection responses.

Discussion

The present work is the first to apply the capacity coefficient to a multitasking situation, where the number of tasks is manipulated while the features within each task (when present) remain unchanged. Current results indicate that some tasks benefit from additional workload demands, while others are slowed. The capacity coefficient can capture both types of effects. This more nuanced characterization can then be used to inform computational and process models of multitasking (e.g., Salvucci & Taatgen, 2008), and to study task switching and divided attention strategies.

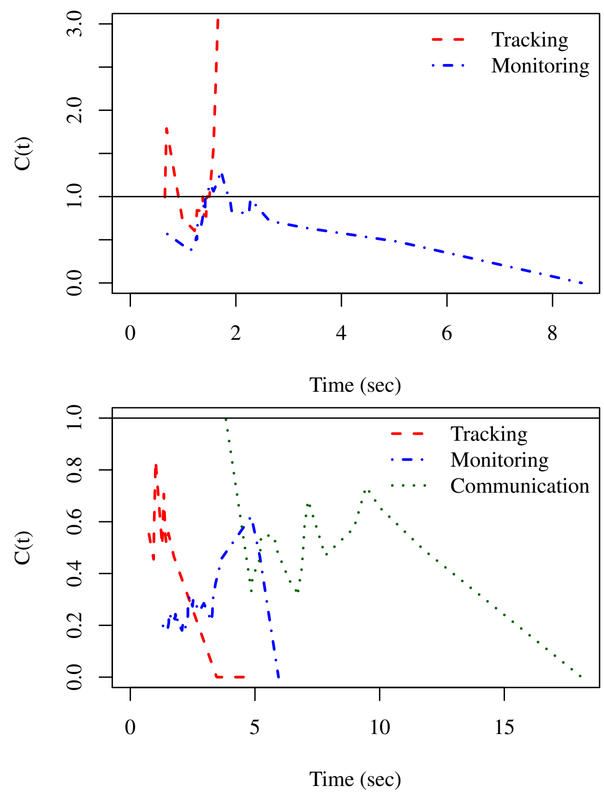

Figure 2: Capacity coefficient results for a typical participant in the dual task (upper) and multitask (lower) conditions.

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