Comparing Capacity Coefficient and Dual Task Assessment of Visual Multitasking Workload

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Abstract. Capacity coefficient analysis offers a theoretically grounded alternative approach to subjective measures and dual task interference assessment of mental workload. Workload efficiency is a human information processing modeling construct defined as the efficacy with which the system responds to increases in the number of cognitive processes. In this paper, I explore the relationship between capacity coefficient analysis of workload efficiency and dual task interference response time measures. I examine how the relatively simple assumptions underlying capacity coefficient analysis parallel those made in dual task interference workload assessment. For the study of visual multitasking, capacity coefficient analysis enables a comparison of visual information throughput as the number of tasks increases from one to two to any number of simultaneous tasks. By using baseline models derived from transformations of response time distribution, capacity coefficient analysis enables theoretically grounded interpretations of workload. I illustrate the use of capacity coefficients for visual multitasking, compared to dual task interference analysis, on sample data from dynamic multitasking in the modified Multi-attribute Task Battery.

Keywords: Capacity coefficient · Workload · Dual-task · MAT-B · Multitasking

1 Introduction

Visual multitasking is the simultaneous execution of at least two distinct visual tasks. In visual multitasking, each task is comprised of separate, potentially unique, visual stimuli, independent events and timing characteristics, and separate decisions and responses. For example, texting while driving requires visual attention to the environmental cues external the car to maintain lane position, as well as attention to the screen and buttons of the mobile phone to input responses to the incoming messages. When multiple simultaneous tasks require the same perceptual processing resources, degradations in performance are often observed as the number of tasks increases.

The goal of the present work is to explore the applicability of workload efficiency analysis to the study of performance in multitasking situations. Workload efficiency, or processing capacity, is the information processing modeling

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construct that characterizes the response of cognitive information processing mechanism to changing tasks demands [28,29]. That is, as the number of decisions (processing stages or subtasks) increase, how do information processing rates respond? There exists a set of theoretically grounded, model-based measures for workload capacity, derived from the distributions of task response times, that may offer useful insights about multitasking, both about the mechanisms involved and about the mental workload demands for a given situation. In the following, I will explore the use of the capacity coefficient, in particular, as a potential metric for multitasking workload efficiency. I compare it to the very similar notion of dual task interference effects, which are often utilized as an objective metric for mental workload when clear, repeated behavioral measures can be collected empirically.

1.1 Characteristics of Multitasking

Salvucci and colleagues have defined several dimensions along which multitasking scenarios can be characterized. First, the multitasking continuum defines the timescales at which activity occurs before a person switches between tasks [24,27]. At one end of the continuum are tasks that require seconds to complete, like driving and talking. The other end of the multitasking continuum is tasks requiring hours to complete before switching, such as cooking and reading a book. Another facet of multitasking is the degree to which tasks are concurrent or sequential in execution [25,26]. True sequential tasks are performed with discrete yet well-defined boundaries between tasks, such as switching between writing an email and making a phone call. One task is completed before the next is initiated. Concurrent tasks are executed simultaneously with overlapping temporal events, such as simultaneously baking a cake and holding a conversation with someone else in the kitchen. The concurrent-sequential nature of the tasks has implications for the organization of the mental resources, including perceptual, memory, decision making, and motor resources, needed to support effective performance. Note that these dimensions (concurrency and time scale) of multitasking can be defined separately for any given combination of tasks. However, concurrent tasks typically require frequent attention switching on the order of seconds, and so they often align with the shorter time scale end of the multitasking continuum. Likewise, sequential tasks often occur on longer time scales at the upper end of the multitasking continuum [26].

Multitasking tasks can further be placed on an application continuum based on the real-world nature of the tasks under observation. The application continuum ranges from abstract laboratory tasks (e.g., visual or memory search for simple targets) to real-world multitasking (e.g., management of attention while driving busy city streets involving other cars, signals, and pedestrians). Finally, the abstraction continuum is used to characterize the nature of theories developed to characterize multitasking as well as the related methodologies developed to study multitasking through those theoretical lenses. The abstraction continuum is akin to Newell's bands of cognition, defining the timescales at which behavior can be decomposed and appropriately measured and modeled [2,20].

The information processing mechanisms of interest in the present work fall into the cognitive band, on the order of seconds for the completion of individual mental operations or single task units.

1.2 Dual Task Assessment of Workload

In many ways, the assessment of performance during multitasking falls into the general problem of measuring operator mental workload, from both the objective behavioral impacts and the subjective experience of changing processing demands. Generally, mental workload is conceptualized as the demands placed on information processing resources, which are recognized to be limited [36]. The assessment of mental workload, however, is difficult as the workload experience is a latent factor and can only be assessed indirectly. The goal of workload assessment measurements is to translate the subjective experience of workload together with the impacts of varying workload into something quantifiable, like a numerical scale [18]. Approaches include subjective assessments of workload, such as the popular subjective workload assessment technique (SWAT [22]), or the NASA task-load index (NASA-TLX [11]). While popular and easy to administer, subjective techniques have faced extensive criticism for being only indirect measures of resource allocation and information processing capacity. Objectively, the impacts of multitasking on behavioral performance are often addressed with a measure of dual task interference, derived from total task accuracy or mean response times. To perform a dual task interference assessment, the difference between a task performed in isolation and the task performed in multitasking conditions is computed to assess the degree of impact of the multiple competing task demands. Drops in performance or increases in subjective workload can successfully describe some aspects of the impact of multitasking.

The popular terminology for the components of dual task assessment is primary and secondary task measures. Primary task measures are defined as some aspect of performance on a task of interest, which has generally been predetermined by the experimenter. Secondary tasks are then used to load more cognitive demands onto available processing resources, to impact the primary task measures in some way. There are two ways in which a secondary task can be used empirically. First, in a task loading paradigm, participants are asked to maintain high performance on the secondary task, at the expense of the primary task. The second approach uses the secondary task in a subsidiary role, in which the participant is asked to maintain high performance on the primary task. In this latter case, the secondary task serves to degrade the primary task by distraction or utilizing needed resources. A balance of both approaches could be engaged in laboratory settings to assess bi-directionality of interference effects, though there are often practical limitations to this being accomplished.

There is a set of critical assumptions that must be met for effective assessment of workload using dual task interference approaches [5]. The first is that baseline measures can be taken from both the primary and secondary task, separately and independently of the dual task scenario. This would mean being able collect data from at least three total experimental conditions: (1) primary task alone,

(2) secondary task alone, and (3) dual task combination. The second assumption is that both the primary and secondary task tap into common resource requirements, which is considered critical for the tasks to interfere or compete for the limited resources. This reflects the notion that performance in multi-task situations can be limited in different ways, and that it is possible for two concurrently performed tasks to draw from different pools of cognitive resources [21].

The next assumptions are that the secondary task places continuous demands on the user and that the participant has had sufficient practice on the secondary task to achieve stable performance. Both are necessary for the secondary task to offer competing resource demands on the user but not to distract the participant from the primary task onto training of the secondary task. Because practice and task learning can improve performance, it is possible that a secondary task performed without initial practice can result in enough learning that the secondary task becomes trivial and no longer places enough demands on the user to compete with the primary task for resources. Additionally, multiple levels of difficulty can be used in the secondary task to vary the level of effort needed (e.g., [35]). This, in turn, influences the degree of interference the secondary task places on the primary task, which can affect both the dual task interference effects and perhaps the subjective experience of workload.

2 Workload versus Workload Efficiency

In their efforts to assess mental workload, researchers have consistently found that mental workload may be a multi-faceted or multidimensional construct. This is because the subjective experience of higher workload may result from cognitive moderators, like stress, that influence physiological responses, in addition to the information processing and motor response demands of the tasks themselves [9,19,37]. Certainly one of the key dimensions that should be considered in the assessment of workload is the degree to which cognitive information processing mechanisms are able to effectively perform the work demanded of them.

Workload efficiency is a human information processing modeling construct defined as the amount of information that can be processed by the cognitive system given a specified of amount of time. The range of time is defined by the range of response times required for the task under consideration. Here, I emphasize visual tasks, so the information processing mechanisms entail visual perception and decision making. In the visual domain, workload efficiency measures are typically applied to redundant targets task designs, such as the identification or discrimination of multiple features within a single visual object (e.g., eyes, nose, and mouth within a face [34]) or the visual search in a redundant targets array (e.g., [17]). The workload capacity of a system describes the way in which changes in information processing demands influence the rate of processing. If increases in demands slow processing, then the system's efficiency is termed limited capacity. If increases in demands do not change the processing rates, then the system's efficiency is termed unlimited capacity. If increases in demands increase the speed of processing, which seems counterintuitive but has been observed (e.g., Gestalt processing [14]), then the system's efficiency is termed super capacity. In this framework, three broad classes of workload efficiency are defined in terms of task completion rates, which can be measured with completion or response times.

Workload capacity analysis makes a set of basic assumptions similar to those required by effective dual task interference analysis. First, the multiple tasks used should require comparable demands on the participant as each other. That is, they should both be similarly discrete or continuous over the course of task performance, and be at a similar level of complexity (i.e., both are single perceptual or choice decisions, or both are at the same level of realism on the application continuum). It is also assumed that all tasks have been practiced to a similar degree of stable performance such that learning and practice effects are accounted for in all tasks. Workload capacity analysis assumes that performance can be assessed for the component tasks alone as well as for the tasks combined, identical to the assumption in the dual task approach. However, the component tasks need not necessarily tap into the same cognitive or perceptual resources for capacity analysis to work. With this approach, available information processing models offer some degree of characterization of the system regardless if the component tasks utilize all, none, or partially overlapping resources. As discussed in the next section, capacity characteristics reflect situations in which tasks can interfere with each other, not interfere at all, and even cases when they facilitate each other. In terms of processing resources, these cases, respectively, may reflect situations wherein the two tasks compete for resources, may not need common resources, or mutually augment the resources available to a single task alone.

Identical to dual task interference analysis, workload efficiency requires that separate measurements be taken from the component tasks as well as performance on the combination of tasks together. For two-task cases, this means collecting data from the same three experimental conditions: (1) primary task alone, (2) secondary task alone, and (3) dual task combination. This requirement is necessary to formulate model-based predictions for multitasking performance. And similar to the recommendation for dual task interference analysis, the difficulty level of the tasks can be varied. However, because of the use of model-based predictions as workload efficiency baseline estimates, it is important that if the difficulty levels are varied, then data must be collected in both the single-task and multi-task conditions at the same difficulty levels. This ensures that the capacity interpretation reflects the workload manipulations without potential confounds of task difficulty.

3 The Capacity Coefficient

Capacity coefficient analysis enables inferences about information processing efficiency by comparing the amount of cognitive work completed while multiple tasks are performed together to a prediction about cognitive work made by a baseline model. Cognitive work is measured with the integrated hazard and reverse hazard functions of response times. The hazard function is defined as $h(t) = \frac{f(t)}{S(t)}$, where $f(t)$ is the probability density function and $S(t) = 1 - \int f(t)$ is the survivor function. Hazard functions can be interpreted as the amount of instantaneous effort or energy in a system at any point in time, t [29]. Consequently, the integrated hazard, $H(t) = \int_0^t h(\tau)d\tau = -log(S(t))$, can be interpreted as the total amount of work completed from the start of a task to time t. Similarly, the reverse integrated hazard function, defined as $K(t) = \int_0^t \frac{f(\tau)}{F(\tau)}d\tau = log(F(t))$ is interpreted as the amount of work left to be completed by the system after t time has passed. Note that when applied to a cognitive task, t is measured as the response time on each trial, or the time between some stimulus or alert and the observer's response.

The baseline performance model engaged in capacity coefficient analysis is an independent, parallel, unlimited capacity (UCIP) model system. In a UCIP system, the number of tasks can be increased without changing the speed at which any individual task is completed. For multitasking, this means that a person can complete a combination of multiple simultaneous tasks at the same speed as when completing the tasks individually. The system exhibits unlimited processing capacity. An implication of this is that the amount of mental effort should remain consistent under increasing demands. Against the UCIP baseline, if additional tasks slow processing, the capacity coefficient analysis will show limited capacity. If additional tasks should benefit the person and speed up performance, the capacity coefficient analysis will indicate super capacity.

The choice of hazard or reverse hazard function and the specific definition of the UCIP model depend on the nature of the task under study, particularly the nature of the stopping rule governing the termination of processing to make a response. For dynamic visual multitasking, I consider the case in which each task engages a single cognitive decision in response to a single alert event, separate and independent of the decisions made in the other tasks. Using information processing modeling terminology, this is a single-target self-terminating (ST-ST) stopping rule. This means that for each task at a given time there is a single target event that triggers a response, and that the response can be made after that target event has been observed by the participant. Cognitive work for ST-ST processing is typically measured with the integrated reverse hazard function. For ST-ST processing, the amount of work predicted by a UCIP baseline system for each individual task during multitasking is identical to the amount of work completed on each task performed individually. That is, for given task A among a set of tasks M, the UCIP baseline prediction is defined as $K_A(t)$, estimated from the participant performing task A alone. Then the observed performance of A during multitasking is defined as $K_{A,M}(t)$. The capacity coefficient for ST-ST processing is defined as

$$C_{\mathrm{ST}}(t) = K_A(t) - K_{A,M}(t). \tag{1}$$

If the processing efficiency for task A during multitasking is unlimited, then $C_{\mathrm{ST}}(t) = 0$. Limited capacity is inferred if $C_{\mathrm{ST}}(t) < 0$, and super capacity is inferred if $C_{\mathrm{ST}}(t) > 0$.

Note that these inference reference values are similar to those used in dual task interference effects at the mean level, when applied to response times. If there is no decrement in performance under dual task conditions, then the difference in mean response time for the primary task between the single and dual task conditions will be zero. Interference caused by an increase in workload under dual task conditions will produce a negative impact on response time in that $\overline{RT}_{Single} - \overline{RT}_{Dual} < 0$. Though not common in the workload literature, should moving from a single task to dual task condition improve performance, then a dual task facilitation could be inferred, when $\overline{RT}_{Single} - \overline{RT}_{Dual} > 0$.

The key difference in these approaches is that $C_{\mathrm{ST}}(t)$ provides a functional measure of the influence of multitasking on workload efficiency. That is, we get a value over the entire range of response times. This allows for a more nuanced interpretation of the impact of moving from a single task to dual task situation. With the capacity coefficient, it is possible to observe $C_{\mathrm{ST}}(t)$ values that vary between levels of efficiency over time. For example, fast detection responses may be super capacity in nature, $C_{\mathrm{ST}}(t) > 0$. But if the observer did not immediately detect a stimulus and performed a more effortful target search, then the responses may reflect limited capacity processing, $C_{\mathrm{ST}}(t) < 0$. In this way, we can get a more detailed but still objective description of the impact of increasing cognitive load on task performance.

4 Application to Dynamic Visual Multitasking

I demonstrate the dual task response time analysis and capacity coefficient analysis on sample data from two-task combinations from multitasking software that supports up to four simultaneous tasks. Consistent with the traditional applications of the capacity coefficient, tasks were selected because they all entail reactionary responses to alerting events. The alerting events can be considered the stimulus onset event, and the reactionary response times can be recorded. In this way, a distribution of response times can be collected that is similar to the response time distributions collected in single visual decision tasks in which capacity analysis has been previously utilized.

A key difference between discrete trial experiments and dynamic visual multitasking is that dynamic visual multitasking does not include well-defined intertrial intervals. But such intervals are not a critical assumption of capacity coefficient analysis. A potentially larger challenge in dynamic multitasking is that the time of an alerting event may not be the identical to the time at which the participant observes the alerting event. This is because the alerts may not occur while the participant is foveating on the alert, as is expected in discrete trial experiments with centrally presented stimuli. However, I leave treatment of this detail to future efforts. For the present, I make the reasonable assumption that response time can measured from the timestamp of an alert to the timestamp of keyboard or mouse response.

The tasks herein can be characterized using the various continua discussed above. On the multitasking continuum, these tasks are continuous and concurrent in nature. Participants must monitor all activity in the tasks for alerting events. The alerting events occur on the order of seconds, with response times also on the order of seconds or even milliseconds. Along the application continuum, these tasks represent a laboratory abstraction of pilot-like multitasking. The nature of the task is a realistic reflection of some demands occurring in real-world pilot multitasking. However, the display and details are greatly simplified. Thus, these tasks reside more toward the first third-to-half of the application continuum.

4.1 Task Environment

Sample data from one well-practiced team member were captured in both single and dual visual decision making tasks within a JavaScript implementation of a modified multi-attribute task battery (mMATB-JS; [8,10]).[1] This lightweight, web-based version of the MAT-B contains up to four simultaneous visual tasks: continuous object tracking, alert monitoring, communication (channel cuing), and resource management. Any individual task within the mMATB-JS can be used as a single visual decision making task; any combination can be leveraged for visual multitasking. The specific combinations of tasks used herein are shown in Fig. 1. Note that the resource management task is a strategic task requiring participants to manage simulated fuel levels. It is not used in the current demonstration, so is not depicted in Fig. 1.

The monitoring task (upper left quadrant, Fig. 1), consists of a set of sliders and two color indicator blocks. The participant's task is to provide the appropriate button press (F1–F6, labeled on each indicator/slider) if a parameter is out of its normal state. For the sliders, this means moving above or below ±1 notch from the center. Participants must respond with the appropriate button press before the slider moves back into the central range; if the slider returns to the central range before a response, then an event miss is recorded. For the indicators, the normally green block might turn black, or the normally black block might turn red. The participant must respond before the event timeout, when the color reverts to the normal value.

The continuous tracking task (upper right quadrant, Fig. 1 top and middle) requires the participate to continuously track a moving circular target with the mouse. At any time, one of the circles can turn red, indicating it is the target to be acquired and tracked. When this occurs, the participant clicks to acquire the target (which turns green) and then tries to keep the mouse cursor centered on the target as it moves along an ellipsoid track. A target will remain in an alert (red) state until either acquired by the user or the next alerting event occurs, which is recorded as an event miss.

The communications task (lower left quadrant, Fig. 1 middle and bottom) requires the participant to adjust channel frequencies when cued. The display includes four channels, labeled INT1, INT2, OPS1, OPS2, together with the current channel values; the topmost line gives a target channel and value. If a red cued target appears in the top box, the participant uses the up/down

[1] Available online at http://sai.mindmodeling.org/mmatb/index.html.

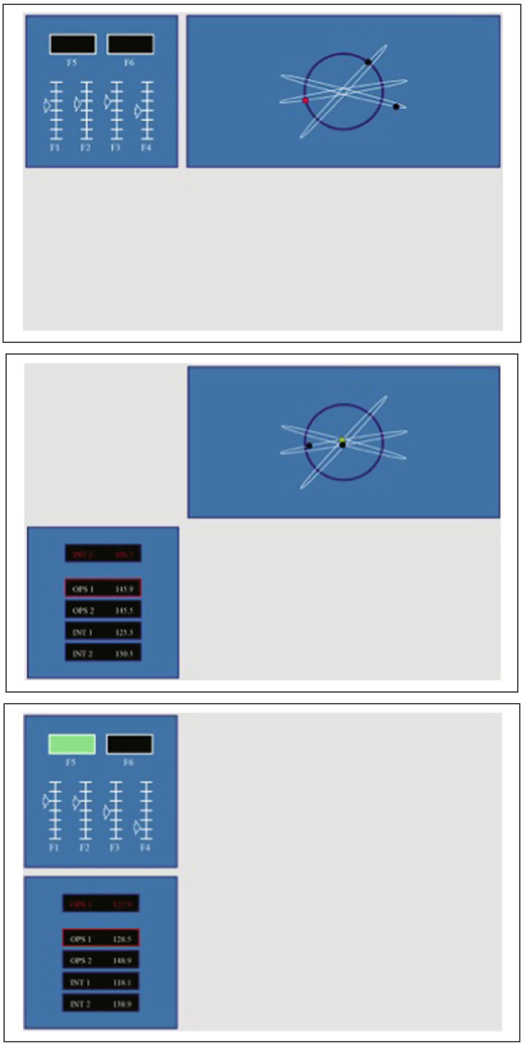

Fig. 1. Screen shots of the three dual tasks combinations used in the present demonstration. The top shows the monitoring-plus-continuous tracking condition (MCT) with the F5 color out of state (black) and the tracking task in a cue alert (red) state. The middle shows the communications-plus-continuous tracking condition (CCT) with the communications cuing a new channel value for INT2 and the tracking in a target acquired (green) state. The bottom shows the communications-plus-monitoring condition (CM) with the slider F4 out of range and a new channel value cued for OPS1. The frame indicates edges of the monitor, and the layout and sizing of the tasks are preserved from the full four-task mMATB-JS environment. (Color figure online)

arrow keys to select the cued channel and the right/left arrow keys to adjust the channel value to the new cued value. The enter key submits the corrected channel, which changes the topmost cue box to white until the next channel cue appears. The cued target remains red until either the correct channel adjustment is input with the enter key or the operation times out, which is recorded as an event miss.

As illustrated in Fig. 1, three dual task conditions were created to capture different task/response characteristics. These dual task combinations were: monitoring–plus–continuous tracking (MCT condition), communication–plus–continuous tracking (CCT condition), and communications–plus–monitoring (CM condition). For both the MCT and CCT conditions, the continuous tracking task was designated as the primary task. For the CM condition, the communications task was designated as the primary task. The observer was instructed to prioritize the performance of the primary task over the secondary task. The MCT condition required two-handed responding, in that the monitoring task uses the non-dominant hand for single-button responses and the dominant hand for mouse clicking and tracking. The CCT conditions similarly required two handed responding, but the communications task uses multiple button pushes for each response. The CM condition required only button pushes by the non-dominant hand. For consistency across all conditions, during the CM task, the dominant hand remained on the mouse, and only the non-dominant hand could be used for all keyboard inputs.

4.2 Task Parameters

In the mMATB-JS, all task parameters are configurable to support varying levels of task difficulty. In the present, a fixed set of parameters were selected to illustrate the analysis concepts, rather than assessing performance under variable conditions. Alert times are governed by random variables that add a random inter-trial interval to the offset time (either by response or timeout) following each event. For all tasks herein, the onset times of alerting events were drawn from a uniform random variable between 8 and 14 s. For a 20 min session, this results in an expected value of approximately 109 events per task. The timings within each event are handled as independent event sequences. Simultaneous events across tasks are possible, but simultaneous alerts within a task are not possible. The additional parameter settings for each task are as follows:

Communication. Frequency ranges were 110–160, with random starting values chosen; maximum frequency differential per alert was 6.

Monitoring. The slider speeds were 2 s/tic, 1.4 s/tic, 1 s/tic, and 1.6 s/tic for F1 through F4, respectively. Timeout rate for F5 and F6 was 8 s.

Tracking. For all paths, path interval set to 30; satellite radius was 13 pixels. The movement refresh was 100.

Capacity analyses were completed in R using the *capacity.stst()* function in the sft package [13].

4.3 Results

Table 1 shows the traditional dual task interference effects for the two-task scenarios in all three conditions. Interference effects were computed by taking

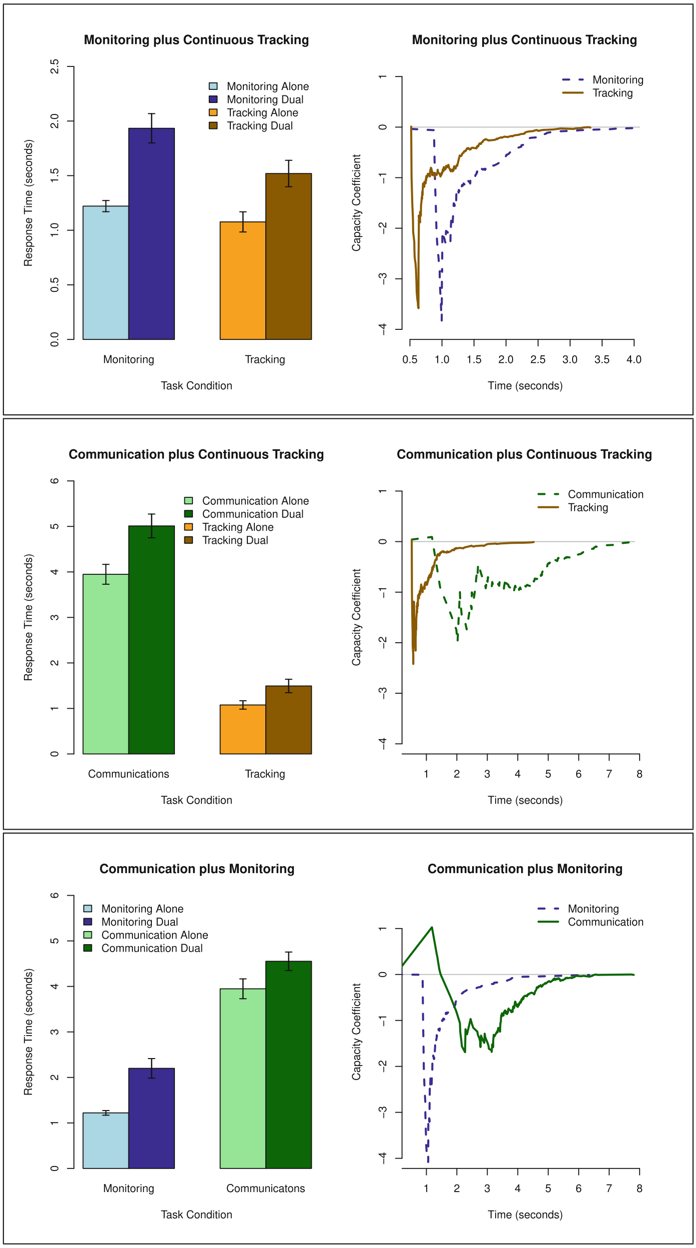

Fig. 2. Plots of the mean response times (left column) for the single and dual task conditions; corresponding capacity coefficient functions (right column). From top to bottom, the figure contains the MCT, CCT, and CM conditions. Error bars show ±1 standard error of the mean.

Table 1. Magnitude in seconds of the dual task response time interference effects

	Single task mean RT	Dual task mean RT	Interference effect
Monitoring plus continuous tracking			
Monitoring	1.22	1.93	−0.71
Tracking	1.08	1.52	−0.44
Communication plus continuous tracking			
Communication	3.94	5.01	−1.06
Tracking	1.08	1.49	−0.42
Communication plus monitoring			
Monitoring	1.22	2.20	−0.98
Communication	3.94	4.55	−0.61

$\overline{RT}_{Single} - \overline{RT}_{Dual}$ for each task. The corresponding plots of the single and dual task mean response times are shown in the left column of Fig. 2. Consistent with dual task expectations, all tasks show an increase in mean response time under dual task conditions, relative to the single task conditions. This is regardless of whether the task was designated primary or secondary; both tasks show performance interference.

The right column of Fig. 2 shows the capacity coefficient results for all tasks. Note that in all plots, the task designated to be primary is drawn with a solid line, and the secondary task capacity is drawn with the dashed line. As expected, and consistent with the interference effects at the mean level, we observe limited capacity during multitasking for all tasks. For the CM condition, we observe some surprising evidence of super capacity $C_{\mathrm{ST}}(t) > 0$ for the early response times in the communication task. This means that the additional task demands placed on the participant by the monitoring task actually boosted performance on events when the participant made a fast detection response. It is not clear from this analysis alone if that boost resulted from an increase in attentional resources to support the task, or an increase in motor resources to support the need to use one hand for two concurrent tasks. Either way, the capacity analysis suggests that workload efficiency during multitasking may not be a simple unidirectional effect on processing speed. Similar nuances are not reflected in the traditional dual task decrement analyses.

5 Discussion

Capacity coefficient analysis and traditional mean response time dual task interference analysis for mental workload rely on similar assumptions and techniques for assessing the impact increasing task demands have on performance. Both require the use of single and multiple task conditions, and leverage response time as the dependent measure of task performance. Both attempt to assay the degree to which tasks require common resources and impact cognitive effort through measurable interference (or lack thereof). As I have illustrated herein, when applied to two-task visual multitasking, with tasks that tap into common visual perception and motor response mechanisms requiring concurrent performance on the order of seconds, both measures lead to consistent interpretations about limitation in workload capacity. The presence of workload capacity limitations means that the information processing mechanisms must work harder to achieve the same amount of information throughput in any given amount of time. That is, capacity limitations imply a higher mental workload.

So why bother with a more complicated analysis that seems to give us the same basic interpretation? Capacity coefficient analysis, because of its theoretical grounding in information processing modeling and the use of a baseline model, immediately provides hypotheses about the mechanisms producing the observed workload efficiency. When observed performance is not equivalent to the UCIP model, we have three candidate mechanisms to investigate. First, performance could be non-UCIP if the assumption of parallel processing architecture is not correct. In the visual multitasking herein, the tasks are concurrent in nature. However, the organization of the mental information processing channels could be parallel (cues from each task processed simultaneously) or serial (cues from each task process sequentially). The latter implies fast mental switching between tasks is required, which is possible if attention is regularly switched between the task quadrants and independent alerting cues. If a person engages a standard serial processing architecture, then the resulting comparison to the UCIP baseline will produce limited capacity performance. Additional tests of processing architecture are available (see, e.g., [13,31]).

The second mechanism that can be tested is the degree to which the information processing mechanisms are operating independently. Process independence refers to stochastic dependencies between the information processing channels. Non-independence can arise from correlated inputs or cross-talk between the channels over the course of task execution [32]. This is not the same as concept of independence as resource independence, in which two or more tasks require the use of separate mental resources, such as visual and auditory perceptual mechanisms [36]. Inhibitory stochastic dependencies between the tasks will produce limited capacity performance relative to the UCIP baseline.

The third mechanism producing non-UCIP performance is the employment of a stopping rule or decision mechanism different from the one assumed by the $C_{\mathrm{ST}}(t)$ implementation. In the present effort, a single-target self-terminating stopping rule was assumed based on the nature of the concurrent visual alert response tasks. However, other decision rules are possible, such as an exhaustive cue processing strategy in which all cues within a task are examined before a decision-response is made. Use of a strategy requiring more decisions to be made than the ST-ST assumption will result in limited capacity performance relative to the baseline UCIP model defined for the assumed stopping rule (see [16] for an example of people engaging a stopping rule other than the one specified by the task).

There are additional sources of capacity limitations that may play into mental workload that are not captured by the capacity coefficient analysis. Working memory capacity, for example, represents a different set of mental resources that are known to be limited in nature but that are not assessed by a measure of information throughput. Recent work has attempted to determine the ways in which working memory capacity and workload efficiency capacity may reflect any common resources or may be measured conjointly [12,38]. However, evidence suggests the two are uncorrelated, consistent with multiple resource theory of mental workload [36].

Capacity coefficient analysis can scale to multitasking that includes more than two tasks, which is more difficult for dual task interference measures. While mean response times can be collected for any number of tasks, the generalization of the dual task comparison approach would be similar to an analysis of variance with pairwise comparisons between subsets of tasks. This approach based on purely empirical comparisons offers little theoretical foundation for predicting and interpreting the underlying mechanisms behind the empirical observations. Capacity coefficient analysis, together with other variations on the component hazard functions, naturally generalize to $n \geq 2$ tasks by straightforward extension of the baseline UCIP model [4]. The interpretation of the mechanisms of workload efficiency remain consistent because the fundamental baseline model remains consistent [30,32].

Objective, functional assessment of cognitive workload efficiency with the capacity coefficient offers a novel tool to support the goal of real-time cognitive state assessment [6,23]. Real-time state assessment is the process of inferring some aspect of a person's state, such as fatigue [3] or workload, online during task execution. Development of such a capability is considered critical for developing effective automation or adaptive machine aiding to mitigate the negative effects of cognitive moderators (e.g., task overload). Subjective measures of workload are considered too disruptive to be used frequently for online assessment; psychophysiological data streams can be measured continuously but they offer only indirect correlates of the cognitive states of interest. If a task offers a behavior for which response time can be measured with some regularity, then the task has the potential to leverage capacity analysis for objective assessment and mechanistic interpretation of cognitive states. There is much work left to be done in order to determine minimal task and data requirements to support robust inference, as well as to hone techniques for estimating the capacity models continuously. But the consistency of the interpretation of workload between standard dual task approaches and capacity analysis suggest this is a fruitful workload assessment technique to continue developing.

For multitasking scenarios in particular, real-time state assessment of workload will support adaptive machine determining when to interrupt tasks or to switch between tasks. Evidence consistently supports that task switching is most effective at points of low mental workload [1,7,33]. Iqbal and Bailey [15] demonstrated efficacy of this principle by using task models to predict points of low workload for best switching opportunities. Such task models, however, are not dynamically adaptive to changing environment, task, or human operator state demands. Model-based approaches to workload assessment, like the capacity coefficient, could supply critical input data for adaptive computational models that might be embedded into human-machine systems engaging adaptive machine intelligence to provide external support for effective multitasking or that attempt to mitigate cognitive overload.

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