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The Impact of Sleep Loss on Time Estimation: Reconciling Conflicting Results through Modeling

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Abstract

Short-term prospective time estimation is an important part of many tasks and there is a large body of research on the topic. However, the relationship between time awake and time estimation performance is unclear due to mixed and conflicting results. This paper focuses on two studies: one that provides evidence of a relationship between time estimation performance and time awake, and one that does not. In the former, the task required participants to estimate 10s time intervals, while the latter used a motion extrapolation paradigm. Using computational cognitive models, we implemented a mechanism to fatigue the timing module in ACT-R, which leads to one possible explanation for contrasting results in these two task paradigms.

Keywords: ACT-R; time estimation; sleep deprivation; cognitive model.

Introduction

Prospective short-term time estimation is an integral—and often overlooked—component of cognitive performance that plays a role in many daily tasks. When we drive to work, for example, short term time estimation might be used to gauge whether we will traverse an intersection before a street light switches from yellow to red. Short-term time estimation is also used extensively during human-computer interaction. Computer performance is often such that clicking a button does not produce instantaneous results, which we have learned to accept, but still interpret as an error if no response is evident within some short period of time.

Perhaps in response to the prevalence of cognitive activities that entail prospective time estimation, a large literature has emerged. Some of the earliest work revealed evidence of a relationship between time estimation performance and body temperature (Francois, 1927). Over the subsequent years, many other factors have been linked to time estimation performance, including age (Gilliland & Humphreys, 1943), light intensity (Morita, Fukui, Morofusi & Tokura, 2007), caffeine (Stine, O'Connor, Yatko, Grunberg & Klein, 2002) and others (see Panda & Pati, 2010, for a survey).

Most of these factors also have relationships to performance under conditions of sleep loss. For example, diurnal body temperature fluctuations are associated with

circadian rhythm (Kräuchi & Deboer, 2010), and are often used as a dependent measure in sleep deprivation research. Age also influences performance under sleep loss conditions (Philip et al., 2004; Webb & Levy, 1982), as well as light intensity (Lewy, Wehr, Goodwin, Newsome & Markey, 1980), and caffeine (Zwyghuizen-Doorenbos, Roehrs, Lipschutz, Timms & Roth, 1990).

Given the large number of common relationships that time estimation and sleep deprivation share, it seems reasonable to hypothesize some impact of sleep loss on time estimation performance. However, the literature on this subject is sparse and contradictory (Miró, Cano-Lozano, Espinosa-Fernández & Buela-Casal, 2003).

Many studies have reported no change in time estimation performance with sleep loss. For instance, Balkin, O'Donnell, Kamimori, Redmond, and Belenky (1989), found no effects in time estimation during 48 hours of restricted sleep, despite significant effects in seven other tasks testing a variety of aspects of cognitive performance. Similarly, participants performing a dual time estimation and tracking task (Bohnen and Gaillard, 1994) showed no significant effects in the time estimation portion after one night of sleep loss. Lastly, Ashcroft (1998) found no relationship between time awake and short-term time estimation performance in a study that examined the effects of living underground with a free-running circadian rhythm.

In contrast, Miró, Cano, Espinosa-Fernández, and Buela-Casal (2003) did find evidence for effects of both circadian and time awake on participants' ability to judge a 10 second time interval over the course of 60 hours of sleep deprivation. The circadian findings were subsequently confirmed by Kuriyama et al. (2003; 2005).

Although this more recent evidence seems to support the conclusion that a relationship exists between time estimation performance and alertness, it raises questions about the earlier results. Some researchers have noted that ambiguity in terminology has contributed to confusion in interpreting time estimation study results (Pana & Pati, 2010).

Beyond the terminology, the myriad factors that can influence time estimation performance may easily confound results as well. For example, Hancock, Vercuysen, and Rodenburg (1992) explain discrepancies in time estimation effects in their study as resulting from an interaction

between gender and time-of-day. Zakay (1990) has noted methodological issues in time estimation research that may contribute to the mixed results in past research.

In this paper, we use cognitive modeling as a tool to re-examine the results found in two of the papers mentioned above: Miró et al. (2003), which found significant effects of sleep loss on time estimation performance, and Balkin et al. (1989), which did not. We begin by describing a cognitive model that performs the Miró et al. (2003) counting task, and use it to develop and validate a fatigue mechanism for time estimation. Next, we describe two alternative cognitive models of the Balkin et al. (1989) motion extrapolation task and demonstrate that the models' performance characteristics change little when the fatigue mechanism is applied. Based on the modeling results, we examine how characteristics of the tasks used in the original empirical studies influence how time estimation is calibrated, leading to a dissociation in the observed impacts of sleep loss on performance in the model.

Counting Task

In Miró et al. (2003), participants performed a time estimation task every two hours during a 60-hour period of sleep deprivation. In their task, participants were instructed to estimate a 10-second interval by counting. They received no feedback regarding their accuracy. In this study, Miró et al. (2003) found clear evidence of both circadian and homeostatic effects on participants' ability to judge a 10 second interval over the time duration of the experiment. The results are shown in Figure 1.

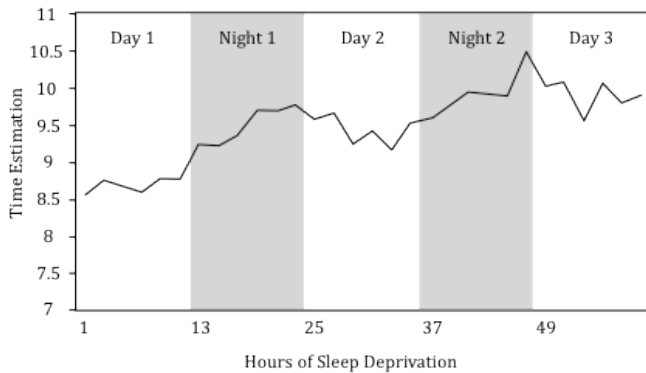


Figure 1: A reproduction of the original Miró et al. (2003) findings, showing mean 10s time estimates from participants over the course of 60 hours of sleep deprivation.

Counting Model

We used the ACT-R cognitive architecture (Anderson, 2007) to create a computational model to perform the counting task. The ACT-R software is well documented, and includes an 8-unit tutorial for beginners with several models discussed in each. The very first unit includes a simple model that counts, and that model formed the basis for our model of the Miró et al. (2003) time estimation task. As provided, the model counts as quickly as possible, so

some additions were required to count in timed intervals. Specifically, we made use of the temporal module (Taatgen, van Rijn, & Anderson, 2007) – an ACT-R component that adds cognitively plausible timing mechanisms. The temporal module provides an empirically validated instantiation of the “internal-clock” model that is frequently referenced in the time estimation literature (Matell & Meck, 2000).

The internal-clock model is comprised of three components: the clock component, the memory component, and the comparison component. The clock component is a repeatable stream of successively longer pulses or ticks that is triggered upon receipt of a start signal. These are exposed as a tick count in the temporal buffer in ACT-R. The memory component provides the basis for remembering the number of ticks related to an event. Taatgen, van Rijn, and Anderson (2007) rely on the standard ACT-R declarative memory system to fill this role. Lastly, the comparison component provides the mechanism for making decisions based on comparisons of tick counts from memory to the current pulse stream. The ACT-R production matching system allows for buffer comparisons between temporal and declarative memory buffers to provide this service.

In our model of the Miró counting task, the internal clock is signaled to start at the same time that a request is made to declarative memory for the next number in the counting sequence. Using the ACT-R tutorial model as the foundation, we added a constraint on the production that responds to the result of the declarative memory retrieval so that it could not fire until a specified period of time had passed.

We consider the subjective time span of 1 second to be a piece of knowledge, much like a math fact, and it is coded directly into the model as the number of ticks to wait before count increments. Under the alert condition, participants underestimated the 10s interval and produced a mean estimate of 8.5s. The corresponding number of ticks per second to produce that estimate can be calculated by solving Equation 1 for k :

$$t = \sum_{n=0}^{k-1} t_0 a^n \Rightarrow .85 = \sum_{n=0}^{k-1} (.011)(1.1)^n \quad \text{Equation 1.}$$

where t_0 is ACT-R's *:time-master-start-increment* parameter, which indicates the initial tick duration, and a is ACT-R's *:time-mult* parameter, which is the factor that is used to compute the increase in each subsequent tick duration. Using default values for t_0 and a , the resulting value for k is approximately 23 ticks.

Based on their findings, Miró et al. (2003) theorized that internal clock ticks slowed down under conditions of sleep loss. For modeling purposes, this translates directly into slower clock ticks in the temporal module in ACT-R. Both *:time-master-start-increment* and *:time-mult* could accomplish such a slow down. Without experimental data to distinguish between the two potential mechanisms, the work

in this paper arbitrarily leverages `:time-mult`. The default value is 1.1, meaning that each subsequent tick becomes 10% longer. By increasing this value, we can effectively slow down ACT-R's internal clock much the same way that Miró et al. (2003) described.

We then fit the model to the final session in the experiment by adjusting the `:time-mult` parameter in the fatigue module. We found that a value of 1.112 resulted in time estimates of approximately 9.5-10s, corresponding to participant performance after 59 hours awake (Figure 1). To estimate parameter values for the intervening sessions, we scaled this parameter using a biomathematical model of fatigue developed at Washington State University (McCauley, Kalechev, Smith, Belenky, Dinges & Van Dongen, 2009). The biomathematical model produces predictions of fatigue based on functions representing time awake and circadian rhythms. Using the estimated values for `:time-mult` for the first and last sessions, combined with estimates of fatigue from the biomathematical model for each session, we were able to identify a linear function to map fatigue values onto values for `:time-mult` as follows:

$$:time-mult = .0011 B(t) + 1.1 \quad \text{Equation 2.}$$

where $B(t)$ is the biomathematical prediction of fatigue at time t .

Results

Figure 2 shows model performance using the `:time-mult` values from Equation 2 where t ranged from 1 to 59 in two hour increments as in the original study. We also enabled stochasticity in production firing times. The remaining parameters were unchanged from the original ACT-R counting model provided in the tutorial.

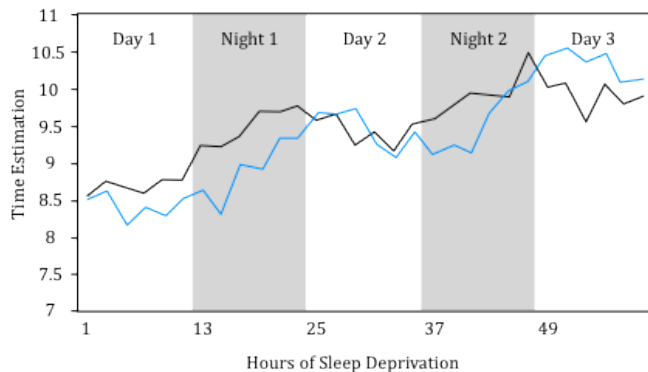


Figure 2: Counting model predictions of a 10s time estimation (blue) shown with a reproduction of the original Miró et al. (2003) findings (black).

We ran the model 1000 times to produce a consistent central tendency, and compared its performance to estimates of the original Miró et al. (2003) data. This comparison produced a root mean square error (RMSD) of .41 sec and a correlation of .86.

Discussion

While the counting model reproduces the trends of participant performance fairly well, Figure 2 shows a phase difference between the model and empirical data. It has been shown that an individual's chronotype (i.e. whether they are a "morning person" or an "evening person") can play a role the phase of their circadian rhythm (Kerkhof & Van Dongen, 1996), which may account for some of the phase difference between the empirical data and the circadian predictions from the biomathematical model.

To simulate the course of 60 hours of sleep deprivation, the `:time-mult` model parameter was manipulated. In the first hour it was left to its default value of 1.1, but it was explicitly adjusted to 1.112 to fit performance in the final hour of the experiment. Even though the delta is only 1.2%, it is enough to produce approximately 2 seconds difference in mean time estimations. This provides an illustration of how quite modest fluctuations in the underlying cognitive mechanisms can produce substantial changes in observed behavior.

Dropping Ball Task

The Balkin et al. (1989) protocol consisted of 24 hours of sleep deprivation, followed by 6 hours of sleep recovery, and another 18 hours of sleep deprivation. Some participants received an injection of triazolam prior to the recovery period, the effects of which were the focus of the study. Every two hours participants were asked to perform a battery of tasks, one of which involved observing a ball dropping at a constant velocity on a computer screen until it was occluded in the lower third. Participants responded with a key press to indicate their prediction of when the ball would cross a notch at the bottom of the screen. The ball's traversal of the screen to the notch was consistently 10s, so that would be the ideal response time. There were 10 trials per bout. Participants received no feedback on their performance during the course of the experiment.

As mentioned in the introduction, Balkin et al. (1989) failed to find any significant effects of sleep loss in their time estimation task over the course of sleep restriction, independent of the triazolam administration. Presumably due to their null findings, they did not report any data. To establish the validity of the model's baseline behavior, we chose to recreate their task and conduct a study to gather data under baseline conditions.

The task was originally described as part of the Walter Reed performance assessment battery (Thorne, Genser, Sing, Frederick & Hegge, 1985), and our recreation was based on that description. The task was written in Python using Pygame, and the graphics were constrained to an effective 14 inch diagonal area to account for the smaller screens in 1989. We also altered some of the colors, to aid in clarity for the instructions. The original task instructions were not described in the Thorne et al. (1985) report, so we opted to focus on the task goal without providing any guidance for strategy (see Figure 3). We increased the number of trials to 100, and collected data from 6

participants (4 males and 2 females), with ages ranging from 19 to 44.

- 1) You will see a ball drop from the top of the screen towards a black rectangle at the bottom.
- 2) The blue area will cover the ball as it is dropping.
- 3) Press the space bar when you think the ball has reached the black rectangle.

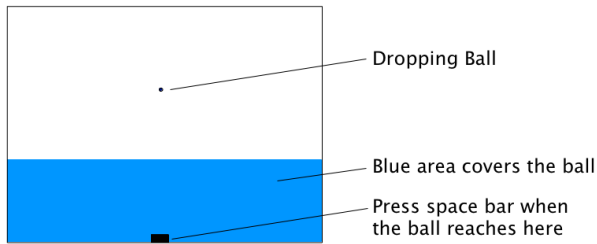


Figure 3: Instructions and diagram of the dropping ball task.

Following the experiment, participants were queried about the strategy they used to inform the development of the model. The task itself is very similar to one used heavily in the motion extrapolation literature (Peterken et al., 1991), so we expected to model a motion extrapolation process. At the same time, all participants in our study reported developing a timing strategy. They learned how long to count during the period where the ball passes behind the occlusion before responding. We developed cognitive models of both strategies to explore the capacity of each to capture baseline performance and to evaluate the impact of our fatigue mechanism in both cases. We did not, however, model strategy selection or transition.

Motion Extrapolation Model

The motion extrapolation model of the dropping ball task was based on findings by Lyon and Waag (1995). Using a circular version of the task, they conducted several experiments that helped isolate the mechanisms and strategy that participants used. The mathematical model that best explained participant performance in their task was one in which motion was extrapolated based on a steady velocity, with variability arising from error in velocity estimate. The first of our ACT-R models uses the same strategy that Lyon and Waag (1995) identified in their paper.

We tested three modeling approaches to implementing the tracking process in ACT-R. The first approach employed the commonly used two-stage attend and encode paradigm, but it proved to be problematic because the object was moved before the encoding could successfully complete. An ACT-R parameter to adjust the movement tolerance during encoding could have been adjusted, but it would add an additional degree of freedom to the model.

The second approach we tested used ACT-R's visual tracking feature, which allows an object's motion to be tracked after it has been encoded. This approach worked

reasonably well once the object was encoded, but again, it required an adjustment to the visual movement tolerance parameter for the initial encoding of the object to succeed.

While the ACT-R visual system accepts requests for visual locations, it can also identify location information automatically, without a request. This approach, known as "buffer stuffing," was used in our model. As the ball is the only moving object on the screen, the ACT-R visual system proactively provides the ball's location information in the visual location buffer. The visual location is all the information that is required by the model to calculate the distance traversed. Since there is only one moving object in the task, encoding for identity information is unnecessary.

As a result of the visual location buffer stuffing process, a production fires regularly that tracks the location of the ball. The effect is identical to what occurs when using ACT-R's visual tracking feature, without the necessity to pre-attend the object.

Within the goal buffer, the distance and time (i.e. the components of speed) of the ball's motion are tracked after each sighting. The occlusion of the ball in the task is accomplished by simply removing the ball from the virtual task screen. At this point the model begins predicting the ball's position using the last observed speed. We used the last observed speed as opposed to an averaging technique because it leads to greater variability in time estimates that more closely matched human performance. The now-imaginary ball's position is repeatedly updated with the same speed until it reaches the bottom of the virtual window. At this time, the model responds with a key press.

Timing Model

Participants reported varying strategies to determine how long to count while the ball is occluded. Our second model uses a strategy that relies on recognition that the occlusion area is 1/3 of the vertical distance, but other approaches would produce similar model results. While the ball is visible, the model counts in estimated one-second increments until the ball is occluded.

Counting was implemented in the same fashion as the counting model: 23 ticks were used to approximate a second, and the timer was reset after at the start of each increment. All parameters values were identical to the counting model.

After the ball is occluded, the model recounts half the amount at the same rate, and responds with a key press. The task provides no feedback to the model, so there is no opportunity for learning and correction.

Results

Both the motion extrapolation model and the timing model were run 1000 times to reveal the central tendency for comparison with the empirical data. In the absence of any fatigue mechanisms, the motion extrapolation model produced a mean response time of 10.13s with a standard deviation of .46, while the timing model produced a mean response time of 9.77 with a standard deviation of .31.

The mean response from participants in our study was 9.80s, and the individual mean response times produced a 95% confidence interval ranging from 9.06s to 10.54s. The mean standard deviation was .46, with a 95% confidence interval ranging from .32 to .76. The model's mean predictions fit within expected human performance range (see Figure 4), although the standard deviation of the timing model is slightly low.

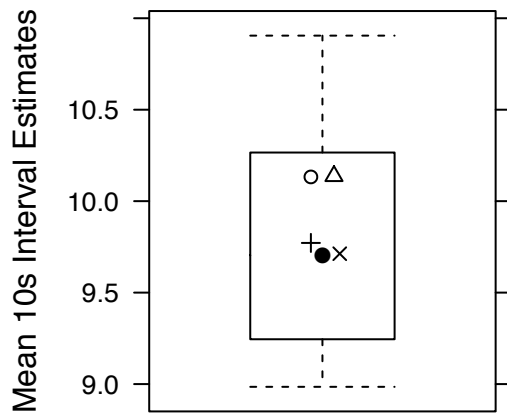


Figure 4: Box plot of mean participant estimates of 10s intervals under baseline conditions. Model predictions from motion extrapolation under alert (o) and fatigue (triangle) conditions, as well as the timing model under alert (+) and fatigue (x) conditions are also shown.

To simulate 59 hours of sleep loss, we set :time-mult to 1.112 in both models, matching the value we estimated in our analysis of the counting model for the task in Miró et al. (2003). Under fatigue conditions the motion extrapolation model produced a mean response time of 10.14s, while the timing model's mean response time was 9.71s.

Discussion

The mean response times for both models fell within the confidence intervals of the empirical data under alert, baseline conditions. We then applied the temporal fatigue mechanism (previously validated with the counting model) and showed that the performance of both models was still within the confidence interval of alert human response times from our baseline study (see Figure 4). These results are consistent with the null effects found by Balkin et al. (1989), though, as mentioned above, they did not report any data from this task. Still, an analysis of the models provides a clear explanation for the lack of impact of sleep loss on performance in this task.

The critical distinction between the counting task and the dropping ball task is one of feedback during the trial. In the counting task, the participant receives no feedback whatsoever. In contrast, during the dropping ball task, the speed of the ball at the start of each trial provides the

participants (and both models) with an opportunity to calibrate time estimates to the task.

Recall that the ACT-R mechanism to simulate fatigue in the temporal module increases the tick multiplier. Thus, for a given distance of traversal for the dropping ball, the model will estimate that it took more ticks under alert conditions than it would under sleep deprivation conditions. As speed is described by distance divided by time, a smaller number of ticks would make the ball appear to be moving marginally faster under conditions of sleep loss.

Even though the model perceives the ball moving faster or slower depending on :time-mult, this has little impact on its motion extrapolation or timing performance. The models predict that the performance impact would be the same as that of predicting balls moving at slightly different speeds.

It is interesting to note that in Figure 4 the timing model more closely matches participant performance than does the motion extrapolation model. This may reflect an early strategy shift from motion extrapolation to timing so that most of the trials are representative of the timing strategy.

Conclusion

Our model for the task used by Miró et al. (2003) was based on a very well known and heavily scrutinized model of counting in ACT-R. With minimal changes we were able to fit the empirical data well across 30 sessions of data spanning 60 hours of total sleep deprivation. A significant contribution of this model was the development of a mechanism that affects the tick multiplier of the temporal module based on sleep patterns and time awake. The mechanism amounts to an instantiation of the general theory proposed by Miró et al. (2003).

The mechanism was parameterized using the Miró et al. (2003) data and it was found that modest changes to the tick multiplier parameter (1.2%) in the ACT-R temporal module could account for significant performance changes observed over the course of 60 hours of sleep deprivation. The mechanism was then tested in a different context with the Balkin et al. (1989) time estimation task. Two model strategies were tested, and when combined with the previously established mechanism for temporal fatigue we were able to provide a possible explanation why the original experiment may not have found any significant time estimation effects.

Analysis of a task very similar to the dropping ball experiment (Peterken et al., 1991) showed that performance was most closely correlated with the amount of time that the ball was obscured. Thus, the design seems like a reasonable way to measure time estimation performance. However, our model suggests that the experiment provides indirect feedback to the participant that allows them to adjust to any internal clock slow down. Our model is able to reveal the potential weakness of this task for exposing changes in that component of cognitive functioning.

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