Counting On ACT-R to Represent Time

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Temporal issues consistently factor into decisions, yet surprisingly few research studies have explored how to model temporal cognition. We developed an Adaptive Control of Thought – Rational (ACT-R, e.g., Anderson & Lebiere, 1998) model to help account for how people estimate time, one of many issues in temporal cognition. According to the model, people adjust the lengths of words through abbreviation or extension and produce the words at a rate in tune with the rate of environmental events. This procedure allows an individual to synchronize with regular intervals of time in the environment and produce just-in-time responses to events. This type of approach incorporates a behavioral aspect to time estimation and an ACT-R model of temporal cognition that requires no changes to the architecture of ACT-R.

INTRODUCTION

Temporal cognition is a field given surprisingly little attention in cognitive modeling. Here, we focus on a counting task in which rhythmic intervals improve cognitive performance (Carlson & Cassenti, 2004) over unpredictably timed intervals and describe an ACT-R (Anderson & Lebiere, 1998) model that matches these data and outlines a mechanism of time estimation (see Cassenti, 2004, for details).

Empirical study

Carlson and Cassenti (2004) conducted a study in which participants were asked to count thirty to eighty white asterisks (total determined randomly) that appeared one-at-a-time in the center of a black background. Each participant had ten trials with intervals of fixed step duration (onset of one asterisk to the onset of the next) of 550 ms. Another ten trials were presented with a varied interval length, randomly selected every trial from a pool of interval lengths – 400, 500, 600, or 700 ms. For every step, 200 ms was devoted to the asterisk appearance and the rest of the time for that step (e.g., always 350 ms in the rhythmic conditions) was devoted to a blank screen. All thirty-three participants were instructed to count all the asterisks and type their final count into a response box that appeared at the offset of the final asterisk.

Carlson and Cassenti (2004) filtered the data to exclude all trials in which responses exceeded correct by an absolute error of five (these infrequent errors were typically off by about ten suggesting a typing error or a participant-derived strategy of counting by ones and misremembering the ten's digit). Participants counted with greater accuracy on rhythmic trials (82.9% correct) than varied trials (52.7%). In addition, a distinct pattern of errors (i.e., the response minus the correct answer) emerged from the data. The distribution of errors on rhythmic trials showed predominant undercounting (i.e., response lower than correct answer) and the distribution of errors on varied trials showed predominant overcounting (i.e.,

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response higher than correct). The average signed error of each timing condition (i.e., the size and direction of response from correct) were –0.163 and 0.405 for rhythmic and varied trials, respectively.

Theoretical framework

Carlson and Cassenti's (2004) pattern of results suggests that participants tuned a temporal cognitive mechanism to approximate the rhythmic interval duration and decreased the frequency of overcount errors. Undercount errors are therefore errors that naturally occur from some mechanism of cognition and cannot be prevented through the temporal mechanism. Indeed the frequency of undercount errors is about the same in both rhythmic and varied trials with the frequency of additional overcount errors in varied trials overwhelming the number of undercount errors in average signed error.

The temporal mechanism not only tuned to the rhythmic interval in the rhythmic condition, but it may have tuned to the shortest of the varied intervals in the varied condition (i.e., to ensure that the system was always ready for the next count, Cassenti, 2004). In the varied condition, overcounts may have predominated because the system counted twice, once while waiting for the next event and once when the item appeared. Undercounts may result from using the same number twice and would occur regardless of whether the temporal mechanism tuned to the event rhythm.

Previous model of timing

The challenge in modelling the above theoretical framework is how to represent the temporal mechanism. Taatgen, van Rijn, and Anderson (2004) described a model of temporal cognition that used direct readings from a mental clock to provide an up-to-date number representing interval length and a degree of normally-distributed noise. The model was based on research by Matell and Meck (2000) that proposed a neuropsychological timekeeper that provided an explicit representation of time. The present model represents a different approach to modeling a timekeeper mechanism. Instead of including a modular timekeeper that provides interval length directly, the present model estimates time through its own behavior.

COUNTING MODEL

As with Taatgen et al. (2004), we chose to use ACT-R (Anderson & Lebiere, 1998) as our modeling architecture. ACT-R is a cognitive architecture, defined as: a theory for simulating and understanding human cognition. As research continues, ACT-R evolves towards a system that can perform the full range of human cognitive tasks: capturing in detail the way we perceive, think about, and act on the world.

The ACT-R architecture is realized as a production system, by representing procedural knowledge in the form of if--then rules (productions) to process, store, and retrieve declarative memory, in a hybrid semantic network. ACT-R is also capable of compiling these productions to generate new procedural knowledge.

ACT-R has two classes of declarative memory, chunks and goals (which technically are a special type of chunk). The goals specify the information from the current step and guide production activation. The goal-specified production transforms the state of the problem in the environment or in memory and depends on chunks to provide information needed in the problem. In the present model, the chunks are primarily numbers and the productions increment the running total in synchronization with the appearance of items.

The model operates by following a prescribed sequence of productions for each step. The model begins each step by retrieving the name of the current number and covertly producing the name. Once the number name is produced, the model either waits to perceive the next item or, if the item appears directly after the name productions, immediately perceives the item. After perception productions fire, the model chooses a new number to assign to the perceived item. If the new item is a response request, the model reports the current number in memory rather than retrieving a new number.

The model increments by using ACT-R's activation mechanisms. When a number is selected, it adds activation strength to the number one higher than itself. A new number is selected if it passes a retrieval threshold set by the model developer. While the current number is in use, its activation decreases through ACT-R's decay mechanism and typically falls below the retrieval threshold, leaving the next number as the only number in memory to exceed the threshold.

Whereas overcounts are caused by a strategy of timing new counts to occur before the appearance of a new item, the model suggests that undercounts are caused by system-wide declarative memory activation noise. Noise in ACT-R is defaulted to zero. In the present model, noise was set to 0.028. This small level of noise causes the activation of the current number to rarely exceed the next number, resulting in a small number of undercounts.

The model estimates time by pronouncing each number in ACT-R's output buffer. The time to speak a number is manipulated by changing the default production times on all speaking productions to equal the rhythmic interval length or the minimum length of the varied intervals. This strategy creates a mechanism by which the model can produce just-in-time responding in the rhythmic condition and a mechanism to prepare the number as soon as it might be needed in the varied condition. This is implemented in the model by including syllable slots in the number chunks and designing the syllables to be constrained around two or three syllables to keep all numbers at a constant length. In the varied condition, number names are constrained to two syllables (e.g., twenty-five is twen-five) and in the rhythmic condition number names are three syllables long (e.g., twenty five is twent-ty-five). This strategy is analogous to the one used by children playing hide-and-go-seek, who turn around with eyes covered and repeat, "One Mississippi, two Mississippi . . ." to some pre-arranged number. Hinton and Rao (2004) demonstrated that this type of strategy improves performance in a temporal task.

When the speaking productions end before the item appears (i.e., in approximately 3/4 of varied trials and rarely in rhythmic trials) the model will call a wait production to give the item time to appear. In the model there are two wait productions, one to wait and one to wait but also increment to the next total. In order to match the results of the experiment, the utility of picking the wait-and-increment production was set to 0.01 the utility of the wait-and-not-increment production with an expected gain noise of 1.8. These parameter changes gave a small chance that the model would overcount in a given sequence. Activating the second production can be seen as a failure to inhibit the prepotent response of incrementing when finished producing the name of the current total.

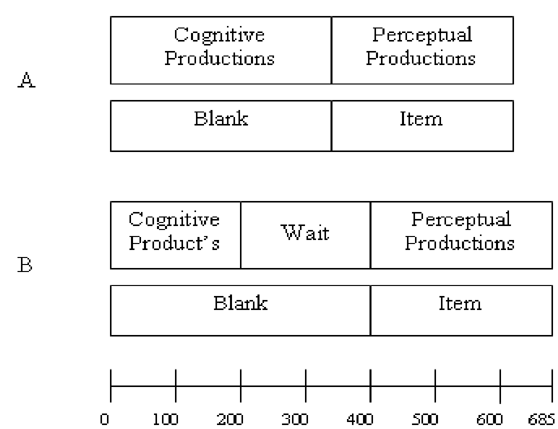

Figure 1. Time sequence of one step of model. Panel A shows rhythmic counting, tuned to the event rhythm. Panel B shows varied counting, when the step interval is 200 ms longer than the cognitive productions cover. The wait period may result in an overcount.

Table 1 and Figure 2 display the model fit to Carlson and Cassenti (2004). The model replicated the data reasonably well in all conditions after we removed the data from one participant. The participant's data skewed the marginal mean of varied signed error (the error filter which removed all errors greater than five in magnitude left only one trial of positive five for this participant and left the average signed error higher than reflected in the other data points).

Table 1. Comparison of model to empirical (human) data including Pearson correlation (*r*) and a measure of the amount of variability accounted for by the model (R^2).

	Rhy. Acc	Var. Acc	Rhy. SignedE	Var. SignedE
Human	0.837	0.544	-0.165	0.262
Model	0.878	0.431	-0.153	0.078
r	0.940	0.953	0.932	0.937
R^2	0.883	0.908	0.868	0.877

* Note: Rhy stands for rhythmic condition, Var stands for varied condition, Acc stands for accuracy, and SignedE stands for signed error.

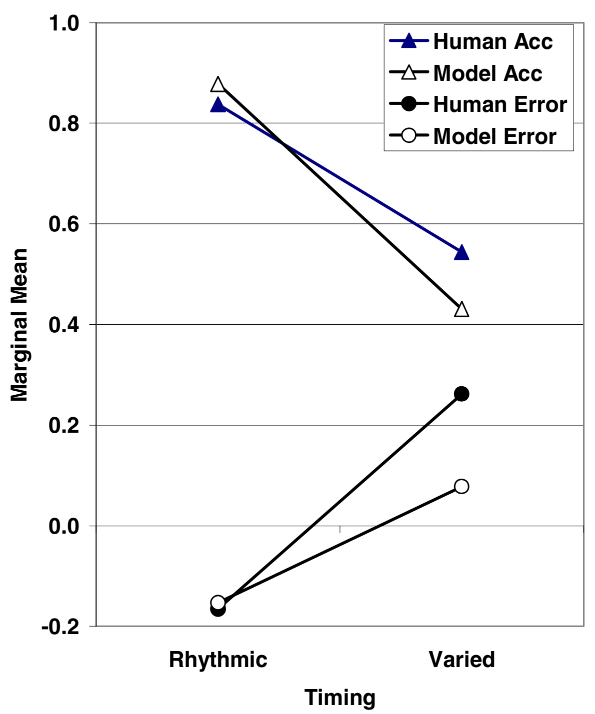

Figure 2. Comparison of human and model accuracy (Acc) and signed error (Error).

Neurological basis

The Taatgen, et al. (2004) model adopted the neuropsychological approach of Meck and Matell (2000), which cited the basal ganglia as the most likely brain region corresponding to a mental timekeeper. Researchers have traditionally tied the basal ganglia to motor control, however Meck and Matell (2000) simply attach the new function of timekeeper to the basal ganglia rather than establishing a connection between motor behavior and time estimation.

Jones and Boltz (1990) suggest that effectors are muscle groups that help people maintain a rhythm (e.g., a guitarist tapping a foot to a beat). An alternative to the Meck and Matell (2000) theory that timekeeping is an additional function of the basal ganglia is that the basal ganglia move effectors and adjust those effectors to a rhythm in the environment. The basal ganglia would not then contain a timekeeper module, but instead control muscles to adjust the movements to temporal feedback provided by the environment. This is analogous to the coordination of spoken syllables in the present model and precludes the need for an additional temporal module in ACT-R as suggested by Taatgen et al. (2004).

Multi-tasking model extension

Brown (1997) demonstrated that people who estimate time, while engaging in a secondary activity show a decline in temporal performance. A revision of the present model might also show a decline in performance as Taatgen, Anderson, Dickison, and van Rijn (submitted) demonstrated for the Taatgen et al (2004) model. In a possible revision, the model may simply adjust the timing of actions required to perform the secondary task to the temporal interval required in the time estimation task. This strategy should reveal decline in either the temporal or secondary task performance as the model attempted to fit likely opposing temporal structures upon one another. Reproducing the syllables of numbers is more temporally malleable than performing the required actions of a secondary task.

Limitations of model

The present model fits the intended empirical data; however more work is necessary to model other temporal studies and other temporal processes. First, the present model does not address the learning of rhythmic intervals. Although Cassenti and Carlson (2004) show that learning a rhythmic interval approximating the one in the present empirical study occurs within about the first ten steps, temporal learning must still take place. Taatgen et al. (2004) address learning in their model, but the present model needs further work to model this aspect of temporal cognition.

Another limitation of the model is the lack of correspondence between the timing conditions of the empirical study and those in the model. Currently, the model presents to-be-counted items 85 milliseconds (ms) longer than in the actual rhythmic condition (as shown in Figure 2) and 300 ms longer in varied due to the relative slowness of ACT-R's perceptual processing and the unpredictable timing of the end of the wait production, respectively, compared to the people in the experiment.

CONCLUSIONS

The present model represents an interpretation of the mental processes that produced the results in Carlson and Cassenti (2004). The current approach represents an alternative representation of temporal cognition to Taatgen et al. (2004) by removing the necessity of adding a new module to ACT-R and thereby changing the structure of ACT-R. The present version of the model is undergoing revisions, such that later versions should encompass more temporal cognitive phenomenon and produce an effective and realistic model of a previously inadequately explained portion of human cognition. Temporal factors are important to virtually all decisions and a model of temporal cognition may help guide human factors engineers design better training regimens or products that rely on existing human timing mechanisms.

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