Time Perception: Beyond Simple Interval Estimation

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Abstract

Reasoning about and with time has never been studied extensively in the context of cognitive architectures. We present a temporal reasoning system that can make accurate predictions for two classic interval estimation experiments by Rakitin et al. (1998) and Penney et al. (2000). The system is implemented as an additional module for ACT-R. In combination with ACT-R's other mechanisms, it makes accurate predictions about experiments that go beyond just estimating time. We demonstrate this by modeling data from a choice-reaction task by Grosjean et al. (2001).

Temporal Reasoning

Despite the fact that most cognitive architectures make predictions about time, they do not support models that reason about time itself. People on the other hand usually have a good sense of the passage of time, and use this capability, often implicitly, to handle time intervals in their reasoning. The classical example is approaching a traffic light that turns from green to yellow. The decision drivers are faced with is whether to brake or drive on, which depends on their (earlier established) sense of time about when the light will turn red. A sense of time may also be necessary in the coordination of multi-tasking. For example, when driving a car and keying a number on a cell-phone at the same time, it is necessary to keep track of elapsed time between consecutive checks of the road condition. In interaction with computers, it is not uncommon that some time elapses between the user's input and the computer's response, especially when it concerns the internet. It is important for the user to be able to assess whether the waiting time is reasonable, because an interval that is too long might indicate a problem (either in the software or the user's understanding of the interface).

When one wants to model the estimation of time intervals in a cognitive architecture, the important question to ask is whether or not interval timing is an architectural feature or something that can be modeled with an appropriate set of knowledge. The only way to keep track of time in the context of the ACT-R architecture[1] (Anderson & Lebiere, 1998) is explicit counting, making it almost impossible to account for tasks in which an implicit sense of time partly determines behavior. Even more, experimental results indicate that humans can assess time intervals when explicit counting is discouraged or forbidden. There are also biological and neuropsychological reasons to favor an architectural solution. It is well-known from the behaviorist literature that animals can learn time intervals. For example, if rats or pigeons receive a reward when they press a bar, they quickly learn to anticipate this. However, when this reward is only given every 30 seconds, the rats will increase their bar-pressing when the 30 second deadline approaches, clearly showing a sense of the duration of the time interval (Gibbon, 1977).

More recent neuropsychological research suggests that there are particular areas in the brain related to the estimation of time intervals. Based on several studies, Matell and Meck (2000) have constructed a model of interval timing, which we summarize in Figure 1a. The general idea is that certain stimuli can synchronize neurons in a certain region of the cortex, effectively acting as a starting sign. As each of the neurons produces its own particular pattern of activation in time, each moment in time is associated with an unique pattern of activation. These patterns are recognized by striatal spiny neurons, whose activations are then integrated by certain basal ganglia output nuclei (globus pallidus, entopeduncular nucleus and substantia nigra reticulata), and then relayed to the thalamus for behavioral expression.

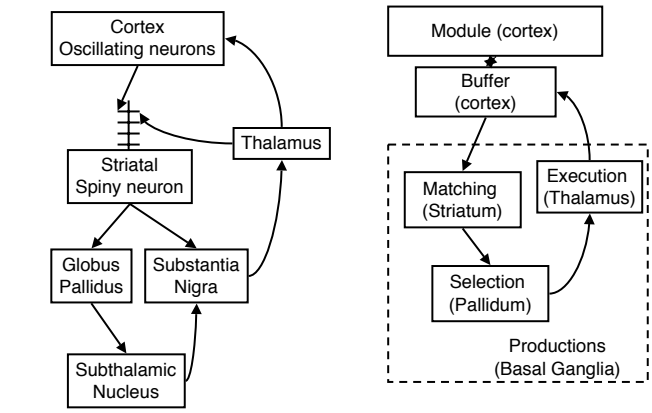

Figure 1. Matell and Meck (2000) model and the general ACT-R production matching schema

The neural mechanisms proposed by Matell and Meck show a close resemblance to the mappings from ACT-R onto the brain, shown in Figure 1b. ACT-R assumes several cortical buffers corresponding to the goal, retrieval,

[1] Note that time is used for utility calculations. However, ACT-R has no direct access to subsymbolic quantities.

perceptual and motor systems. The contents of these buffers are matched in the striatum, after which one production rule is selected in the pallidum. The thalamus then takes care of the execution of the production rule, which can for example reset the internal time. We therefore propose to model time estimation by adding an extra module to ACT-R that implements the perception of time. Mapping the M&M model onto ACT-R produces a model in which most systems correspond to general architectural areas, with the exception of the special-purpose temporal buffer and module.

The Temporal Module

The general idea, based on Matell and Beck (2000), is that an internal timer can be started explicitly to time the interval between two events. Matell and Beck hypothesized that a start event resets the cortical neurons. Given that different neurons have different associated firing patterns, each point in time is characterized by a different subset of firing neurons. Therefore, at any given point in time, the state of the neurons is a representation of the time passed since the resetting of the clock. Since some neurons have a greater periodicity than others, similar durations will be associated with similar patterns. As coarse time-grained neurons are the main determiners of the time elapsed for longer intervals, timing becomes less precise for longer durations.

To approximate this process in the simulation we represent the current neural pattern by an integer. A reset event sets this integer to zero, after which it is increased as time progresses. The idea is that the temporal module acts like a metronome, but one that starts ticking slower and slower as time progresses. The interval estimate is based on the number of ticks the metronome has produced. More precisely, the duration of the first tick is set to some start value:

$$t_0 = \text{starttick}$$

Each tick is separated from the previous tick by an interval that is *a* times the interval between the previous two ticks. Each interval has some noise drawn from a logistic distribution added to it. The distribution of this noise is determined by the current tick-length.

$$t_{n+1} = at_n + \text{noise}(mean = 0, sd = b \cdot at_n)$$

We have estimated values for the parameters in these equations on the basis of an optimal fit to the first experiment, interval estimation. There we found 11 ms for start tick, 1.1 for *a*, and 0.015 for *b*. These values also provided excellent fits to the other experiments discussed in this paper.

The starting of the timer is triggered by a production action. This timer generates incremental timestamps that virtually represent firing neurons. The current state of the timer can be matched in the condition of a production. This match can take two forms. The first form is reading out the current value of the timer. This occurs when the variable being matched is not yet bound to a value. In that case the variable is instantiated to contain the current value of the timer. If we store this time pattern in the goal or in declarative memory, it can be saved for future use. This future use is also the second form of using the patterns: by matching the temporal buffer to a specific value. The match only succeeds if the buffer (approximately) has the value we try to match, thereby making it possible to have production rules "wait" until their time to fire.

Example: Estimate and Reproduce a Time Interval

Suppose we want to reproduce a time interval, as represented in the first horizontal bar in Figure 2, that is defined as the time between the start of a trial and the moment a light comes on.

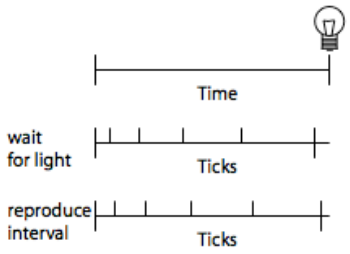

Figure 2. Illustration of the temporal module

A first production will start the timer:

(p start-learn =goal> isa reproduce-interval state begin ==> +temporal> isa time =goal> state wait)	IF the goal is to reproduce an interval THEN initiate the time module AND wait

The "+temporal>" on the right hand side initiates the time module by resetting the internal timer. After the timer has been reset, it starts recording the increasing ticks as shown in the second bar of Figure 2. As soon as the light comes on, a second production rule fires and reads out the current tick value:

(p respond-to-light =goal> isa reproduce-interval state wait =visual-location> isa visual-location =temporal> isa time ticker =time ==> =goal> time =time state wait-again +temporal> isa time)	IF the goal is to reproduce a pattern and we are waiting AND a visual stimulus has been found AND the current time is *time* THEN store *time* in the goal AND restart the timer

As the temporal module's state is in the interval between tick 5 and 6, the value read from the buffer will be 5. Now that we have a pattern, a new production rule can initiate the key-press after approximately the same amount of time has elapsed. Note that in the above production rule, the time module is reset again, so a new series of ticks, represented in the bottom bar of Figure 2, is initiated. As soon as the temporal state resembles the stored value, in the example in Figure 2 slightly later due to noise, the production rule below initiates a key press.

(p respond-to-predicted-light =goal> isa reproduce-interval state wait-again time =time =temporal> isa time ticker =time ==> +manual> isa press-key =goal> state done)	IF the goal is to reproduce an interval and we are waiting for interval *time* to pass AND the temporal buffer has reached value *time* THEN press the key

The estimation process here seems to under predict the interval because the real time is rounded down to the lower tick (integer) value. In practice this effect is much smaller than the effect of the noise.

Model of Interval Estimation

In interval estimation experiments, participants are exposed to a certain time interval a number of times, and are then asked to reproduce it. We modeled Experiment 3 from Rakitin et al. (1998). In this experiment participants were first trained on a certain time interval (8, 12 or 21s). Training consisted of 10 trials in which a blue rectangle appeared on the screen, which changed to magenta when the time interval had elapsed. In the 80 test trials they had to predict the interval by pressing a key when they expected the rectangle to change color. In 25% of the test trials the rectangle changed color when the interval had elapsed. The results are based on the remaining 75%, in which the rectangle stayed blue. Participants were forbidden to count.

Figure 3-5 show the scaled density plots of the responses (triangles). The peak of the distribution is at the appropriate time, the variance grows with the length of the interval, and the distribution is slightly skewed. The distributions satisfy the so-called scalar property of time estimate, in that the variance in the estimates grows linearly with the duration of the interval.

The model of this experiment closely resembles the example model outlined in the previous section. The learning phase is used to estimate the number of ticks in the interval (the model takes the average of the ten presentations), and during the testing phase the model waits until the appropriate number of ticks has passed. We estimated the three model parameters (multiplication factor, initial tick and noise) to obtain the best (least-squares) fit (shown by the solid lines).

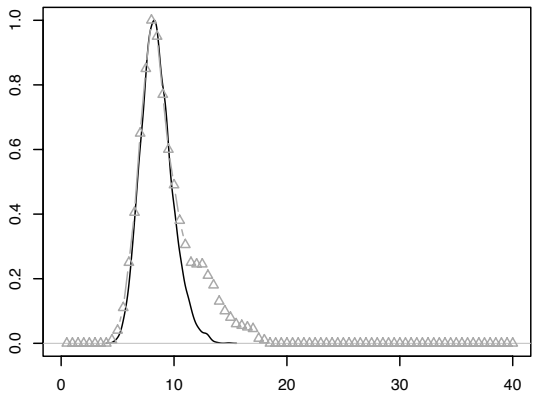

Figure 3. Data (triangles) and model (line) for 8 seconds

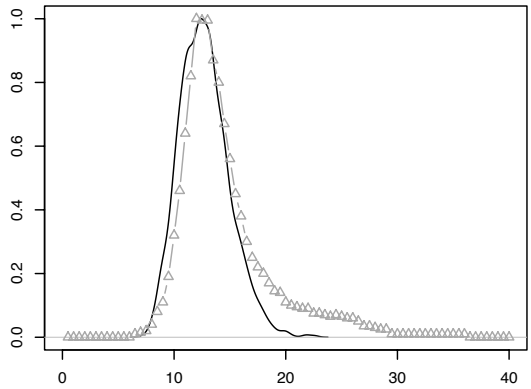

Figure 4. Data (triangles) and model (line) for 12 seconds

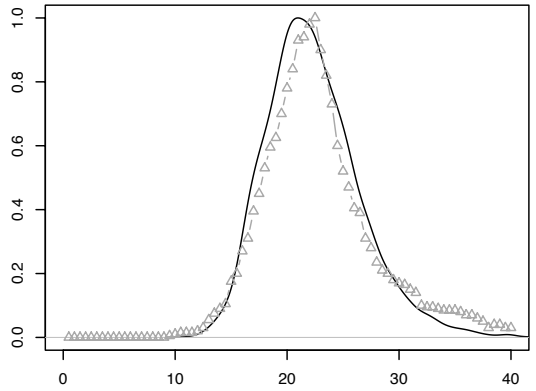

Figure 5. Data (triangles) and model (line) for 21 seconds

The fit between model and data is overall very good. The only aspect of the data that the model does not predict is the tail of the distribution for the 8 and 12 second conditions. In Experiment 1 of Rakitin et al. (1998), which is similar to Experiment 3, the tails of the distributions are much shorter. We therefore decided to leave the temporal mechanisms as simple as possible and to let further experience with the temporal buffer determine if an extension is necessary.

Model of Bisection Experiments

Another paradigm in time perception are so-called bisection experiments. In these experiments, participants are first trained on two time intervals, one short interval and one long interval. After this learning phase, they are exposed to new time intervals that are either equal to the short or the long interval, or somewhere in-between. Participants are then asked to judge whether the presented interval is closer to the short or to the long interval. We will model Experiment 2 from Penney, Gibbon and Meck (2000). In this experiment, three short-long pairs of intervals were used: 3 and 6 seconds, 2 and 8 seconds, and 4 and 12 seconds. In the training phase 10 tones of either the short or the long duration were presented to the participant. After that participants were tested for 100 trials, 30% of which were anchor point intervals (short or long), and 70% were tones of intermediate duration.

The model uses the training phase to determine the timing for both the short and the long interval. During testing, it times the presented interval, and then compares the value to both anchor intervals. If the value is closer to that of the short interval, it chooses that, if it is closer to the long interval, it decides that it is long. The parameters for the model are identical to that of the earlier fitted interval estimation experiment, that is, they have not been estimated anew for these data.

Figures 6-8 show the results of the experiment and the model. A property of both participants' behavior and the model's predictions is the fact that the interval that is judged long 50% of the times is shorter than the mean of the short and long interval. For example, in the 2-8 second version of the task (Figure 7), the 50% point is at 4 seconds instead of 5. The model explains this by the fact that its "ticks" increase in duration: there are approximately the same number of ticks between 2 and 4 seconds as between 4 and 8 seconds.

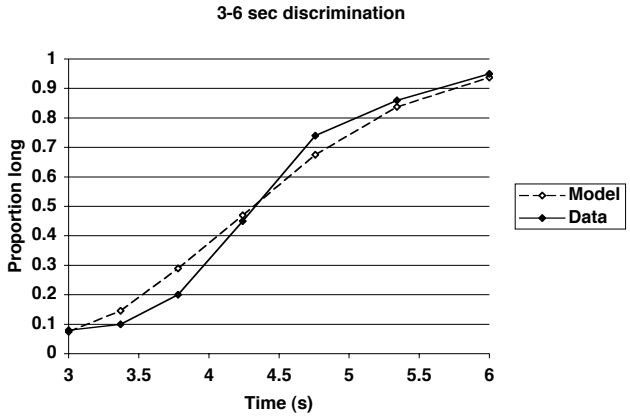

Figure 6. Proportion of "long" responses for intervals between 3 and 6 seconds

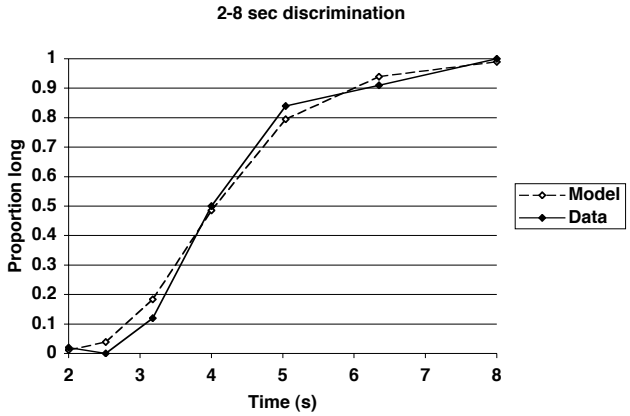

Figure 7. Proportion of "long" responses for intervals between 2 and 8 seconds

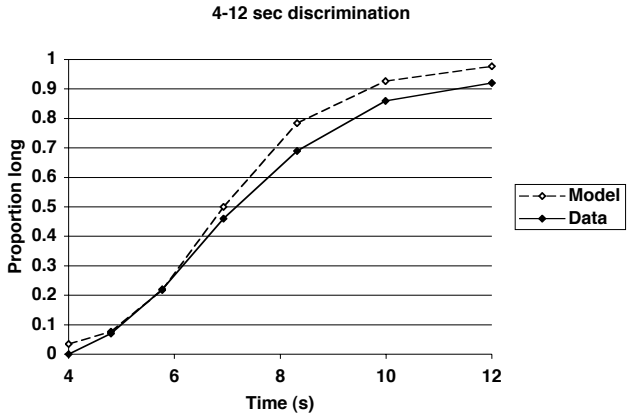

Figure 8. Proportion of "long" responses for intervals between 4 and 12 seconds

Role of timing in choice-reaction tasks

The previous two models show the validity of the temporal module, but they do not go beyond estimation and judgment of time intervals. To show that the temporal module has more than marginal value for an integrated cognitive architecture, we will now examine an experiment in which timing is important, but where it is not the focus of the experiment. It concerns a choice-reaction time experiment by Grosjean, Rosenbaum and Elsinger (2001, Experiment 1).

The experiment itself is straight-forward: on each trial a "+"-like figure appeared on the screen, of which the vertical line was always in the same place, but the horizontal either had two-thirds of its length to the left or to the right of the vertical line. Participants were instructed to press the "d" key if the horizontal line would be more towards the left, or the "k" key when it would be more towards the right.

The manipulation in this experiment was the inter-stimulus interval (ISI), here defined as the elapsed time between the key press of the previous trial and the presentation of the next trial. Each block consisted of 16 trials. This ISI was kept constant for the first 15 trials, but was changed on trial 16. More specifically, there were three

conditions: **Shortened:** the ISI on trial 1-15 was 700 ms, while the ISI on trial 16 was 467 ms, **Control**: the ISI in all the trials was 467 ms, and **Lengthened**: the ISI on trial 1-15 was 350 ms, while the ISI on trial 16 was 467 ms. Figure 9 shows the reaction times for these conditions per trial.

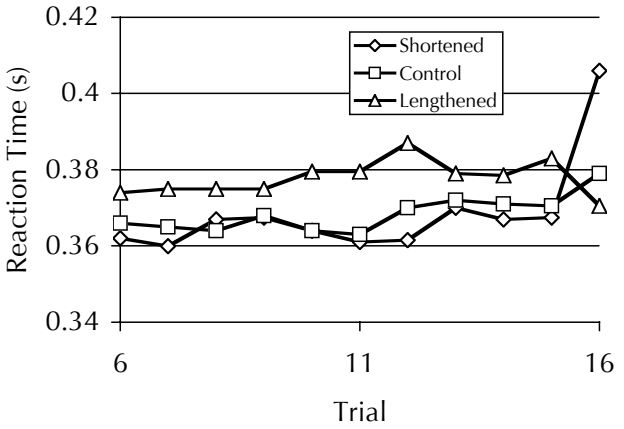

Figure 9. Results of the Grosjean et al. (2001) experiment

The strongest effect in the results is the increased reaction time on trial 16 in the shortened condition. Apparently, there is an advantage of knowing when the stimulus will arrive, and when it arrives early this advantage is cancelled. In our model we assume that the advantage of knowing when and where the stimulus will arrive allows one to start attending the stimulus at just the right time. In ACT-R, attending a stimulus normally takes two steps. First, it is detected that there is something on the screen (a visual-location). Then a production rule has to fire to direct attention to this location. Firing a production rule takes 50 ms, so this is the amount of time we can save if we can direct attention to the right location at the right time. Let us examine the model in more detail.

First, a rule starts the timer, and waits for the stimulus:

(p start-timer =goal> isa crt status start ==> +temporal> isa time =goal> status waiting)	IF the goal is a choice-reaction-task THEN start the timer and wait

When a stimulus appears on the screen, the model starts attending it, but at the same time it stores the time and location on which it appears in the goal:

(p found-visual-location =goal> isa crt status waiting =visual-location> isa visual-location =temporal> isa time ticks =time ==> +visual> isa visual-object screen-pos =visual-location =goal> time =time loc =visual-location status wait-visual	IF the goal is a choice-reaction-task and we are waiting AND there is a visual stimulus AND time *time* has elapsed THEN attend the visual stimulus AND store the time and the location of the visual stimulus in the goal

Other rules then handle the visual stimulus and make the appropriate key presses. On the next trial, the model uses the stored time and location to estimate when the stimulus will appear, and already starts the attention process:

(p expect-visual-location =goal> isa crt status waiting time =time loc =loc =temporal> isa time ticks =time ==> +visual> isa visual-object screen-pos =loc =goal> status wait-visual)	IF the goal is a choice-reaction-task and we are waiting, and the previous stimulus came up at time *time* and location *loc* AND time *time* has elapsed THEN attend location *loc*

This rule can fire before the stimulus comes up, and can therefore, in principle, save up to 50 ms. Let us examine in some more detail how the model manages to do this. If the *expect-visual-location* rule is to be of any benefit, it has to fire before *found-visual-location*. If the time estimate would be completely accurate, this would never happen: both rules would have their conditions satisfied at the same time. However, timing is inaccurate. Suppose the value in the timing buffer is 20 after the first stimulus presentation. For the next trial, the *expect-visual-location* can fire when the temporal buffer becomes 20. If this happens before the stimulus comes up (because the timer is a bit faster than the previous time), then *expect-visual-location* will fire, and will produce some benefit on the reaction time. However, if the timer is slow on this trial, *found-visual-location* will fire, because the stimulus appears before the timer runs out. In that case, the value of the timer is lower at the moment the stimulus appears, for example 19. The *found-visual-location* rule stores this new value in the goal. Therefore there is a downward pressure on the value of the time estimate until this value consistently causes *expect-visual-location* to fire before *found-visual-location*.

For the model results we have used the same temporal module parameters as in the previous models, and used the default ACT-R parameters for all other modules. Figure 10 shows the results of the model. There is a 25 ms difference between all the model's predictions and the data. Although we could have easily mended this by lowering the visual-attention parameter from 85 ms to 60 ms, defending this by the fact that this 85 ms normally also includes a here unnecessary eye-movement, we chose to leave the results as they first came out of the model. The model reproduces the main effect in the data, that is, the slower reaction time on trial 16 when the ISI is shortened, but also shows two other effects present in the data. A first effect is that in the lengthened condition the reaction time on trial 16 is slightly faster than the reaction time for the control condition. This can be explained by the fact that if the predicted time on trial 16 is shorter than the ISI, the model will always save the full 50 ms, while in the control condition it can be less.

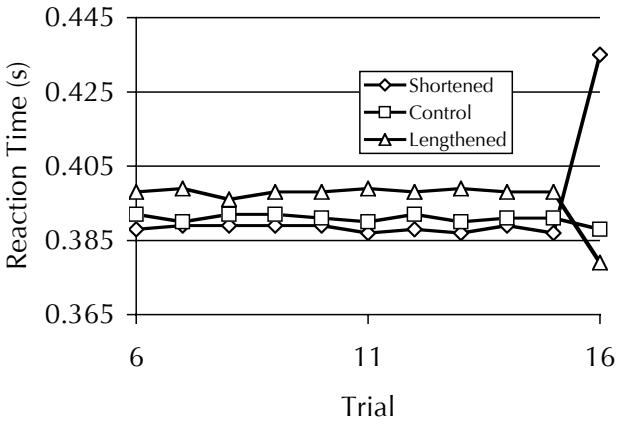

Figure 10. Results of the model for Grosjean et al. (2001)

A second effect that the model produced was the small difference in reaction times on trials 6 to 15. It appears that the longer the ISI, the shorter the reaction time, an effect normally attributed to the need to prepare for the next trial. As the model needs no preparation, but also shows the effect, this model offers a different explanation for this stereotypical effect: with the shorter ISI's, the model is more accurate in estimating the interval. However, in this case being accurate is counter-productive. Inaccuracies in the time estimate will cause the model to lower its value of the time estimate. The lower this value, the higher the gain in reaction time (up to 50 ms).

Discussion

The temporal module we propose is a simplification of the neural model that Matell and Meck (2000) outline. Instead of complex neural patterns ordinary integers are used. Nevertheless it matches the behavior shown in experiments. The integers in the temporal buffer can be considered to act isomorphically to the more complex patterns in a neural implementation. It is not clear to what extend the neural representation allows all the operations that can be done on integers (comparison, subtraction, etc.). We therefore are careful in specifying what can and cannot be done with the values in the temporal buffer, currently limiting the actions to simple comparisons.

The temporal buffer is not the answer to all issues regarding time. It can be used for intervals up to a minute, but certainly not for longer intervals. Its performance can however be augmented by the appropriate cognitive strategies. For example, by allowing a model to count, it can become much more precise in its estimations, mirroring human performance.

The model of the Grosjean et al. data produces some surprising explanations, and poses some new questions. One assumption is that it is no problem to attempt to attend a location early. Why don't people do that all the time? Maybe the attention process is effortful, and people try to avoid expending too much effort. Another explanation might be that by already attending a certain location, other new information may be missed. This is irrelevant in this particular experiment, but may be important in general. Indeed, ACT-R will normally automatically attend new stimuli, provided that the visual system is available. This means that timing the onset of a stimulus is a good strategy because other stimuli can be attended to in the period before the stimulus, and visual attention can be directed to the right location at exactly the right time.

Acknowledgements

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