A Model of Time-Estimation Considering Working Memory Demands

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Abstract

A model of prospective time-estimation is introduced which explains the interplay of working memory demands on duration estimation. The approach is integrated into a cognitive architecture and tested by estimating the duration of a task that varied coordinative and sequential demands on working memory. The comparison with experimental data shows that the model is able to simulate the influence of these demands on human time-estimation.

Keywords: Time-estimation; Computational cognitive modeling; Cognitive architectures; Coordinative working memory.

Introduction

The cognitive ability to be aware of the passage of time is beneficial in dynamic environments. Time-judgments are important to stay tuned to this environment, to plan steps in a task, and to identify problems (e.g. after an expected duration of booting a computer the monitor stays blank).

In the context of human-machine interaction, the knowledge of temporal dependencies is of great interest. For example, in order to drive safely, drivers need to divide their visual attention in a reasonable way between traffic and secondary tasks such as In-Vehicle-Information-Systems. Operators can deduce a malfunction from the system's temporal behavior in comparison to the temporal properties of a functioning system (Schulze-Kissing, 2007).

The goal of this paper is to introduce a computational model of time-estimation that shows how a demanding task disrupts the ability to judge time. In this model, the need to maintain and update information (e.g. a number in arithmetic) during a task distorts the construction of time representation during this period. The approach is integrated into the cognitive architecture ACT-R (atomic components of thought – rational analysis; Anderson et al., 2004). In this way the influence of cognitive processes and demands on the construction of time representations can be explored in a cognitive context. For a cognitive architecture, it is valuable to have an integrated component that simulates temporal human behavior. This is especially important for modeling switching tasks, multitasking and tasks under time-pressure.

The integrated timing-model is tested within a counting task (Dutke, 1997) with varying demands to compare human data to the performance of the model. With this task we show how computational cognitive modeling can improve understanding of cognitive skills such as time-estimation.

Psychological Models of Time-Estimation

The research field of human time-estimation explains differences in estimates on a number of factors such as the duration of the interval, the kind of instruction given to the subjects, when and how an interval is estimated (production, reproduction), or the number of incidents experienced during a given interval.

It is generally found that a demanding task affects time-estimation. Time-estimates are shorter when compared to less demanding conditions (Zakay, 1993; Dutke, 1997; Brown, 1997). A number of authors (e.g. Block & Zakay, 1996; Brown & West, 1990) assume that attention-allocation is the responsible factor for the interference between task and time-estimates. A number of other authors assume a strong influence of working memory on time-estimation.

Attention Allocation Models

In their Attentional Gate Model, Block & Zakay (1996) assume that a mental pacemaker regularly generates pulses to measure time. If a person directs attention to the *course of time*, a gate opens and the pulses are accumulated in a cognitive counter. When attention is distracted by a secondary task, the gate remains closed, pulses are not accumulated and the time-estimation is distorted. At the end of an experienced time interval, the time-representation is stored in working memory. For a comparison with another time interval, the time-representation is placed into reference memory and can be compared to the growing time-representation of the new interval in the cognitive counter.

Working Memory Approach

While the Attentional Gate Model is able to explain many aspects of time-estimation, it does not explain how attention is directed to the *course of time*, e.g. what kind of attention is addressed and what aspects of a task lead to which degree of distortion in time-estimates. These questions are addressed by Working Memory Approaches. Brown (1997) investigated whether there is a bidirectional influence of tasks and time-estimation. He found that all tasks interrupted timing. But concurrent time productions only reduced performance in mental arithmetic. He concluded that timing suffers when the resources of the central executive are reduced by being directed to the coordination of temporal and non-temporal tasks. The central executive is assumed to be responsible for controlling and coordinating the activities of the subsystems and for coordinating processes related to concurrent tasks (Baddely, 1986). Brown (1997) argues that not the general resources of attention as proposed by attentional allocation models, but specific resources of working memory are crucial for the construction of time-representation.

Dutke (2005) examined whether the overall demands of a task, such as attention allocation or specific working memory resources, are responsible for distortions of time-estimates. In the "counting task", Dutke (1997) was able to vary sequential and coordinative demands separately. The results show that both demands influenced task-performance. However, only high coordinative working memory demands lead to shorter and less precise time-estimates. According to Mayr, Kliegl and Krape (1996) sequential complexity refers to task variations that affect the number of simple and independent processing components. Coordinative complexity refers to tasks in which the information flow between interrelated processing components needs to be coordinated. Coordinate functions are tasks that demand intermediate storage of information, switching between processing components and inhibiting currently irrelevant information.

To apply these approaches to human-centered system design the theories have to be specified further. In order to examine the influencing parameters in more detail we developed a model of prospective time-estimation that incorporates coordinative working memory demands. This model has been integrated into a cognitive architecture. With this model it is possible to examine quantitatively how coordinative working memory demands influence time-estimations during various tasks.

Computational Modeling

We chose to work with the cognitive architecture ACT-R because it offers a number of advantages. ACT-R provides a theory of human cognitive processing which is based on numerous facts derived from psychological experiments. The architecture uses production-rules to simulate procedural knowledge. This production system is part of the symbolic structure of ACT-R, which also contains modules which can be seen as specialized and largely independent brain structures. Within production-rules a number of modules can be requested via their corresponding buffers. Some modules like the visual module and the manual module can interact with experimental environments, involving reading letters on screen or pressing keys.

The declarative module holds the knowledge of facts (chunks), which have a number of slots with corresponding content. Chunks of the declarative memory can be retrieved by the retrieval-buffer. A memory-retrieval request for certain information is initiated by the model within a production-rule. After a while (e.g. depending on number of uses) the retrieval-buffer holds the best fitting chunk and the model can use that bit of information in another production rule. The idea for the buffer concept is that access to modules is restricted, that is why each buffer can only hold one piece of information at once.

The use of independent production rules allows cognitive models both to react to external stimuli and to simulate experiments in which subjects have to interact with problems presented onscreen. ACT-R also works at a subsymbolic level which controls a number of symbolic processes. This subsymbolic processing is important for learning and working memory and other concepts described later on. Furthermore, ACT-R is extendable, allowing us to include a module for time-estimation.

Models of Time-Estimation in ACT-R

Three models of time-estimation are already implemented in ACT-R (Dzaack et al., 2007; Taatgen, van Rijn & Anderson, 2007; Byrne, 2006). While the first model utilises the number of fired productions within a task but accounts for retrospective time-estimation, the approaches on prospective time-estimation both introduce a pacemaker and depend on attentional processes to come to a time representation. The model that refers to the Attention Gate Model (Byrne, 2006) assumes that attention of a cognitive system is always directed on the production that fires at that moment. A special production requests the pacemaker to increment the pulses in the accumulator. This production only fires when no other production is firing. Time-estimation in this case relies much on the way a task is modeled. The third model (Taatgen et al., 2007) uses an increasing pulse rate over a specific time interval. This explains why longer intervals are larger underestimated and vary more than short intervals. The assumption of this model for the influence of a demanding task is that people may forget to estimate time if a task is very demanding. In this case, people have to restart the accumulator. However the probability of forgetting time within a task has to be estimated by the modeler in advance.

Both models are not capable of reproducing empirical effects of working memory demands which emerge from differences in the tasks. One model (Byrne, 2006) would only predict differences in estimates that occur by differing densities of firing productions which would not capture changes in working memory demand. The other model (Taatgen et al., 2007) has no real account why differences in demands distort time-estimates differently and when people have to restart their estimates.

Therefore we introduce an alternative approach that is focused on the involvement of working memory processes in time-estimations. It explains characteristics of time judgments by means of mechanisms which are already provided by the working memory of ACT-R.

Working Memory in ACT-R

Lovett, Reder & Lebiere (1999) name three important aspects of working memory. (1) Working memory can be allocated to enable the maintenance and processing of information; (2) It is inherently limited; (3) It differs in supply across individuals. All of these points are addressed by the subsymbolic mechanisms of ACT-R such as base-level-learning, spreading activation and associative strength that act upon declarative knowledge.

The chunks in declarative memory hold different levels of activation depending on how recently and how often this chunk was used. In the process of retrieval, the chunk holding the highest level of activation is retrieved from a number of potential candidates. This kind of learning, involving noise and decay, is called base-level learning.

The current goal contains the information in the focus of attention of the cognitive system. Its contents are either established by previous processing or by external stimuli. The goal propagates attentional activation to declarative memory. This raises the accessibility of some chunks relative to others. The goal's attentional activation (called source activation) is divided among the goal slots and multiplied by the associative strength between chunks of the goal slots and chunks in memory. For detail see Lovett et al. (1999). The main implication is that the relevance of a fact to the current goal and its past uses jointly determine the chunk's accessibility.

Quantitative Time-Estimation Model

The approach introduced in this paper focuses on prospective time-estimation. Subjects know in advance that the duration of an interval is important. The model consists of four parts: a pacemaker that generates pulses, an accumulator which collects pulses for short durations, a process of construction which updates the time representation, and a procedure which finally estimates time, e.g. by comparing an old time representation with a new interval as in the reproduction task. The first two parts are modeled in ACT-R by adding a timing-module to the architecture. The third and forth parts of the approach integrate the output of the new timing-module with already existing processes and modules of the cognitive architecture.

The Pacemaker

The idea of a neural pacemaker used in this model is similar to the pacemaker used in a number of other time-estimation models (Treisman et al., 1990; Block & Zakay, 1996; Gibbon, 1977). The frequency of the pacemaker is assumed to rise with the amount of arousal, which is not yet integrated in our model.

The pacemaker runs in an extra module (the timing-module) within the architecture ACT-R. The pulses are generated with a constant frequency. The frequencies reported in literature (e.g. Treisman et al., 1990; Rammsayer & Ulrich, 2001) differ widely from 179 to 12.4 Hz. As our model is not sensitive to this parameter (see section "process of construction") we choose to take a pragmatic value of 0.3 sec..

The Accumulator

The accumulator holds the number of pulses which have been accumulated since the last request.

When a memorable incident occurs during a task we assume that this releases a new short time-estimate based on the accumulated pulses and resets the accumulator. The accumulated pulses are going to be integrated with further information derived from the process of construction explained later on. The result is stored in memory including information about the incident that occurred.

There are two reasons for the assumption that such incidents cause short time-estimates. Several authors found that the temporal nature of repeated incidents during a task is learnt by subjects without them being instructed to do so (e.g. Dutke, 1997; Grosjean et al., 2001). Other authors assume that the stored information about an incident is connected with the information about when it occurs (e.g. Michon, 1990; Block & Reed, 1978). We assume that during a longer period, a number of short time-estimates are successively connected to each other in the process of construction.

In terms of ACT-R, a request is sent to the timing-buffer by the task-model following certain previously defined incidents. The timing-buffer collects the accumulated pulses from the timing-module which starts to accumulate anew. For example, such an incident occurs if a target is found in a set of stimuli. When this happens, the pulse count is transferred from the timing-module to its buffer. Once the accumulated pulses are in the timing-buffer this information can be processed further.

The Process of Construction

The short time-estimates and the process of construction are the novelties in our approach compared to prior approaches. At the start of the time-estimation, a time-chunk with zero pulses is placed in declarative memory. Subsequent incidents cause a retrieval of the latest time-chunk in the declarative memory and an integration of the newly accumulated pulses. Hence, a new time-chunk is stored in memory while the former remains. With a perfect memory the new chunk will be retrieved by the next incident (see fig. 1) because it is the most recent generated chunk, but we do not have a perfect memory. Therefore, we assume that the cognitive system has to invest some effort to maintain the latest time-chunk until the next short time-estimate is performed. Maintaining information is a classical function of working memory. If a secondary task is very demanding and additional information has to be maintained, time-chunks can be confused. Instead of the latest time-chunk, an older one is retrieved and is updated with the pulses in the accumulator. This would result in shorter time-estimates, because the preceding short-estimate is lost if the second latest chunk was retrieved. Contrary to other timing-models, this model assumes a perfect pacemaker, a perfect accumulator, and no attentional-gate that is opened or closed, but distortions of time-representations that emerge by means of memory processes.

The model is based on the assumption that the demands on the working memory over a period influence the quality of the final time representation. The demand on working memory is changing throughout a task. It seems that the coordinative demands during a period of time and not the demand at the end of the period cause the distortion of the final time-representation. Therefore, it is plausible that the time-representation is continuously updated during a task.

Constructing time-representation this way explains why short intervals are estimated more precisely than long intervals which is generally reported. A number of authors in the field of scalar expectancy theory (SET) (e.g. Gibbon, 1977) examined this finding. One property of the SET model states that the standard deviation of time judgments grows as a linear function of the mean; therefore longer durations are estimated less precise. Furthermore, longer durations are also underestimated for a larger amount (e.g. Vierordt, 1868) than short durations. Our model is able to explain these frequently reported effects. During longer durations, more occasions arise where time-chunks can be confused, which also causes more room for differences between estimates. This results in a larger underestimation and a larger variability in estimates for long compared to short intervals.

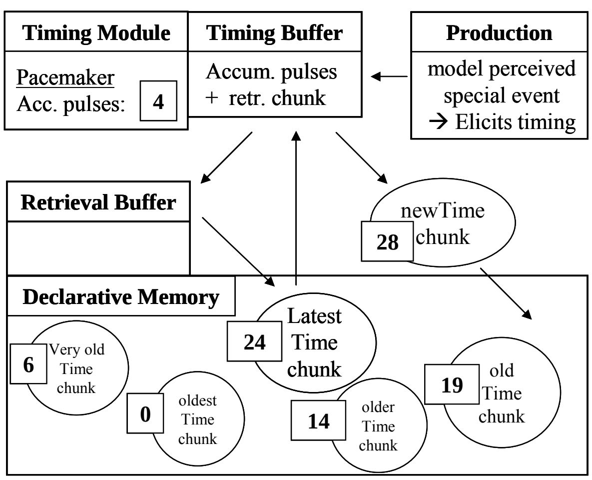

Figure 1: Process of construction in ACT-R

In terms of ACT-R, a request is initiated by the timing-module to retrieve a time-chunk. According to base-level-learning, the latest time-chunk should be retrieved, because it holds the highest activation-level. As time goes by, more time-chunks accumulate in memory and the associative strength decreases. This is why the number of chunks with identical contents rises. Hence, the longer a time period, the higher is the probability of retrieving an older chunk.

Short estimates between incidents might be lost in the construction process due to memory processes. Therefore, certain proportions of a time representation with a certain variability of the overall estimation are lost and different chosen frequencies of the pulse rate would not affect the final estimation.

The Comparison Process

The comparison process is very simple. When the time interval is completed, a final time-representation is constructed and can be used later for time-reproduction. Within an experiment which applies the reproduction method, a subject would be asked to wait after a signal until the same amount of time has elapsed as they had spent on some task.

It is assumed that subjects compare the actual time-construction regularly with the prior time-representation. When they are equal, the subject gives a stop-signal. In the reproduction task, subjects seem to use mental simulation if they are questioned about properties of a previous situation (de Kleer & Brown, 1982; Johnson-Laired, 1983).

For the comparison process within the task-model, the final time-chunk is retrieved when a reproduction is to be made, and the final number of pulses is put into the goal. The timing-module starts counting from zero (with a new ID for the new time-representation in one of its slots). Each time a new time-representation is constructed, the pulses of the new time-chunk are compared to the target (old time-representation). A special production fires when the two are equal, and the model gives a stop signal.

Testing the Timing Model

To test the timing model, we chose the counting task used by Dutke (1997) which varies the demand on working memory and the amount of sequential processing.

The subjects were asked to search lists of ten two digit numbers for either one or three targets (conditions 1 and 2: “16”; condition 3 and 4: “16”, “38”, and “67”). The sequential demand was varied with the overall number of targets in all lists presented (either 14 or 27 targets can be found within 40 lists). If a target was found, the subjects had to remember how often this target had appeared so far. If it appeared for the first or second time, they were told to press a key marked “No”. On the third encounter, they were told to press a key marked with the target-ID, and then start counting again. If no target appeared in the list the answer was also “No”. In the high sequential conditions (2 and 4), the counter of the target(s) had to be updated more often. This is assumed to be more difficult than the low sequential demands in condition 1 and 3.

Before the task started the subjects were told that they will later be asked to reproduce its duration. After completing the counting task after 400 sec., subjects were asked to reproduce the duration by pressing a key when they felt that approximately the same amount of time had elapsed as they had experienced previously.

The Model and the Task

Starting from the appearance of the first list, the developed task-model begins to build up a time-representation. For every new list the model first remembers the targets it has to look for. Which means it retrieves the corresponding chunks and keeps them in the goal until the list disappears. After remembering the target(s), the model starts to read the numbers one after the other. It checks whether every new number is a target. If a target is found the model tries to retrieve the chunk with the latest update of the target's occurrence. According to the retrieved number of occurrences the answer is given by a key press. The number of occurrences is updated and subvocally repeated twice to keep the activity level high until the next retrieval. This strategy was derived from reports of subjects in an exploratory study. After the whole list is checked for targets, the model waits until a new list appears. After 40 lists, the stop sign appears on screen and a final time-representation is stored in memory. To reproduce the time, the pulses of the final time-representation are written into a slot of the goal and a new time-estimation is started by updating chunks that hold a different ID than the first estimate. For the reproduction process we used a similar context as in the previous counting-task but without targets. This was done because of the mental simulation mentioned previously. As soon as the same number of pulses is collected as during the task, the model presses a key that indicates the end of the reproduction.

Comparison of the Model with Human Data

The performance of the model as well as the reproduction-error were compared to performance and reproduction-error in experiment 3 in Dutke (1997, p.128). Dutke assigned 56 subjects randomly to the four experimental conditions that result from the 2x2 between-subjects design (two levels of coordinative demands, two levels of sequential demands).

Dutke (1997) found that almost all participants underestimated the duration of the counting task. Increased coordinative demands on working memory, produced larger reproduction errors than low coordinative demands (figure 3, black columns) [$F(1,52) = 16.39$, $p< .01$; partial $\eta^2= .24$]. The reproduced duration is shorter under high than under low coordinative demands. However, for increased sequential demands the reproduction error was unaffected by the manipulation.

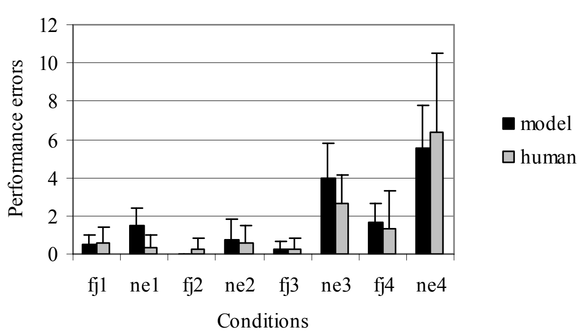

Figure 2: Human and model performance of errors (split into *ne*- and *fj-errors*) in all four conditions

For the evaluation of performance in the counting task, two kinds of errors are crucial: An *ne-error* occurs whenever a target is in the list for the third time but no according answer is given. An *fj-error* arises when a target is in the list and the answer "yes-target-x-found" is given, but the target does not appear for the third time. The grey columns in figure 2 show the performance of the subjects (Dutke, 1997). For high coordinative demands the variation of sequential demands shows explicit differences in performance errors. Therefore, increased sequential demands seem to increase the difficulty of the task, but do not influence performance in time-estimation.

The overall fit of the model's performance to the experimental data is very good in all four conditions. It might seem surprising that there are slightly more errors in condition 1 than in condition 2 which should be more demanding due to higher sequential demands. However, for the easy conditions, in terms of coordinative demands, it is easy to maintain the number of occurrences of a single target. If the target appears more often, frequent updating is even helpful because the activity of the chunk stays high and ensures better retrieval. In the empirical data the error rates in condition 1 and 2 hardly differ and therefore do not contradict this assumption. Hence, the task-model seems to simulate user-performance in the counting task well and can be used to test the timing-module in conditions of different levels of working memory demand.

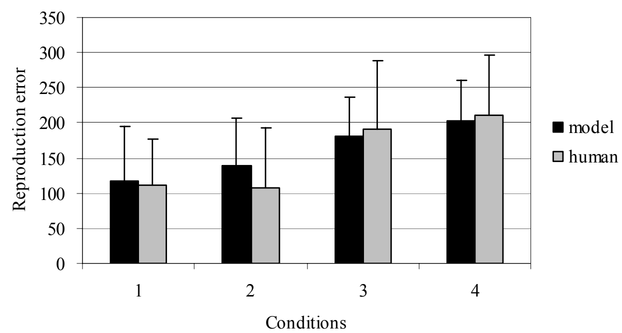

Figure 3: Human and model reproduction error

Figure 3 shows the reproduction error comparing the differences of mean time-estimations and objective time. In low coordinative conditions (1 and 2) the reproduction error is much smaller than in the high coordinative conditions (3 and 4). Similar to Dutke (1997), we found larger reproduction errors under increased coordinative demands than under low coordinative demands (figure 3, grey columns) [$F(1,56) = 12.23$, $p< .01$; partial $\eta^2 = .19$]. For increased sequential demands the reproduction error was unaffected by the manipulation [$F(1,56) = 1.25$].

As can be seen, the model shows a comparable time-estimation to human data in all four conditions. The model even produces a similar variance in time-estimates. Therefore the new approach integrated in ACT-R is able to estimate time with the same influence of working memory demand of a concurrent task as is reported in a number of time-estimation experiments.

Discussion

The approach under discussion explains the way working memory demands effect duration estimation. For a time-estimation, the temporal representation during an interval has to be updated continuously. In order to do this the latest representation has to be maintained in working memory. A task that calls upon working memory mechanisms interferes with the working memory mechanism of maintaining the latest time-representation. Compared to other theoretical accounts of duration estimation, this model is more parsimonious in that no additional elements like an attentional gate or processes of a central executive are necessary to explain observable distortions of the estimation process. Furthermore, the Attentional Gate Model would not be able to explain why coordinative and not sequential demands influence time-estimation, because attention is needed for both kinds of demands.

The timing approach was integrated in a cognitive architecture and the influence of working memory demands were explored within a task-model that simulates the counting task (Dutke, 1997). The results show that the timing approach is able to simulate the reproduction-error found in the different conditions of the experiment.

The next steps to further explore the nature of human time-estimation with the methodology of computational modeling would be to test the integrated timing-module within different kinds of task. Especially interesting would be variations of the duration and different tasks with other working memory demands.

Furthermore, it would be beneficial to expand the integrated timing-module by a concept of time-pressure and/or arousal and expectation for the length of certain processes.

Acknowledgments

This work was sponsored by VolkswagenStiftung (Research Group *Modelling of User Behaviour in Dynamic Systems*) and Deutsche Forschungsgemeinschaft (DFG Research Training Group *Prospective Design of Human Technology Interaction,* GRK 1013). The authors gratefully acknowledge the help and support given by Robert Lischke and Jeronimo Dzaack.

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