A Computational Model of Time Estimation Involving Influences of Task Demands

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Abstract

The duration of incidents in complex dynamic systems represent crucial information for system analysis and the regulation of task-performance. The influence of task demands on time estimation has been proven in numerous experiments. This kind of distortions can cause severe errors in interacting with safety-critical systems such as process-control systems.

To identify and predict performance-errors due to distortions in time-estimation a quantitative model of prospective time-estimation was developed which explains distortions by means of memory processes. The approach was integrated into a cognitive architecture ACT-R (Anderson, 2004) and has been tested with a user model of the counting task (Pape & Urbas, 2008).

This paper reports two experiments which test the time estimation-model in a more realistic task, including supervision and interaction with a complex system in experiment II. According to the model, sudden changes in specific task demands lead to under- or overestimates of time, depending on the direction of change. The empirical results go in line with the predictions of the model. In addition, we found overestimations caused by task variations that were unfamiliar to the participants.

The Role of Time Perception in Human-Machine-Interaction

To not just classify human errors but to identify the cause of human errors it would be helpful to have a model which can predict human errors. This way error prone system designs could be prevented in early phases or appropriate support could be given to the user.

The focus of this paper is to predict distortions of human time perception and its impact on user behaviour. The connection between time perception on human-machine-interaction (HMI) has been topic in a number of different contexts such as planning of action and analysis of events (e.g. Decortis und Cacciabue, 1988) or evaluation of workload inducing driver-information systems (Totzke et al., 2006).

Temporal reasoning, temporal judgement and temporal decision-making are important components of control processes in complex dynamic systems. Designing human-machine systems therefore requires knowledge about the characteristics of human temporal cognition.

Although lots of different surveys try to tackle the topic of time perception in HMI, a number of problems hinder the examination of the nature of time perception especially in a realistic environment. Causes of human errors are normally not explicitly reducible to distortions of time perception because a number of factors might have caused the error. Then subjective time perception is not directly tractable. Just by means of interval reproductions or by referring to another reference system like seconds and minutes, one can try to report the subjective impression of duration. And finally, there is no agreement about the factors that cause distortions of time perception.

One way to face the first two problems is to integrate a quantitative model of human time perception in a cognitive architecture to identify the errors that are caused by distortions of time perception under certain circumstances or tasks.

To model temporal expectation of upcoming events is a crucial ability to get prepared in time for actions that have to be carried out after an upcoming event, or to identify a malfunction of the system if an event does not occur in time (Schulze-Kissing, 2007).

Models of time perception

Existing models of time perception name different factors which should be responsible for distortion of time perception. Some models focus on attentional resources (Block & Zakay, 1996), others on the number of events or context changes that occur during an interval (Block & Reed, 1978) and again others build on working memory (Brown, 1997; Dutke, 2005). The Attentional Gate Model (Block & Zakay, 1996) is the most prominent model which belongs to the first category of models. The authors assume that a pacemaker generate pulses which accumulate as long as attention is focused on time. Whenever attention is directed on a task, a gate closes and no pulses can be accumulated. The number of accumulated pulses represent the duration of an interval. The problem is that the model does not differentiate between specific and general attention, therefore it is not possible to predict to what degree a task distorts time perception.

Brow (1997) showed that just specific resource accounts such as working memory resources can explain the distortions of a number of different tasks. Dutke (2005) showed in a number of experiments that especially coordinative working memory demands distort time estimation, but not sequential working memory demands. According to Mayr, Kliegel & Krampe (1996) sequential complexity refers to tasks 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. In the counting task used by Dutke (2005) participants had to work on a number of lists that appear on-screen. The task is to count the occurrences of either one target or for three different targets independently (low and high coordinative demands). Within 40 lists either 14 or 27 targets occur (low and high sequential demands). For every third occurrence of a target the participant has to press a button that is labeled with the number of the respective target. The participants has to work for 400 seconds on the task and is then asked to reproduce the experienced duration by pressing a button twice to indication the beginning and end of the estimation. Both demands increased performance errors in the high specification. But for the estimation, just coordinative demands showed significant differences.

The Model of Task Depending Time Estimation

Our new account builds upon episodes that result from segmenting the stream of consciousness by meaningful events, such as the detection of target stimuli. The model assumes a pacemaker that provides the temporal information in the episodes. In addition the automatically formed episodes carry information about the meaningful event. An intentional estimation of an interval starts with a first temporal chunk that is stored in memory carrying the temporal information of zero pulses, which is updated with every new episode (see figure 1). Older representations remain, but normally the latest representation is retrieved because it has a higher level of activation due to recency. But sometimes – if working memory demands in the task are high additional activation, called “spreading activation“ (Lovette et al. 2002) spreads unequally to the temporal chunks of because they carry contextual. At the end of an interval a final representation is stored in memory. This representation can be used for comparison with other intervals.

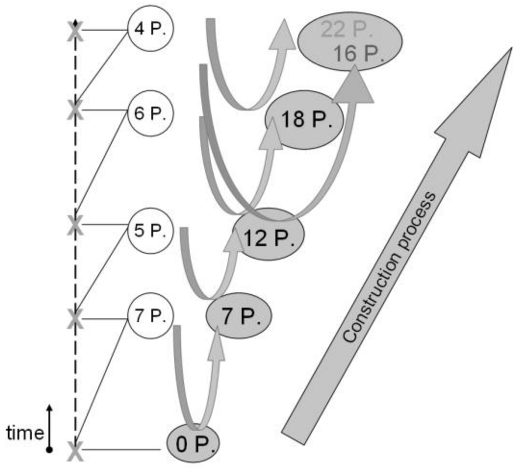

Fig. 1: The dashed line represents pulses generated by a pacemaker. The ‘X’ represents meaningful events that segment perception into episodes which carry temporal information (white circles). If an interval should be estimated, a construction process starts with a representation with zero pulses and updates this representation by adding the temporal information of every new episode to the retrieved time chunk (grey circle). For demanding tasks retrieval errors might occur so older representation instead of the latest is retrieved (see topmost grey circle).

Variations of the counting task

The task and the influences of different task demands on time estimation have been modelled successfully (Pape & Urbas, 2008). The same task model was used for the model predictions of temporal behaviour in load change scenarios (Pape & Urbas, 2009). The new task setting differed to the original task in a number of aspects:

- The duration of the presented interval was just 100s instead of 400 to test whether the model also accounts for much shorter intervals.
- Instead of reproducing the perceived interval without a task, we choose to present the task in the reproduction phase because this represents a more natural situation.
- The reproduction phase was repeated for a number of times within the same condition to give the subject the opportunity to build up a robust interval representation (inload-trials). After each reproduction the participants received a visual feedback about the quality of the estimation.
- After a number of inload-trials a switch-trial followed that was either more demanding or less demanding than the inload-trials. This was done to mirror a situation of sudden incline or decline of workload that operators are often confronted with.

The experiments were planned as a between design for group Low and group High. For the inload trials a baseline was calculated, taking the mean estimation of all inload-trials, and compared it to the estimation in the switch trial.

Model predictions

The prediction of the model was an interaction effect between the group condition (High/Low) and trialtype (inload/switch) $F(1,42)=7.5$; $\eta^2=0.15$; $p<0.01$ (see figure 2a). For both groups the model ran 22 times for each of four different trials, two inload and two switch-trials. The model predicts good estimations in inload-trials with an average around 100 seconds. For group High the model predicts an overestimation when demands switch to low demands. For group Low the model predicts underestimations when demands switch to high demands. The model relies on memory processes and on the retrieval of the ‘right’ temporal chunk amongst others. Therefore small differences in activation cause large differences in estimates between model runs. This result in a deviation of data points that is larger than in the usual model data where runs are quite similar to each other. This way, it is possible to compare model and empirical data by means of distribution.

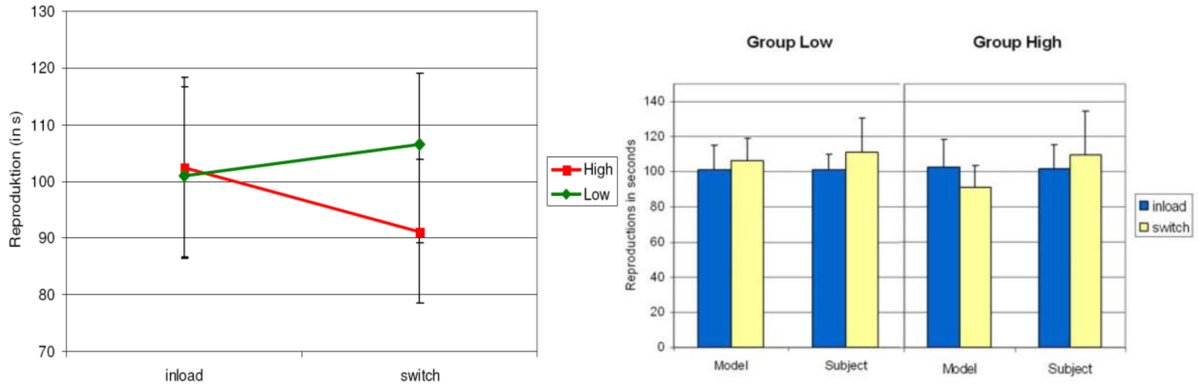

Fig. 2: a) Model prediction for load switch. Bars indicate standard deviation; b) Comparison of model predictions and empirical results. The bars represent the standard deviation

Experiment I

Participants and Procedure

Forty-two participants (aged 21-48 years, 17 female, 25 male) were randomly assigned either to the High or the Low group. The participants receive identical training of the low and high coordinative demand condition. The session started with a sample trial of the condition matching the group the participant was in. The sample trial stopped after 100 seconds. The participants had to reproduce this duration in each of the following 8 trials by stopping the task they were working on with a special key. Before a new trial started the participant was informed about the target(s) that would appear in the upcoming lists. After each reproduction the quality of estimation was given by a visual feedback. A blue bar informed how close the estimation was to the original duration indicated by the green area in the vertical bar. A structured interview was conducted after the experiment. To offer no additional cues to the participants except for the perceived duration for the estimates, the number of lists in a trial was varied as well as the length and duration of the lists. Participants were aware about this.

Results

For reproductions the two-way ANOVA (group/trialtype) with repeated measurement on trialtype revealed an effect for trialtype ($F(2,43)=7.78; p<.05; \eta^2=0.35$) but the predicted interaction was not found. The predicted overestimation in group low was found and even the standard deviation was similar (see figure 2b), but the predicted underestimation in group High was not found.

Discussion

The model predictions were consistent with the experimental data for group Low. For group High we had a number of factors that might have obscured the predicted effect. Therefore we decided to use a more complex task to prevent participants to reflect on there acquired experiences of time perceptions. In the interview participants of the High group reported that they had adjusted their response in the switch trial due to their experiences of time perception.

Experiment II

For the second experiment we used a Microworld scenario (see figure 3a) that resembles an operator task in a chemical plant. The operator has to monitor the upcoming alarms and to search for important alarms (either alarm 18, 34, 59 or all of them). If an important alarm occurs three times, a special button has to be activated to resolve the problem. This task resembles the counting task. Furthermore the operator has to supervise the level of blue liquid that should remain between the white triangular bounds. The level can be regulated by opening and closing a valve. This can be seen as sequentially demanding and should not influence time estimations. The participants were told to press a “message” button to indicate the end of an interval and the expectation of an event that should occur.

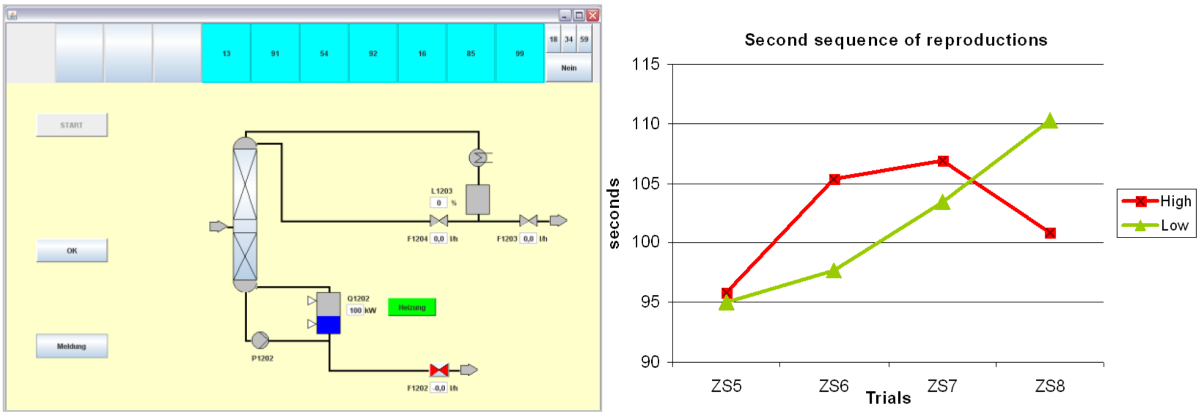

Fig. 3: a) Microworld scenario used in experiment II. A blue alarm bar, dark blue liquid to supervise and a red valve to regulate the liquid; b) Experimental results of experiment II

Participants and Procedure

Fifty-three participants (25 female, 28 male) were assigned to the two groups and trained in the different tasks. The experiment started with a sample trial stopped after 100 seconds. The next three trials were inload-trials and the forth trial a switch trial. Then another sample trial followed in the inload condition to ‘recalibrate’ the participants and another three inload and one switch-trial followed. This way the participants were used to the switch trial in the second half of the experiment. Apart form the reported differences the experiment resembled the first experiment.

Results

The interaction (trialtype/group) did not reach significance for the first sequence (trial ZS1 to ZS4), but for the second sequence there was also a significant interaction (trialtype/group) $F(1,51)=5.537$; $\eta^2=0.95$; $p<0.05$ (see figure 3b).

Discussion

The interaction effect found in the second sequence of the experiment resembles the predicted interaction by the model. It seems that the unfamiliarity of the switch-trial puzzled the participants or led to additional cognitive processing in order to find a good strategy or to compare the unfamiliar condition with the earlier condition. This additional effect was largest for experiment I where 7 inload-trials were conducted until the switch trial occurred. In the first sequence for experiment II just 3 inload-trials were conducted before the switch–trial therefore the expectation was smaller as the overestimation effect. The effect disappeared for the second sequence of experiment II because switches were expected.

General Discussion

It was shown that time dependent expectancies can be predicted in a load-switch scenario in correspondence with experimental data. Even experimental data derived in a microworld scenario with additional sequential demands correspond to the modelled predictions. The model did not predict that participants would overestimate if the condition changed to an unaccustomed condition. The theoretical model could explain this by additional workload that arises if a participant tries to adopt to the new circumstances. More studies are needed to look carefully at this effect and to include it into the computational model of time perception. This model is the first step towards predicting temporal human errors in dynamic complex systems.

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