Too soon?: A cognitive modeling approach to interval timing and risk perception

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Abstract

The aim of this paper is to study the effect of risk perception (RP) on interval timing. We approached this issue by adapting a motor task in different RP settings from (Maloney, Trommershäuser, & Landy, 2007) as well as building a cognitive model of interval timing and RP, based on the "pool" model from (Taatgen & Van Rijn, 2011). In our experiment, after 5 training trials, subjects had to reproduce an interval of 750 milliseconds in 4 different RP contexts or "blocks". Each block was associated with a punishment: "none", "low", "high" and "none".

Behavioral results show, that, despite the different "severity" of penalty each block, performance remained stable across the whole experiment. Punishment severity had a significant impact on reaction times. This indicates that participants were able to "adapt" their response times to each block, while still remaining accurate.

The cognitive model reproduced behavioral results accurately. The impact of RP on interval timing was modeled as an avoidance dynamic: Negative feedback would cause the model to encode "avoidance" chunks, whos "strength" depends on the magnitude of punishment. Correct answers would not incur any "avoidance".

Keywords: Interval timing, ACT-R, cognitive model, risk perception

Introduction

Be it in daily life, or in professions like medicine, piloting or deep sea diving, the ability to accurately estimate the duration of a certain process is vital for the successful execution of most work-flows. The impact critical events, risk perception (RP) or time-pressure has on professionals' situation awareness or attentional mechanisms during work, has received much attention in the context of human factors. While there is literature addressing the human capacity to time intervals or to predict when a future event is most likely to occur, relying on the "inner clock" (Taatgen & Van Rijn, 2011), (Taatgen, Van Rijn, & Anderson, 2004), the issue in relationship with RP has somehow eluded investigation.

Thus, the present study aims at providing insight in how RP affects subjects' interval timing. This was accomplished by conducting a behavioral study, adapted to the time estimation domain from (Maloney et al., 2007). In addition, to gain insight in the cognitive mechanisms underlying interval estimation and RP, a cognitive model was conceived, based on the *pool model*, proposed by (Taatgen et al., 2004). The model allows building concrete hypothesizes and comparison thereof with the behavioral data. Mahoney et al.'s work provided insight in how participants would perform a motor task in different RP conditions. More on this below.

Maloney and colleagues (2007), conducted an experiment where subjects had to tap in quick succession a reward area, which overlapped with a punishment area. Two factors influenced the subjects' performance: the size of the punishment area (the bigger the area, the easier it was to accidentally tap said area), and the subjects' "inherent" motor accuracy. Results show that the subjects concentrated their tapping on the location which ensured successes most, taking the punishment area and their own accuracy into account. Punishment area size is conceptualized here as RP. The details of the adaptation of Mahoney et al.'s experiment to the time domain are provided in the "Methods" section.

While the motor and time domain are hardly equivalent, we expect subjects to adapt similarly when estimating time intervals as when quickly performing motor actions. In both cases, subjects have no access to their "inherent accuracy", but need to rely on performance feedback to adjust their actuations, which strengthens our belief in our hypothesis.

The cognitive underpinnings of the observed adjustment to RP were not explained by Mahoney et al. We aim to offer a viable hypothesis of this phenomenon with the extension of the mentioned cognitive model, which is based on Taatgen et al.'s *pool model*. Our hypothesis is, that negative feedback gets "encoded" and added to the declarative memory as a relevant behavioral guide. The "effect size" of the encoded "chunk" on memory and the current performance depends on the magnitude of RP. This means, should a subject get strongly punished, an analogously strong "chunk" will impact further interval timing. We also envisioned a fairly complacent system, which, in case of not getting negative feedback, does not take special actions. The details of the model and the implementation of our hypothesis can be found in the "Methods" section, below.

Methods

In this section, first, I will explain the details of the behavioral experiment, then, I will explain the cognitive model and the implementation of our hypothesis regarding RP and cognition.

The behavioral experiment

Subjects and Design: 36 healthy, predominantly male adults with ages between 18 and 35, which were enrolled in the course "Cognitive Modeling: Basic Principles and Methods 16/17", offered by the Faculty of Science and Engineering (University of Groningen), participated in the experiment. Participation was mandatory as course component and was not rewarded.

The experiment had a training and experimental phase. The purpose of the training phase was to familiarize the subjects with the target interval of 750 milliseconds, which they would have to reproduce throughout the experiment. The training phase was comprised of 5 iterations showing a white fixation dot in the screen center for 1500 milliseconds, then, a yellow dot (screen center, approx. 60 pixels diameter) for the duration of the target interval and then again, the fixation dot for 1500 milliseconds. A button press would advance the iterations. The subjects were exposed to the training phase only once, before the experimental phase.

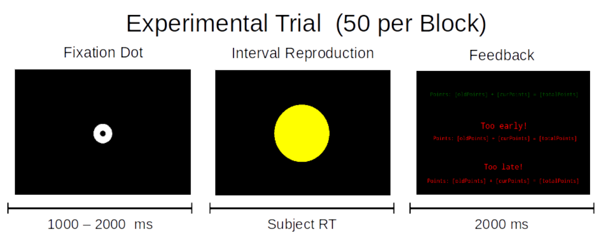

Figure 1: *Structure of a experimental trial, from left to right.*

During the experimental phase, subjects had to reproduce the target interval, learned in the previous phase, in 200 experimental trials. This phase was divided into four blocks (which means 50 trials per block). All target interval reproductions between 637.5 and 862.5 milliseconds (an error-margin of 15%) were counted as correct. For correct trials, 5 points would be gained. If the response times were lower than 637.5 milliseconds, subjects would loose an amount of points depending on the type of penalty (or win 0 points in case of no penalty blocks). The blocks were arranged as follows: "no penalty" (no consequences of incorrect interval reproduction), "low penalty" (5 points would be deducted), "high penalty"(30 points would be deducted) and again, "no penalty". All subjects underwent the same order of experimental conditions. Feedback was administered in all cases: too long, too short and correct responses. The layout of a experimental trial is illustrated in Figure 1: It is initiated by a fixation dot in the screen center between 1000 and 2000 milliseconds. The "offset" for the target interval reproduction was again, a yellow dot in the screen center. Subjects marked their response by pressing the "space bar". Feedback on the performance and showing the current points would follow and stay for 2000 milliseconds. After that, the fixation dot of the next trial appears.

In this design, the amount of points deducted per block (induced RP) is the independent variable, while the target interval production in milliseconds was a continuous repeated-measures dependent variable. The score (in points) is a derived indirect measurement of performance.

Materials and Procedure: Subjects were asked to perform the experiment in their free time at home, on their own computers. They were also instructed to perform the experiment in a quiet environment with no distractions. The experiment has been implemented and executed with the open source software "Open Sesame" (Mathôt, Schreij, & Theeuwes, 2012). When starting up the experiment, after a short instruction screen, the training phase began, followed by the experimental phase. There was a possibility to take a break after block 2. The resulting CSV file with the was uploaded by the subjects.

The Cognitive Model

The cognitive model is based on the "Declarative Memory Module", which is a part the cognitive architecture "ACT-R" (Anderson et al., 2004) and has been implemented in the R programming language (R-Development-Core-Team, 2008).

It features two main components: the "temporal module" (Taatgen et al., 2004) and the "pool model" or "blending mechanism" (Taatgen & Van Rijn, 2011). The temporal module models how "subjective time" is represented by our cognitive system (without aids like counting). Interval estimation is envisioned as a "neural state" where a internal "metronome" ticks as long as the interval lasts, but with the ticks' length increasing the more ticks there are. The number of ticks or "pulses" is then an accumulated, internal, subsymbolic representation of a time interval. Humans are unaware of the quantity of "pulses". As this "conversion process" is not infallible, the model introduces also a noise component. The employed parameters for this component were $t_0 = 11$ (start tick length), $a = 1.1$ (tick "growth") and $b = 0.0125 - 0.0175$ (noise parameter). Each simulated subject had its own noise. This was introduced to simulate the subjects' "inherent accuracy".

Any amount of pulses (any estimated time interval) forms a discrete entity in memory called "chunk". The second component models how the "chunks" are stored and retrieved from memory. The core idea is that the probability of retrieving a certain chunk depends on the number of encounters of that chunk and how recent those encounters were. The longer a certain chunk has not been encountered, the more this memory has "decayed" and the harder it will be to "remember" it. Put more formally, the "activation" of a chunk can be calculated as in Equation 1.

$$A(t) = \sum_{n=1}^{k} log(t - t_{creation})^{-d} \tag{1}$$

$t_{creation}$ stands for the time the current chunk was encountered. d stands for the decay parameter (how fast memory fades). We set this value to 0.9. k is the number of encounters for each chunk. The bigger the difference between t and $t_{creation}$, the less that encounter will contribute to the activation of the chunk.

The "weight" or "retrieval probability of a given chunk" is calculated as in Equation 2 (note that t is a noise parameter, which we set to 60). It is a softmax transform where the sum of all values of P_i add up to 1 as individual chunk activations are divided by the activations of all chunks. The "blended" value is calculated as follows: $BlendedValue = \sum_j V_i P_i$. Each chunks' retrieval probability is multiplied by its value V_i and summed over all j chunks.

$$P_i = \frac{e^{\frac{A_i}{t}}}{\sum_j e^{\frac{A_j}{t}}} \tag{2}$$

The goal of the softmax transform is to "blend" the entries in the current memory and to provide a weighed value based on the number of encounters and encounter moment, effectively "smudging" the values together.

Hypothesis implementation: The above mentioned model was adapted to simulate the behavioral experiment as described in this method section. A training phase would store 5 encounters of a pulse representation of 750 milliseconds, which was the initialization of the "declarative memory". In the experimental phase, the simulated subjects' interval reproduction consisted in the blended value of the whole "declarative memory".
Higher chunk-values have the ability to momentarily "lift up" the retrieved time intervals. We used this property and would commit a "RP-encounter" each time a negative feedback was in order (incorrect trials). The value of this chunk, those RP-encounter belong to, was calculated as in Equation 3.

$$RPChunk = \alpha - \beta\gamma + noise \tag{3}$$

α and γ were free parameters, which were set to 13 and 1.5 respectively (best results were achieved this way). β was the block specific penalty (0, -5 and -30). This means, that each time the a simulated subject would retrieve a incorrect interval reproduction, in addition committing the given "answer" to memory, a encounter of a RP chunk is stored. The value of this "feedback sensible" chunk depends on the "severity" of the punishment. The higher the deduction of points is, the stronger the impact on the simulated behavior. On correct trials, no additional encounters other than the correct answer were added to the declarative memory.

Data analysis

Response time, proportion of correct trials and response time standard deviation (not included) were aggregated by subjects and plotted for each block. Lowess lines mark the trend for experimental data (blue) and simulated data (red). In order to determine if there is a significant difference between the response times each block (if the levels of the independent variable had significant impact and subjects responded differently depending on the RP), a linear model was performed. Response times were predicted by the factor "block".

To assess how well the model fits the experimental data, we followed the indications of (Spiess & Neumeyer, 2010) and (Pitt, Myung, & Zhang, 2002) and opted to not include R-squared as a indicator of goodness-of-fit. Instead, an ANOVA between identical models (one with experimental, and the other with simulated data) was performed. In addition, AIC values for both models have been computed. Finally, visual inspection of the plots is also taken into account.

Results

In Table 1, statistically significant mean estimates for each block can be found for simulated and experimental data. Response times were highest for block 3, where also the RP or punishment was highest. Block 1 and 4 have the lowest response times, closest to 637.5 milliseconds and error commission. This can also be observed in Figure 2. Surprisingly, the amount of correct trials remains constant throughout the entire experiment (see Figure 3). Visual inspection of Figure 2 and Figure 3 suggests that the model reproduces the data quite well. The mean estimates from Table 1 are also very similar. The AIC value for the linear model of the experimental data was 1903.006, while for the simulated data it was 2022.047. The ANOVA did not yield a statistically significant difference between the two models.

	Experiment		Simulation	
Factors	Estimate	t-value	Estimate	t-value
Intercep t	768.875	195.833***	780.118	147.551***
Block 2	39.092	7.041***	33.992	4.546***
Block 3	61.553	11.086***	47.462	6.348***
Block 4	37.410	6.738***	16.404	2.194*

Table 1: *Results of the linear model for the experimental and simulated data. Interval estimation was predicted by the factor "block".*

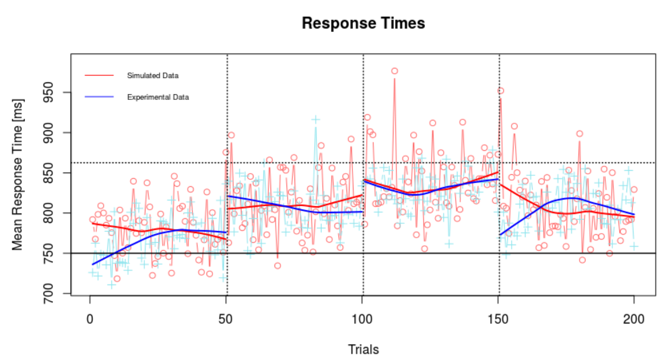

Figure 2: *Mean response times (aggregated over subjects) per trial; blue: experimental data, red: simulated data. The vertical dashed lines differentiate the blocks.*

Discussion

In the present work, we argued that similarly to the findings from (Maloney et al., 2007) in a motor task, subjects would adapt their behavior depending on the risk perception (or punishment intensity) during a time estimation experiment. In Figure 2, it can be observed that the higher the punishment, the higher the response times. The lower the punishment, the closer the estimates remain to the lower error margin. In Table 1, the mean estimates show that this dynamic is present in

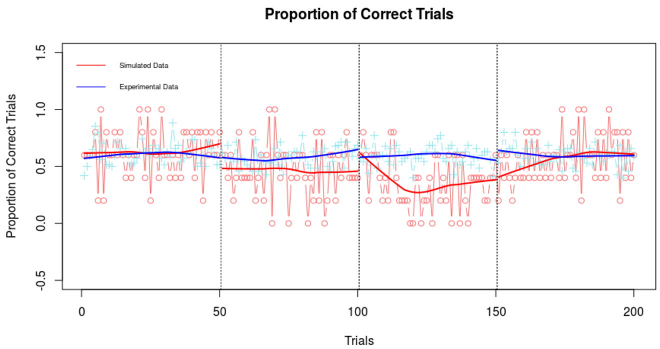

Figure 3: *Mean proportion of "correct" answers (aggregated over subjects) per trial; blue: experimental data, red: simulated data. The vertical dashed lines differentiate the blocks.*

the experimental as well as the simulated data. In Figure 3, we see that subjects remained equally accurate (around 60% successes) during the whole experiment. This seems to indicate, that even if subjects respond differently for each RP condition, performance is not affected. This pattern of "minimal effort" seems consistent with the idea that interval timing is "energy consuming" and shorter interval timing is preferred over longer intervals. Only when strongly "motivated" with high and moderate punishment, subjects prolong their reproduced interval. This raises the question how would this dynamic look like if also "too long" responses were punished. Regarding the experimental results, it can be concluded that subjects indeed adapt their time interval estimations to RP conditions.

Our cognitive model was able to reproduce the experimental findings in a satisfactory way, as can be gathered from Table 1, the AIC values and the non significant differences between experimental and simulation linear models. The implemented hypothesis stated that the negative feedback on error trials, weighted by the severity of the punishment, would be encoded the same way as "usual" interval timing information and stored in the same declarative memory. Is it possible then, that RP is encoded in a domain specific way? When success depends on motor actions, the RP is "embodied" in the motor domain while for time estimation tasks the RP is stored in the declarative memory? The fact that the model is very similar to the experimental results seems to indicate that our hypothesis regarding the cognitive functioning of timing and RP is worth pursuing.

Would a narrower error margin (10% instead of 15%) change how strongly the punishments are perceived? Maybe, longer or shorter intervals are more error prone than 750 milliseconds. There is still much work to do in order to understand how implicit or "covert" cognitive processes influence behavior whose execution is dependent on our "inherent" variability or accuracy.

For instance, interval timing could be reconceptualized as "event prediction" instead of "pulse accumulation". (Downing, 2009) extensively describes subcortical neuronal circuits involved in predictive capacities. The implicated regions (basal ganglia, thalamus, cerebellum, prefrontal cortex), to a certain degree, overlap with those described by (Matell & Meck, 2000). Both authors implicate the thalamus as a relevant relay between subcortical and cortical regions during timing. While no specific brain area has been related to time estimation, is seems to be a phenomenon that lends itself to be characterized through effective connectivity and dynamic causal modeling of fMRI data (Friston, Harrison, & Penny, 2003). This approach would not only allow to determine which brain regions are active during timing, but also to attribute causality (region A is active *because* of the activity of region B). To my knowledge, timing has not yet been studied with effective connectivity analysis.

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