University of Groningen

Time & Other Dimensions

Schlichting, Nadine

DOI:
[10.33612/diss.97434922](https://doi.org/10.33612/diss.97434922)

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2019

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):
Schlichting, N. (2019). *Time & Other Dimensions*. [Thesis fully internal (DIV), University of Groningen]. University of Groningen. <https://doi.org/10.33612/diss.97434922>

Copyright

Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license. More information can be found on the University of Groningen website: <https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment>.

Take-down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from the University of Groningen/UMCG research database (Pure): <http://www.rug.nl/research/portal>. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.

Time & Other Dimensions

Nadine Schlichting

Layout & Cover Design: Nadine Schlichting
Printed by: Ridderprint | www.ridderprint.nl
ISBN (book): 978-94-034-1989-3
ISBN (ebook): 978-94-034-1988-6
© Nadine Schlichting, 2019, Groningen, The Netherlands

university of
 groningen

Time & Other Dimensions

PhD thesis

to obtain the degree of PhD at the
University of Groningen
on the authority of the
Rector Magnificus Prof. C. Wijmenga
and in accordance with
the decision by the College of Deans.

This thesis will be defended in public on

Thursday 31 October 2019 at 11:00 hours

by

Nadine Schlichting

born on 7 March 1990
In Anse-Royale, Seychellen

Supervisors

Prof. H. van Rijn

Prof. R. de Jong

Assessment Committee

Dr. V. van Wassenhove

Prof. N. A. Taatgen

Prof. R. Ulrich

Content

- 1 General Introduction
- 11 Chapter 1
Time & Numerosity (Part I)
- 41 Chapter 2
Time & Numerosity (Part II)
- 65 Chapter 3
Time & Space
- 87 Chapter 4
Time & Stick Figures
- 103 Chapter 5
Time & Other Dimensions
- 119 References
- 137 Summary - Samenvatting - Zusammenfassung
- 145 Acknowledgements

General Introduction

Foreword

My PhD project was part of the EU Horizon 2020 project *Mind and Time — Investigation of the temporal attributes of human-machine synergetic interaction*, an interdisciplinary endeavor to equip artificial agents with human-like temporal cognition. Our working example was a kitchen robot which assists a human in preparing a dish. We quickly learned that, for a fluent human-robot interaction or cooperation, the AI should be able to predict human behavior (e.g., predicting when the human finished cutting tomatoes and needs the opened can of sweetcorn to put in the salad), and have an idea of when to start its own actions in order to match human needs (e.g., the AI should have opened that can of sweetcorn before the human finished cutting tomatoes). The main function of interval timing in behavior thus seems to be anticipation or predicting events in the near future¹. We also quickly realized that there are many open questions and problems in each discipline involved in this project. For example, the scenario described above is oversimplified. As humans, we perform and keep track of the timing of multiple actions in parallel: For example, before cutting the tomatoes we may have put a pan on the stove, and we typically have a feeling for when it is time to add ingredients to it, even if we do something else in the meantime. This thesis is a partial snapshot of where we stand in understanding temporal cognition.

¹In most animal interval timing experiments animals learn to produce/reproduce/distinguish intervals with the help of food rewards (for a review, see Crystal, 2007). In other words, animals anticipate a food reward in the future. Interestingly, even organisms without a central nervous system can learn anticipation-like behaviour (e.g., slime molds: Saigusa, Tero, Nakagaki, & Kuramoto, 2008).

General Introduction

Regardless of one's theoretical framework concerning the nature of time (i.e., whether it exists or not, cf. McTaggart, 1908; Rovelli 2018), we can certainly feel the passage of time, we have a sense of temporal order, and we perceive events as having certain durations. Time is real to us, and it is fundamental to our conscious experience (Dennett & Kinsbourne, 1992; Van Wassenhove, 2017). Strictly speaking, we don't have a *sense* for duration and time as we have for light waves (the visual system) or air pressure waves (the auditory system). This makes the study of how we perceive time mysterious and challenging, but at the same time extremely interesting.

Instead of having a sense for time, the perception of duration seems to be an epiphenomenon of processes within our minds (cf., Gibson, 1975; Hass & Durstewitz, 2016; Matthews & Meck, 2016; Michon, 1990). From an evolutionary perspective, John A. Michon stated that our ability to represent time underlies "... the need to stay in tune with a dynamic, unfolding outside world" (Michon, 1990, p. 55). Within this quote lies another crucial remark: the world we inhabit is dynamic and unfolding, there is no thing, event or activity that is not extended in time and therefore has a duration. In the world we inhabit, changes in time are often accompanied by changes in another dimension or properties, too. Cooking recipes, for example, often use time indications and indications about the change of a specific feature of an ingredient interchangeably: "In a separate pan, heat the oil and 1 small knob of butter over a low heat, add the onions, garlic and celery, and fry gently for about 15 minutes, or until soft but not coloured" (Jamie Oliver, A basic risotto recipe, step 2³). In this example, instead of setting a timer to 15 minutes, one can instead keep an eye on the consistency and color of the ingredients. This thesis explores time in relation to other dimensions.

Within the field of temporal cognition, the main theories of time perception have been formalized in various models (see overview on the next two pages). The models described here can be roughly classified into two camps: dedicated clock models, which assume that interval perception is a "stand alone" cognitive process (e.g., SET and SBF); and those that see time as an intrinsic property of other cognitive processes (e.g., neural energy model, SDN models, CCM and memory decay models). When surveying the literature on timing models, some of the much discussed models do not really belong to either category. First, there is the A Theory Of Magnitude (ATOM) model, proposing one common system for all magnitudes (e.g., time, space, number). ATOM makes no clear or detailed assumptions about the underlying mechanisms of time perception (or of other magnitudes, respectively). The second exception are Bayesian Observer Models and sequential-update models, which are, first and fore-

³You can find the complete recipe at <https://www.jamieoliver.com/recipes/rice-recipes/a-basic-risotto-recipe/>.

Scalar Expectancy Theory

^{1,2} In SET models the internal clock system consists of a pacemaker, which continuously emits pulses, a switch, which acts as a start signal to accumulate pulses in the accumulator. The number of accumulated pulses is then stored in a memory component, and, if necessary, compared to other durations stored in a reference memory in order to make a decision. The rate of pulse generation is thought to be influenced by, e.g., arousal or attention, explaining the commonly found distortions of time perception. The contingent negative variation (CNV), a slow EEG signal that typically develops from stimulus onset until stimulus offset, has been discussed to reflect the accumulation of time in the brain³; while the supplementary motor area (SMA) has been proposed as locus of the accumulator^{4,5}.

A Theory Of Magnitude

^{6,7,8} Time, number, space, speed and other magnitudes that can be experienced as 'more than' or 'less than' are processed by one common magnitude system. The parietal cortex is discussed as a candidate neural substrate for the generalized magnitude system. Behavioural magnitude interference effects (e.g., larger stimuli last longer than smaller stimuli) are interpreted as evidence for the ATOM framework. ATOM does not explicitly specify at which processing state magnitudes are translated into a common metric. Recent behavioural studies suggest that different magnitudes are encoded dimension-specific, and stored in a common memory system^{9,10}

Time/Sequence cells

Cells throughout the brain can encode moments in time (e.g., hippocampus¹¹, medial prefrontal cortex¹², medial frontal cortex¹³, presupplementary motor cortex¹⁴, medial agranular cortex¹⁵, lateral entorhinal cortex¹⁶, and striatum¹⁷). The cells' behaviour can vary from, e.g., ramping activity^{14,16}, time-selective activity¹¹ or other nonlinear activity patterns¹³. Some cells encode time in a relative manner, i.e., their activity patterns are scalable^{13,17}. Importantly, this body of research is mainly concerned with the encoding of episodic or sequential time. Episodic timing does not necessarily require precise metric timing in the sense of interval timing, but duration can be inferred¹⁸.

Time Perception

Striatal Beat Frequency model

¹⁹ SBF models rely on populations of oscillating neurons with different base frequencies. At the onset of an event these oscillators are reset or synchronized. Because of their different base frequencies oscillators will slowly drift out of sync again. At each point in time, multiple oscillators thus create a unique pattern of activation that can be read out by coincide detectors. These detectors are hypothesized to be located in the striatum. While there is empirical evidence for the separate components behaving as proposed²⁰, there is only little evidence for the specific mechanism proposed²¹.

Neural energy model

²² Coding efficiency could act as a signature of subjective duration, in that the amount of neural energy required to represent a stimulus is proportional to the subjective duration assigned to that stimulus. The neural energy model can explain temporal illusions: e.g., subjective time contraction caused by repetition (less neural energy – less subjective time), or subjective time dilation for filled versus empty intervals (more neural energy – more subjective time). It further implies that low-level neural signatures play an important role in duration perception.

Memory decay models

(Short-term) memories of perceived events decay over time, and thus inherently allow to infer duration from decaying memory strength. For example, the memory derived multiple-time-scale (MTS) model^{23,24} incorporates a series of slower and faster exponential leaky integrators from which duration information can be read out. Models developed for processes other than interval timing, e.g., the Temporal Context Model²⁵, can in fact also do interval timing tasks.

State Dependent Network models

^{26,27} Cortical networks implicitly encode temporal information as a result of time-dependent changes in excitatory-inhibitory interactions, which influence the population response to sensory events in a history-dependent manner. Here, durations are represented as spatial neural activation patterns that do not occur in a dedicated system, but throughout the entire cortical system. Evidence mainly comes from simulations and in vitro studies²⁸, while evidence from human and animal recordings is sparse²⁹.

Content Change Model

³⁰ A hierarchical neural network model of visual object classification modified to accumulate salient events when fed with any kind of video (more salient changes, longer estimated durations and vice versa). If the difference between two consecutive frames exceeds an adaptive threshold (i.e., a salient change in the visual scene), a unit of subjective time is accumulated. Salient events are accumulated on different levels of the neural network (higher levels are more responsive to object like features of the visual scene, while lower layers respond to more primitive features). CCM does not rely on any kind of pacemaker or internal clock. When compared to human time estimates, the model exhibits the same biases as human participants do.

Bayesian Timing

^{31,32} The Bayesian Timing framework postulates that a percept of an interval is in fact an integration of noisy sensory information and prior experience. Specifically, in computational Bayesian Observer Models the perceived duration of the current trial (likelihood) is integrated with previously encountered intervals (prior) to obtain the subjective percept (posterior), which will subsequently be used for interval estimates. Neurobiologically, Bayesian integration has been found to be reflected in the geometry and dynamics of neural circuits³³. Bayesian models can model the perception of other magnitudes, too^{34,35}.

Sequential-update models

Similar to Bayesian Observer Models, sequential-update models assume that we rely on an internal reference memory for duration rather than on the current percept. Examples of sequential-update models are the Internal Reference Model (IRM)^{36,37} and the mixed-pool model³⁸. The internal reference memory is dynamically updated by integrating previously presented and current durations as a weighted average.

Overview: Models of time perception (pp. 4-5). ¹Church, Meck, & Gibbon, 1994; ²Gibbon, Church, & Meck, 1984; ³Macar, Vidal, & Casini, 1999; ⁴Coull, Charras, Donadieu, Droit-Volet, & Vidal, 2015; ⁵Coull, Vidal, Nazarian, & Macar, 2004; ⁶Bueti & Walsh, 2009; ⁷Walsh, 2003; ⁸Walsh, 2015; ⁹Cai & Connell, 2016; ¹⁰Cai, Wang, Shen, & Speekenbrink, 2018; ¹¹MacDonald, Lepage, Eden, & Eichenbaum, 2011; ¹²Tiganj, Cromer, Roy, Miller, & Howard, 2018; ¹³Wang, Narain, Hosseini, & Jazayeri, 2018; ¹⁴Mita, Mushiake, Shima, Matsuzaka, & Tanji, 2009; ¹⁵Matell, Shea-Brown, Gooch, Wilson, & Rinzel, 2011; ¹⁶Tsao et al., 2018; ¹⁷Mello, Soares, & Paton, 2015; ¹⁸Buszáki & Llinás, 2017; ¹⁹Matell & Meck, 2004; ²⁰Gu, Van Rijn, & Meck, 2015; ²¹Matell, 2014; ²²Eagleman & Pariyadath, 2009; ²³Staddon, 2005; ²⁴Staddon & Higa, 1999; ²⁵Shankar & Howard, 2010; ²⁶Buonomano, 2000; ²⁷Karmarkar & Buonomano, 2007; ²⁸Goel & Buonomano, 2014; ²⁹Bueno et al., 2017; ³⁰Roseboom et al., 2019; ³¹Acerbi, Wolpert, & Vijaya-kumar, 2012; ³²Jazayeri & Shadlen, 2010; ³³Sohn, Narain, Meirhaeghe, & Jazayeri, 2018; ³⁴Martin, Wiener, & Van Wassenhove, 2017; ³⁵Petzschnner, Glasauer, & Stephan, 2015; ³⁶Bausenhardt, Dyjas, & Ulrich, 2014; ³⁷Dyjas, Bausenhardt, & Ulrich, 2012; ³⁸Taatgen & Van Rijn, 2011
 Illustrations inspired by: Hass & Durstewitz, 2016, Figure 1 (SBF); Buonomano, 2014, Figure 6A (SDN); Roseboom et al., 2019, Figure 1B (CCM)

most, instantiations of a computational framework. I will not discuss or evaluate the models introduced in the Overview here, I will occasionally refer to some of them in the empirical chapters (Chapters 1 to 4), and I will return to the topic in the final chapter, in which I will discuss four selected models in light of the findings presented in this thesis.

In Chapter 1 we initially set out to find EEG markers that are unique to the processing of time compared to the processing of numerosity. In the task we designed (referred to as the Raindrops task) participants saw small blue drops dynamically appearing and disappearing on the screen for a specific duration. Two dimensions of these stimuli were manipulated simultaneously: time (i.e., the interval marked by the appearance of the first drop and the disappearance of the last drop) and numerosity (i.e., the total number of drops appearing). In each trial, we presented two of these Raindrops stimuli consecutively and asked participants to indicate whether the second stimulus was shorter or longer if they were cued to make a judgement about the dimension time; or whether the second stimulus consisted of fewer or more drops if they were cued to make a judgement about the dimension numerosity. In both the time and time-frequency domain EEG signals we found no or only ambiguous evidence for a difference between the processing of time and numerosity. Puzzled by these results, we took a closer look at the behavioral data. In an extensive post hoc analysis we found that, when asked to judge time, participants were influenced by the task irrelevant numerosity information. This effect is also known as temporal interference effect. For example, if the second stimulus was shorter, but consisted of more drops than the first stimulus, participants were more likely to erroneously respond ‘longer’. To quantify these interference effects, we used a Maximum Likelihood Estimation (MLE) procedure to estimate, for each participants and each condition separately, how much temporal and numerical evidence was taken into account when making a judgement. Essentially, the outcome of this procedure were two ML-estimates, one weighing temporal evidence, the other weighing numerosity evidence. We then selected those participants who, according to their ML-estimates, took the task relevant dimension much more strongly into account than the task irrelevant dimension (e.g., in the time judgement task these participants would have a relatively high ML-estimate for temporal evidence, and a relatively low estimate for numerosity evidence), and we repeated the EEG analyses on these subsets of participants. The results were still inconclusive. Event related potentials that once have been related to the processing of time and time only (CNV: Macar, Vidal, & Casini, 1999; but see Boehm, Van Maanen, Forstmann, & Van Rijn, 2014 and Kononowicz & Van Rijn, 2011, for counter examples) were also observed in numerosity trials (less pronounced than during time trials, but evidently observable). What we learned from this study and what inspired us to conduct a follow up study was that, when making temporal estimates,

we use different kinds of information available to us, that is, not only temporal information. The degree of how much we rely on each information source differs between individuals, and can potentially be captured with the MLE procedure. However, an open question that remained after this study was how reliable the ML-estimates are.

Chapter 2 is a report about a behavioral follow up study of the Raindrops task. Participants were invited for two sessions of experiments, separated by six to eight days. In the first session, they completed a shorter version of the Raindrops task as described above (i.e., drops appeared and disappeared dynamically), a static version of the Raindrops task in which all drops appeared at interval onset and disappeared at interval offset, and a numerical Stroop task. In session two, participants were tested again in the Dynamic Raindrops task, another version of the Static Raindrops task, and in a traditional temporal comparison task (i.e., the stimuli were the same on each trial and did not differ in any other property than duration). This design allowed us to test the stability and reliability of the ML-estimates over time (from session 1 to session 2), over similar tasks (Dynamic and Static versions of the Raindrops task), and relate them to performance in traditional timing tasks (temporal comparison task) and other interference tasks (numerical Stroop task). Our main finding was that individual differences in magnitude of interference in the Dynamic and Static Raindrops task were stable over sessions and over different task versions. ML-estimates obtained from the Raindrops tasks were also predictive of performance in the traditional timing task. This means that the amounts of temporal and non-temporal information participants use to make a temporal estimate are a stable trait or bias within individuals. We did not find a relation to performance in the numerical Stroop task. In the studies presented in Chapter 1 and 2 we replicated previously observed temporal interference effects, from a more practical perspective, and we demonstrate how the manipulated dimensions can be disentangled by the MLE procedure.

While the previous two chapters were concerned with the dimensions time and numerosity, Chapter 3 is concerned with the dimensions time and space. We often borrow the dimension of space to think about, talk about and conceptualize time: “My last vacation was too short”, “The future lies ahead of us”, or “The meeting was moved forward one hour”. In interval timing experiments, however, motor reproductions (e.g., pressing a button for the duration of a to-be-estimated interval) are the predominant method of choice. If we cognize about time in terms of spatial dimensions, estimating intervals in terms of spatial dimension seems like a plausible alternative to motor reproductions. In the studies reported in Chapter 3, we tested differences in accuracy, precision and efficiency between motor reproductions, timeline estimates (i.e., spatial estimates of intervals) and verbal estimates in a simple and in a more complex interval reproduction task. We concluded that each translation of time into another

representation (motor, verbal or spatial) has its own advantages and disadvantages: Motor reproductions were slightly more precise (Experiment 1) and more accurate (Experiment 2) than timeline estimates; timeline estimates had the lowest reaction times and are therefore very efficient; and, although verbal estimates were most accurate and precise (Experiment 1), we found a bias towards integer units. Overall, our results suggest that we can flexibly translate time into the task required format, and the choice of the most optimal estimation method is dependent on the experimental design.

Trying to isolate time from another dimension is a cumbersome endeavor. This is because manipulating two dimensions simultaneously (e.g., time and numerosity as in Chapter 1 and 2) gives rise to changes in other dimension, too (e.g., the rate of drops appearing). While this difficulty will be discussed more thoroughly in Chapter 1 and 2, the point I want to raise here is that, in a complex environment, time and changes in many other dimensions are rarely segregated. In Chapter 4, we tested participants' ability to estimate the duration of complex and more naturalistic stimuli. Short videos of an animated figure performing different everyday actions within a kitchen context served as stimuli. What is special about this study compared to the ones described in Chapter 1 to 3 is that i) stimuli had no clearly marked on- and offset; and ii) they varied in multiple properties (e.g., there are more fast movements when the animated figure is chopping vegetables compared to drinking from a cup). We found that, despite increased stimulus complexity, the data adhered to general interval timing laws: Variability of interval estimates increases with veridical duration (scalar property); and estimates of previous trials influence the perceived duration of the current trial (temporal context effects). This study is a step towards studying interval timing in ecologically valid settings and as a component of everyday cognitive performance (cf., Matthews & Meck, 2014; Van Rijn, 2018).

Lastly, in Chapter 5 I will discuss some of the main findings reported in this thesis in the light of different models of time perception, with the conclusion that there may be no need for dedicated timing models. As an alternative and as a future direction for the field of temporal cognition, I will propose to focus on *temporality of cognition* in an inter- and intradisciplinary way, given that all of our cognition is inherently extended in time and carries temporal information.