

Memory-Related Contextual Bias in Temporal Perception May Be Inhibitory Versus Excitatory In Nature

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Abstract

Contextual bias in temporal perception is likely associated with the convolution effects of both general and clock-specific mechanisms. In this study, unique contributions of memory and temporal precision respectively, were simultaneously investigated. The two mechanisms were also modelled based on a declarative memory system of ACT-R, along with a built-in time module. Modelled results adhered closely to the empirical findings, showing effects of general cognitive mechanism of memory on contextual bias, after controlling clock-specific sensory mechanism of temporal precision. Moreover, the modelled results suggest that memory-related process may be inhibitory versus excitatory in nature.

Keywords: temporal perception; declarative memory; temporal precision; mismatch penalty; ACT-R.

Introduction

In temporal perception, a robust phenomenon is demonstrated where reproduced duration of a series of time intervals in a given context tends to regress towards their mean (i.e., contextual bias, Jazayeri & Shadlen, 2010). However, the precise reason for such a bias is less clear. Possible interpretations have been either attributed to the general mechanism of memory, or the “clock-specific” mechanism of temporal precision (for a review, see Maass & van Rijn, 2018). In light of the original study of Jazayeri and Shadlen (2010), this article aims first to briefly review how a) memory and b) temporal precision may independently contribute to contextual bias. Based on the brief review, this article then outlines the aim and hypotheses of the current study.

In Jazayeri and Shadlen (2010), the reproduction of the current time interval is related to a Bayesian process, where the immediate perceived duration (sensory likelihood) is integrated with the previously stored representations (prior) to produce an estimated time interval (posterior). The findings of Jazayeri and Shadlen (2010) can be readily modelled in ACT-R by incorporating the declarative memory module. It is therefore natural to relate contextual bias to a general memory mechanism. From empirical evidences, those with better memory performances often show more accurate estimation of time, and less interferences from the previously held memory (e.g., MCIs vs. control in elderly, van Rijn, under preparation; better vs. worse memory performances in children, van Rijn, under preparation).

On the other hand, sensory likelihood could be also altered due to “clock-specific” mechanisms that even preceded the more general memory mechanism. For instance, if a person’s sensory likelihood is within an exceptionally narrow range, Bayesian integration would become less susceptible to previously stored memory content (prior), and vice versa.

Indeed, empirical evidences have demonstrated that contextual biases were much smaller in those with higher temporal precision (expert drummers vs. string musicians; Cicchini et al., 2012), along with an age-related trend of increasing contextual bias with decreasing temporal precision (Turgeon et al., 2016). Thus, additional to the general mechanism of memory, “clock-specific” temporal precision may also contribute to the extent of contextual bias.

One major purpose of this study is to simultaneously investigate the contribution of a) memory and b) temporal precision on contextual bias in temporal estimation. Firstly, in order to accurately and economically evaluate the magnitude of contextual bias, the study incorporated a simpler version of the time reproduction task (see Maass & van Rijn, 2018). In this task, participants reproduce 2 of the 3 different durations in each of the short or long duration conditions. The rationale for using a shorter task is based on the understanding that a prior can be gradually acquired on a trial-by-trial basis, and the rigid assumption of applying multiple trials (i.e., more than 1000 trials) to generate a “static” prior is thus unnecessary. Using this shorter version, contextual bias effects were produced in previous studies among elderly and children (van Rijn, under preparation).

Purer indicators were also used to precisely assess the convolution effects of general and “clock-specific” mechanisms. For memory, a cross-modality indicator was used that measures participants’ rate of forgetting of pseudo “Swahili words” (see Sense, Behrens, Meijer, & van Rijn, 2016). It is assumed that the rate of forgetting is a general trait-like property of the general memory system. On the other hand, for “clock-specific” temporal precision, short 1-s interval estimation tasks (20 trials) were applied. In the standard time-estimation task (see Maass & van Rijn, 2018), participants were asked to press a key when a monotonous tone has elapsed for 1-s. The “clock-noise” was calculated by a reliable temporal precision index (i.e., $RMSR/\mu$, see Maass & van Rijn, 2018), which carefully accounts for drift and scalar property in temporal estimation. Another novel 1-s “tick-tock” task was also used, which differs with the standard task only in terms of the presentation of 1-s (for details, see Method). Arguably the “tick-tock” task may better control for undesirable system variance from, for instance, the continuous tone.

Another major purpose of this study is to simulate the empirical findings based on a constrained ACT-R model (Anderson et al., 2004). In the declarative memory module of ACT-R, the general mechanism of memory can be conceptualized as a summation of an active retrieval process and a passive decay process. Specifically, the more readily

retrieval of memory traces (A_i) is a “blending” of attention to currently task-relevant memory traces (including spread activation, C_i , and mismatch penalty, M_i), along with a passive decay process that applies uniformly to all previously stored memory traces (baseline activation due to decay, B_i). Thus, the ACT-R declarative memory system can be seen as a cognitively plausible memory-based Bayesian process, which can be briefly expressed as follows:

$$A_i = B_i + (C_i + M_i)$$

For the purpose of accounting clock-specific mechanism, an additional time module is added in the model. This module relates to how time stimulus can be transformed more or less accurately into mental representations (for details, see Taatgen, van Rijn, & Anderson, 2007). For specific details of ACT-R model on declarative memory retrieval, and the built-in time module, please refer to the Appendix.

In this study, the unique contributions of memory and temporal precision on the magnitude of contextual bias are firstly evaluated based on empirical results. It is hypothesized that (a) higher rate of forgetting, and (b) higher temporal precision may uniquely associate with greater contextual bias. Another minor focus is on the validation of a tick-tock task. It is hypothesized that the temporal precision of the standard and “tick-tock” tasks may be correlated. Furthermore, the empirical findings are modelled based on constrained ACT-R model with a built-in time module. It is hypothesized that (c) parameters that are related to higher memory performances (such as high spread activation, mismatch penalty, and/or low decay), and (d) higher temporal precision (less clock-noise) may both predict less contextual bias.

Methods

Participants

In this study, participants comprised of 44 graduate students who enrolled a Master’s cognitive modeling course at the University of Groningen. Of all participants, 34% were females, 79.5% were right-handed, and the mean age was 23.91 years ($SD_{age} = 1.61$, $range_{age} = [21, 28]$). An electronic informed consent was provided and agreed upon at the outset of experiments before the experimental tasks can be loaded.

Procedure

Participants completed the tasks at their own pace in whatever time and location that suited them most. For the Swahili word recall task, participants performed the task through an online platform. For the time perception tasks (i.e., standard 1-s, tick-tock, and trumpet-play tasks), participants were required to run an experiment script via the OpenSesame desktop environment.

Time Reproduction For the trumpet-play task, after participants watched a dog figure becoming animated to play a monotonous trumpet sound (in the encoding phase), they was then asked to try matching the trumpet-play duration (in the reproducing phase) by holding on to a key for some time

before releasing it again. During practice trials, feedbacks were given as to indicate whether participants’ reproduction of time had been correct or out-of-bound (too long/short in duration). In the task, either short (S) or long (L) contexts were reproduced without feedback in four blocks that were counterbalanced in order (SSLL or LLSS). The blocks of S/L duration each consisted of 10 trials. The short context consists trials of 750 or 900 ms duration, while the long context consists trials of 900 and 1080 ms duration.

Swahili Word Game A random array of Swahili-English word-pairs were presented on the computer screen consecutively. After the encoding phase, participants were examined, in a following testing phase, whether they could recall Swahili word array by typing them out in a fully or partly correct manner (i.e., identify correct letter-stems in Swahili words) when only the associated English words were presented on screen. The task was designed adaptive. Initially, only a limited array of the total of 100 Swahili words was presented. During subsequent testing, if a certain percentage of the words were retained by the participant, the task would proceed to the next array of Swahili words. From this task, individual’s rate of forgetting is estimated. It is assumed that rate of forgetting is a stable trait of the declarative memory system (see Sense, Behrens, Meijer, & van Rijn, 2016).

Time-Estimation Two time-estimation tasks were applied in this study. In the standard task, participants were asked to press a key as soon as they thought 1 second had just elapsed, following the onset of a continuous monotonous tone. In the alternative tick-tock task, the design was almost identical except that participants were then asked to estimate termination of 1 second from the more discrete onset of a “tick” sound, by pressing a key to generate a “tock” sound. Familiarization of the tick-tock time estimation task was facilitated by five example trials practiced at the beginning. Both tasks were arranged in one block consisting of 20 trials (with random ITIs set in between 2000 to 3000 ms). To record time with precision, typical soundcard delay was corrected (+ 70 ms at onset), and unreasonably short responses (< 100 ms) were eliminated. In both tasks, a temporal precision index is estimated ($RMSR/\mu$, see Maass & van Rijn, 2018).

Statistical Analysis

In the time estimation and reproduction tasks, response times that were less than 200 ms or greater than 2000 ms were marked as outliers (consists of 1.02%, 1.25%, and .23% of the dataset for the 1-s, tick-tock, and trumpet-play tasks). Generalized linear mixed models were used for estimating the effects of fixed effects of stimulus duration (T_s), task contexts (S/L), and general (alpha) and/or clock-specific mechanisms ($RMSR/\mu$), along with their interactions, on reproduced duration (T_p). All regressional analyses are based on R function of lmer (Boeck et al., 2011). In the analyses, the durations of T_s or T_p was coded into (duration – 900)/1000, while the S/L task contexts were coded into -.5/.5.

Table 1: Empirical and modelled results

	Empirical Results					Modelled Results		
	M1	M2	M3	M4	M5	M(a)	M(b)	M(c)
Duration	.88 ***	.77 ***	1.22 ***	.83 ***	1.08 ***	Duration	.90 ***	.90 ***
Context	.00	.05 ***	-.01	.05 ***	.05 ***	Context	.02 ***	.02 ***
Alpha			.53		.52	M.mp		-.09 .
						M.ga	.00	.00
Wiebligheid				-.01	.00	M.precision	.02 ***	.02 ***
Duration · Context	-.06	-.04	.11	-.04	.04	Duration · Context	.02	.01
Duration · Alpha			-1.59 *		-.89 †	Duration · M.mp		-1.61 ***
						Duration · M.ga	-.02	-.02
Context · Alpha			.19					
Duration · Context · Alpha			-.21					
Duration · Wiebligheid				-.26 ***	-.29 ***	Duration · M.Precision	-.14 ***	-.14 ***
Comparison (Chi-square)				0	615 ***		0	8679 ***

Note. For comparable direction and magnitude, M.mp was set as $-\text{mp}/100$. M.ga is the parameter of spread activation.

M.Precision is a constant random value between 0 and 1, to generate the temporal precision parameters $a' = 1.0 + 0.1 \cdot \text{rand}$ and $b' = 0.015 \cdot \text{rand}$.

† $p < .01$, * $p < .05$, *** $p < .001$.

Results

In our study, since the effect of S/L task contexts was only revealed in a selected pool of participants (see *M2*, Table 1, those with mean reproduced time longer for the long versus short condition), versus the complete sample (*M1*, Table 1; Figure 1A, 1B), it was agreed that only the selected participants would be analyzed for the purpose of this assignment.

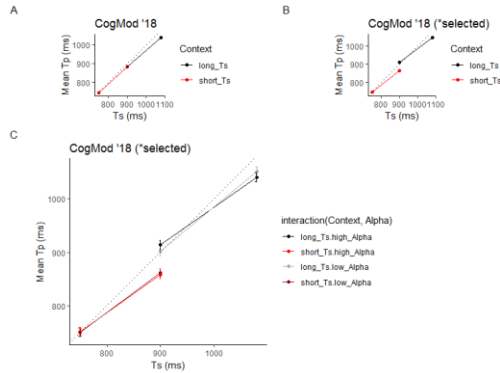


Figure 1: Contextual effects of all (A) and selected (B). Moderation of T_s to T_p , based on high and low levels regarding rate of forgetting (C).

In the selected sample, an interaction of stimulus duration (T_s) and general mechanism of memory (α) was revealed, indicating that the prediction of T_s to reproduced duration T_p is moderated by α (*M3*, Table 1; cf., Figure 1C, the T_s effect on reproduced T_p , between high and low α groups). Noticed carefully that the interaction between task context and α was however not revealed from this model. Nevertheless, the more fine-tuned duration can be seen as context-relevant, though effects are unnoticeable at the S/L

task context level. Interaction of T_s and α on T_p was nonetheless not revealed in the full sample before selection.

Alternatively, another interaction between T_s and temporal precision ($RMSR/\mu$) was revealed, indicating that the prediction of T_s to contextual bias is also moderated by the $RMSR/\mu$ (*M4*, Table 1).

The convolution of general (α) and clock-specific ($RMSR/\mu$) mechanisms can now be distinguished by an additional model. By controlling the clock-specific process, the effect of general memory process was retained, albeit at marginal level (*M5*, Table 1). Moreover, model comparisons (based on *Chi-square* test) suggest that general memory process still contribute uniquely to the model, in addition to clock-specific process.

Model

Firstly, the critical parameters of the model (i.e., *spread activation*, *mismatch penalty*, *decay*, and *temporal precision*) were manually modified to estimate their possible influence on contextual bias. Noted that in this case, particular emphasis was given on just the direction of effects. Outcomes of 100 subject (the modelled task representation was kept similar to the actual experimental task) were produced per parameter change. It is assumed that better general mechanism of memory may interpreted as greater *spread activation/mismatch penalty* and/or less *decay*.

At face level (as depicted in Figure 3A), an increasing value of *spread activation* (ga : 1.0 vs. 0, for *Ci*) or *mismatch penalty* (Figure 3B, mp : 3.0 vs. 0, for *Mi*) produced shifts in reproduced duration (T_p) consistent with the direction of empirical findings. Nevertheless, the opposite direction was found for the *decay* parameter (d : 1.0 vs. 0.5, for *Bi*). Alternatively, an increase of *temporal precision* parameter ($a = 1.01$, $b = 0.0015$ vs. $a = 1.1$, $b = 0.015$, cf., Figure A in Appendix) likewise produced shifts in reproduced duration (T_p) consistent with the empirical findings. Taken together, it is likely that contextual bias may be related to the parameter

of *spread activation*, *mismatch penalty*, and/or *temporal precision*, but it is unclear at this stage what kind of a role the *decay* parameter may play in contextual bias. These findings are only exploratory in nature.

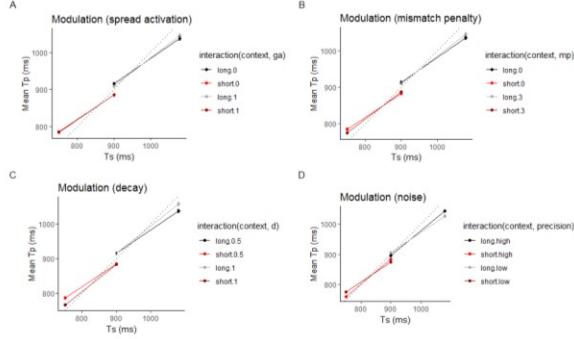


Figure 2: Exploratory findings concerning just the directions of contextual bias, by altering the parameters of *spread activation* (A), *mismatch penalty* (B), *delay* (C), or *temporal precision* (D).

Based on the directions of effects as illustrated in the exploratory analyses, a more generalized model was constructed, with parameters randomly generated for *spread activation*, *mismatch penalty*, and *temporal precision*. Nevertheless, the *decay* parameter that produced contrary outcomes was kept as default and not altered. This was to control for possible confounds of the less clearly identified *decay* parameter to the overall modelled results. Outcomes of 1000 subjects were produced by the more generalized model, and was subsequently analyzed using the generalized linear mixed effect model.

As can be seen from Table 1, the effects of task contexts (S/L conditions) and stimulus duration (T_s) on contextual bias or reproduced durations (T_p) is very similar to the empirical findings. Furthermore, the coefficients of the parameters of *mismatch penalty* (i.e., $-mp/1000$) and precision (i.e., altering a and b parameter, by multiplying a random value between 0 to 1) seems to be closely resembling that of the rate of forgetting (α) and temporal precision ($RMSR/\mu$) in the empirical results (see ACT-R modelled results $M(c)$, Table 1). However, the parameter of spread activation did not show any effects on contextual bias, even when the other active retrieval process (*mismatch penalty*) was dropped from analysis (see ACT-R modelled results $M(b)$, Table 1). This may suggest that the inhibition of the currently task-irrelevant memory traces, may be more likely the mechanism that relates to low memory performance and context-related bias in the empirical results. Nevertheless, the link between experimental variables and model parameters requires further clarification.

Discussion

In previous literature, the possible contribution of general and clock-specific mechanisms on temporal perception were

not simultaneously investigated. Some empirical research focused on memory (in children and elderly population; van Rijn, under preparation), while others on the end of temporal precision (e.g., Cicchini et al., 2012). In this study among a sample of Masters' students, the effects of memory were replicated by a reliable index of rate of forgetting (see Sense et al., 2016), based on a general cross-modal Swahili word task. Alternatively, by calculating the temporal precision index (see Maass & van Rijn, 2018), this study revealed how context-related effects (i.e., T_s on T_p) is gradually reduced by increasing temporal precision. These findings, based on a better controlled methodology, established that general and clock-specific mechanisms could both contribute to contextual bias in time perception.

The main purposes of this paper, however, is to further distinguish the unique contribution of the otherwise convoluted effects of general and clock-specific mechanism. After statistical control was applied, the effects of both processes were retained. In this study with relatively small sample, a robust effect of temporal precision, and a weaker and still presenting effect of memory was demonstrated. It should be noticed that temporal precision is a sensory construct. Thus, the findings highlighted that the general mechanism of memory may be the main cognitive contributor to contextual bias.

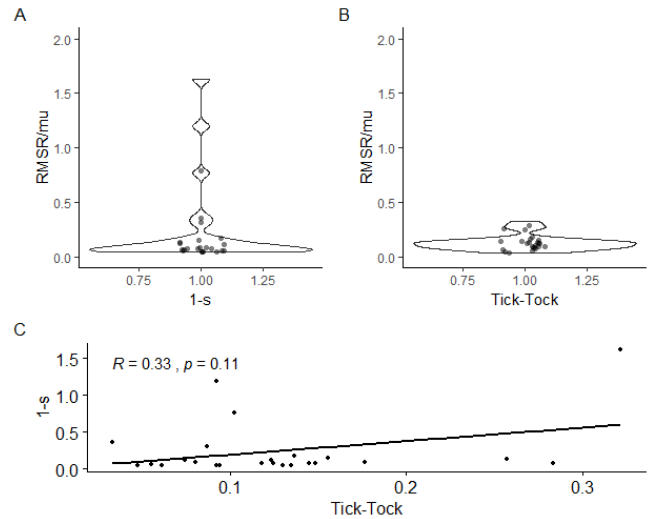


Figure 3: Temporal precision of the 1-s (A), and tick-tock (B) task, and their correlation (C).

One minor purpose of this study is to also compare a novel tick-tock task with the standard 1-s task. In principle, the tick-tock task reduces systematic variance, and therefore better estimates temporal precision. However, its validity was not yet to be established based on insignificant correlation. A follow up power analysis (a priori, with $\beta = .80$) suggests that a two tailed test to detect a correlation of .33 with $\alpha = .05$ requires at least a sample of 69 participants (G*power, Faul et al., 2009). Thus, it does not completely rule out that the tick-tock task may actually be a better measure of temporal precision.

Since the general mechanism of memory is a candidate cognitive contributor to contextual bias, the other main purpose of this study is to model this mechanism based on the declarative memory system of ACT-R (Anderson et al., 2004). From a Bayesian view, such a mechanism can be constructed by taking considerations of both (a) the active retrieval processes (*spread activation*, and *mismatch penalty*) that highlight the currently task-relevant memory traces, and (b) the passive *decay* process that uniformly applies to the strength of all previously stored memory traces (for a detailed description, see Appendix). On the other hand, the clock-specific mechanism of temporal precision is an alternative contributor to contextual bias, albeit at sensory level. The incorporation of a time module in ACT-R (Taategen, van Rijn, & Anderson, 2007) made it possible to also investigate this additional parameter.

From an initial explorative analysis, it was revealed at face level that only the parameters of *spread activation*, *mismatch penalty*, along with *temporal precision* shows likely consistent outcomes with the empirical findings. Therefore, a more generalized model was constructed that randomly generates only the above parameters, but leaving out the less clear *decay* parameter. Based on simulated outcomes, it was revealed that for the active retrieval processes, only the parameter of *mismatch penalty* (vs. *spread activation*) moderates the predictive role of stimulus duration to reproduced duration, which approximates a context-related effect. In addition, temporal precision also effects such contextual bias. Both effects closely adhere to empirical results. Therefore, after controlling sensory precision, the possible declarative memory mechanism that corresponding to higher memory performances and contextual bias, may be more inhibitory than excitatory in nature. From previous literature, efficiency in the inhibiting proactive interference (i.e., what was stored in the very recent past) is a major component related to higher working memory capacity (Aron, 2007; Lustig, May, & Harsher, 2001; Vogel et al., 2005).

Conclusion

This study shows that the generalized cognitive mechanism of memory, on top of the clock-specific sensory mechanism of temporal precision, plays a unique role on contextual bias in temporal precision. This cognitive mechanism is consequently modelled by a constrained Bayesian-like declarative memory system in ACT-R. After controlling temporal precision by applying an additional time module, modelled results show memory effects on contextual bias that closely adhered to empirical findings. To conclude, the study highlighted the contribution of generalized memory-related mechanism in contextual bias. Moreover, such memory-related mechanism is likely associate with the active retrieval of memory traces, and is perhaps inhibitory versus excitatory in nature.

Limitations

A few limitations remained for this study. Firstly, the power of the empirical study was hindered by a relatively small

sample size. Secondly, even though random effects were taking into consideration, the less controlled experiment setting may still increase error variances of the findings. Thirdly, although the stimulus duration by alpha effects approximated contextual bias, the true task context by alpha effects were not yet apparent. This may be enhanced by including stimulus durations with smaller duration increments in a task context (to allow more “contamination” of temporal perception). Last but not least, the link between experimental variables and model parameters requires further clarification to improve interpretation of modelled findings.

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Appendix:

A constrained ACT-R model on temporal perception

From a Bayesian perspective, temporal perception is yet another memory process that updates historical memory traces with active experience. Memory-based Bayesian process can be modelled in a constrained manner based on the retrieval of memory traces (i.e., chunks) from declarative memory; and more specifically, by applying the blending function of ACT-R.

Considering the successive presentation of two duration items, the “first” encoded item (i.e., the chunk containing transformed number of pulses, V_i) would now become the updated prior for the next item. Surely, such a prior would not stay static, and is subjected to gradual decay. Thus, the retrieval of the currently presented item, must take account of (or “blended” with) the updated prior.

Technically, the blending function calculates an average value from previously and currently encoded traces, weighted with respects to their corresponding stages of decay. The weight parameter (or the probability of retrieval P_i), is calculated based on the following equation:

$$P_i = \frac{e^{\frac{A_i}{t}}}{\sum_j e^{\frac{A_j}{t}}} \quad (1)$$

Subsequently, the weighted average (or the average number of pulses V_i), can be readily derived as follows:

$$V_i = \sum_j P_j V_j \quad (2)$$

Since the formation of time representations and the subsequent reproduction are repeatedly dependent on both the weighted average of previous memory traces and the immediately encoded information. Thus the Bayesian-like blending function is always applied in the constrained model.

Candidate processes that modulate the strength of memory traces

As illustrated in equation (1), the calculation of P_i is dependent on A_i , which is the strength or activation of a specific chunk. The activation value A_i is at least dependent upon a few candidate processes. It is already mentioned that stored memory traces are subjected to default decay (i.e., in base-level activation, B_i).

However, the agency of human cognitive processing may still include a more deliberate retrieval process that selectively attends to task-relevant information (i.e., spread activation, C_i) while inhibiting task-irrelevant information (i.e., mismatch penalty, M_i). Therefore, in principle, the activation V_i may be expressed as a summation of outcomes from a few cognitive processes (for a detailed review, see Anderson et al., 2004):

$$A_i = B_i + (C_i + M_i) \quad (3)$$

In this formula, the decay-related base-level activation (B_i) concerns with the odds that a chunk is needed regardless of currently presented time duration. It is dependent on the time since representation (delay time = $t - t_k$), the number of representations ($k = n$), along with a decay parameter ($-d$):

$$B_i(t) = \ln \left(\sum_{k=1}^n (t - t_k)^{-d} \right) \quad (4)$$

The spread activation (C_i) instead actively evaluates the needs of a chunk as relevant to the currently presented time duration. It is dependent on the amount of activation from a particular slot (W_j), and the strength of association between the particular slot j and the chunk i :

$$C_i = \sum_j W_j S_{ji} \quad (5)$$

Alternatively, the mismatch penalty (M_i) actively inhibits the chunks that are dissimilar to the currently presented time duration. It is dependent on the dissimilarity between slots l and I (M_{li}), and a constant penalty parameter P :

$$M_i = \sum_l P M_{li} \quad (6)$$

The memory ability, or the strength to retrieve certain chunk, may thus be either associated with the more active attention/inhibition (C_i/M_i) processes, or the rather passive decay process (B_i). In this model, the modulation of candidate processes on temporal perception are assessed each individually.

An alternative clock-specific process

The model also involves a more preliminary clock-specific module, which transforms duration stimulus into corresponding mental representation. The mental representation is in the forms of transformed number of pulses, analogues to the ticking of a metronome but gradually slows down. The length of pulse function is illustrated below, with the current length of pulse (t_{n+1}) being an extended length of the previous pulse (at_n) along with a Gaussian noise term:

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

The noise term can be modified by altering a and b parameters, without changing the overall length of pulses (Figure A). As follows, distinct distributions of reproduced times (with stimulus durations of 8, 12, and 21s) can be produced. Noted that this is based on a simple function that neglects any memory-based processes (see Taatgen, van Rijn, & Anderson, 2004).

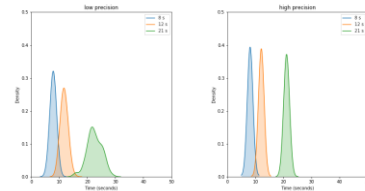


Figure A: distributions of T_p based on differential temporal precision

The model therefore needs to investigate the modulation of temporal precision on temporal perception. If modulation effect is present, they must be controlled at outset to allow better estimations of the effects from memory-based processes.