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Timing of multiple overlapping intervals: How many clocks do we have?

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ABSTRACT

Humans perceive and reproduce short intervals of time (e.g. 1–60 s) relatively accurately, and are capable of timing multiple overlapping intervals if these intervals are presented in different modalities [e.g., Rousseau, L., & Rousseau, R. (1996). Stop-reaction time and the internal clock. *Perception and Psychophysics, 58*(3), 434–448]. Tracking multiple intervals can be explained either by assuming multiple internal clocks or by strategic arithmetic using a single clock. The underlying timescale (linear or nonlinear) qualitatively influences the predictions derived from these accounts, as assuming a nonlinear timescale introduces systematic errors in added or subtracted intervals. Here, we present two experiments that provide support for a single clock combined with a nonlinear underlying timescale. When two equal but partly overlapping time intervals had to be estimated, the second estimate was positively correlated with the stimulus onset asynchrony. This effect was also found in a second experiment with unequal intervals that showed evidence of subtraction of intervals. The findings were supported by computational models implemented in a previously validated account of interval timing [Taatgen, N. A., Van Rijn, H., & Anderson, J. R. (2007). An integrated theory of prospective time interval estimation: The role of cognition, attention and learning. *Psychological Review, 114*(3), 577–598].

1. Introduction

Timing is an essential aspect of human behavior. Is the current pause in the verbal stream long enough to indicate a turn-taking opportunity? How long before the traffic light turns red? And how do we account for time when multiple time intervals – a lull in your passenger's monologue and a light turning yellow – overlap? This question has partly been answered in the context of parallel timing in different modalities (Rousseau & Rousseau, 1996, and see for an overview of modality effects on timing, Penney, 2003). This paper is concerned with a related question: can humans accurately estimate multiple overlapping time intervals *expressed in the same modality*?

In Taatgen, Van Rijn, and Anderson (2007), we have presented a complete and integrated account of time estimation. We proposed a "temporal module" that is part of a larger cognitive architecture (ACT-R, Anderson, 2007; Anderson et al., 2004). This module is a computational implementation of ideas that have been present for more than forty years (e.g., Gibbon, 1977; Matell & Meck, 2000; Michon, 1967; Treisman, 1963). Its core assumptions are that a pacemaker sends steady streams of pulses to an accumulator, and that the number of pulses collected in the accumulator indicates the amount of time that has passed. In this setup, the current value of the accumulator serves as the "clock", indicating the amount of time passed since the beginning of accumulation. The goals of the ACT-R temporal module are mainly functional (to give the cognitive architecture means to reason with time), and behavioral (the ability to produce the same behavior as humans). Other approaches focus on the neuroscience of time estimation (Buhusi & Meck, 2005).

An extensive literature exists on the nature of the above-mentioned clock. Work derived from the scalar expectancy theory (SET) postulates that a Poisson process generates the stream of pulses from the pacemaker, resulting in a linearly increasing accumulator value (Allan & Gibbon, 1991; Gibbon, 1977, 1992; Gibbon & Church, 1981). To account for the Weber-law-related properties of temporal perception (e.g., the positive correlation between the estimate and its variance, referred to as the scalar property), Gibbon (1992) showed that using a Poisson distribution for the accumulator requires variance as a function of time in the "decision and memory factors as well as in the internal clock. These additional sources will be seen to dominate overall variance in performance" (p. 191), emphasizing the important role of cognitive systems in time judgments. Other researchers (e.g., Church & Deluty, 1977; Staddon & Higa, 1999; Stubbs, 1968) located the source of the scalar variance in the "clock" itself. For example, in Staddon and Higa's (1999) proposal, the clock is driven by processes related to the decay of memory traces, which have some logarithmic properties. However, Staddon and Higa (2006) also emphasized the role of memory and decision processes in temporal estimation (cf. Fortin, Champagne, & Poirier, 2007).

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Although the distinction between linear and nonlinear time representations has generated much debate, it is important to realize that it is often difficult to disentangle a linear vs. a nonlinear internal representation on the basis of externally observed behavior, as the empirical predictions of the linear and nonlinear representations are essentially equivalent (see Dehaene, 2001, 2003 for a discussion of number (line) representation).

To quantitatively account for temporal phenomena in complex tasks, and especially to quantitatively account for the memory and decision processes, we embedded our temporal module in an existing architecture for modeling human behavior, ACT-R (Anderson, 2007; Anderson et al., 2004). This architecture contains extensively validated systems for decision (procedural memory) and memory processes (declarative memory). According to ACT-R, facts enter declarative memory when the system encodes information from the environment, or when internal processing generates knowledge (e.g., the fact that "$C + 13 = P$" by executing production rules that sequentially count through the alphabet). The contents of facts that have entered the declarative memory store cannot be altered; new information has to gain sufficient activation to overrule the existing knowledge. The activation of a fact determines if the fact can be retrieved from declarative memory (i.e., it has to be above a retrieval threshold) and how long retrieval will take, but activation cannot be accessed by the system explicitly.

For the implementation of the temporal module we followed Staddon and Higa's (1999) approach, where the locus of the scalar property is in the clock instead of being in the interaction between memory and decision processes (cf. Gibbon, 1992). However, as the activations or "decay values" are not accessible outside the realm of the declarative system in the ACT-R architecture, Staddon and Higa's decay-based account is not consistent with the ACT-R theory. Instead, we combined the nonlinear aspects of Staddon and Higa's (1999) approach with the more traditional information-processing approach proposing a pacemaker–accumulator combination. To this end, we opted for a pacemaker that generates pulses spaced apart with increasing intervals instead of having a constant interpulse interval. The first pulse is set to a fixed start value, t_0. Each subsequent pulse is separated from the previous pulse by an interval that is a times the interval between two previous pulses. Noise from a logistic distribution with a mean of 0 and a standard deviation of b times the current interval is added to the interval: $t_{n+1} = at_n + \text{noise}$ ($M = 0$, $SD = b^* at_n$). The pacemaker and accumulator operate in parallel to the central cognitive processes. When these processes pay attention to the time, the current value of the accumulator can be read out, and stored in memory or compared to earlier stored values. Note that the increasing pulse lengths result in a nonlinear representation of time that becomes less sensitive when time intervals increase. This nonlinear representation, in combination with the added noise, is the basis for the scalar property (Taatgen et al., 2007).[1]

This temporal module can account for phenomena ranging from a bisection experiment (fitting data from Penney, Gibbon, & Meck, 2000) to experiments assessing the influence of attention on timing (Zakay, 1993). In addition, this model has been tested against empirical data from a new complex task in which temporal information was only one of the aspects participants had to take into account. Third, and most notably, the system accurately *predicts* the effects of manipulations within this complex task (Experiment 2, Taatgen et al., 2007).

Note that this describes a system with a single pacemaker and a single accumulator, explaining how single or sequential temporal estimations can be conducted within the framework of a cognitive architecture. However, it has been argued that multiple estimations can be conducted in parallel, in both animals and humans (e.g., Ambró & Czigler, 1998; Brown & West, 1990; Gibbon & Church, 1981; Ivry & Richardson, 2002; Meck & Church, 1984; Penney et al., 2000; Rousseau & Rousseau, 1996; Rule & Curtis, 1985). For example, Rule and Curtis (1985) presented human participants with two different intervals in parallel, and asked them to produce the average of both durations. The relatively high accuracy in this task indicates that the human temporal system is capable of processing multiple time intervals if all intervals start at the same time. In addition, Brown and West (1990, Experiment 1) showed that human participants can perceive a set of multiple overlapping intervals, even in the case of unequal onsets, and reproduce an interval randomly selected from this set with a reasonable accuracy.

At first sight, these results seem to indicate that the presented temporal system in Taatgen et al. (2007) is too simple, as parallel timing is not accounted for (single accumulator, SA, Fig. 1, Panel A). To account for parallel timing, one could argue that a system should contain multiple accumulators, driven either by a single pacemaker (multiple dependent accumulators, MDA, Fig. 1, Panel B, cf. Rousseau & Rousseau, 1996) or by multiple pacemakers resulting in independent accumulators (multiple independent accumulators, MIA, Fig. 1, Panel C, cf. Crystal, 2003, for a similar account linking circadian and interval timing). When multiple pacemakers are present, each pacemaker can be tuned to a separate interval, making parallel timing relatively straightforward (cf. Meck & Church, 1984; Rousseau & Rousseau, 1996). However, a single pacemaker/accumulator combination, such as in our model, could be used to estimate multiple intervals. For example, in the Rule and Curtis (1985) study, both intervals started in parallel, enabling participants to time both intervals sequentially using a multiple readout strategy (i.e., read out the accumulator at the end of interval one and at the end of interval two). By comparing the two readouts, an estimate of the average can be made. The unequal onsets in Brown and West (1990, Experiment 1) prohibit the use of a simple multiple readout strategy for the offset, but it might still be the case that both offsets and onsets are read out from a single timer, and that some form of temporal arithmetic is applied to arrive at the to be estimated interval.

The temporal arithmetic assumption is not uncommon: The influential time-left experiments with human participants (Wearden, 2002) are based on the rationale that participants assess the time that is left of an interval by discounting for the time that has already passed (but see Dehaene, 2001, for discussions of other strategies that might apply).

In this paper, we will present two experiments that test how humans produce overlapping intervals in parallel that have been learned previously. Our explanation is that a single clock is used intelligently by the cognitive system (Fig. 1, Panel A). This would entail dividing the overlapping intervals in smaller parts, estimating them separately, and then adding up these estimates to achieve the desired intervals. Note that these smaller temporal parts can be accurately discounted for by simple additions or subtractions *only if the accumulator increases linearly with real time*. A nonlinear scale should introduce systematic biases in the temporal estimations.

To test this hypothesis, we designed two experiments. In these experiments, participants had to produce two pre-learned intervals that partially overlap. A schematic overview of an experimental trial is presented in Fig. 2. Participants received a start signal for one of the intervals, and after a certain delay (the stimulus onset

[1] As in all theories of temporal perception, a specific onset event is necessary to start the estimation of an interval. In our account, the onset of an interval has to trigger a reset of the pacemaker (resetting the duration of generated pulses) and of the accumulator. SET requires a similar reset (setting the accumulator to 0) and assumes an onset-related refractory period, and the Staddon and Higa (1999) account needs to create a new memory trace (or store the activation of an existing memory trace) to keep track of the amount of decayed activation.

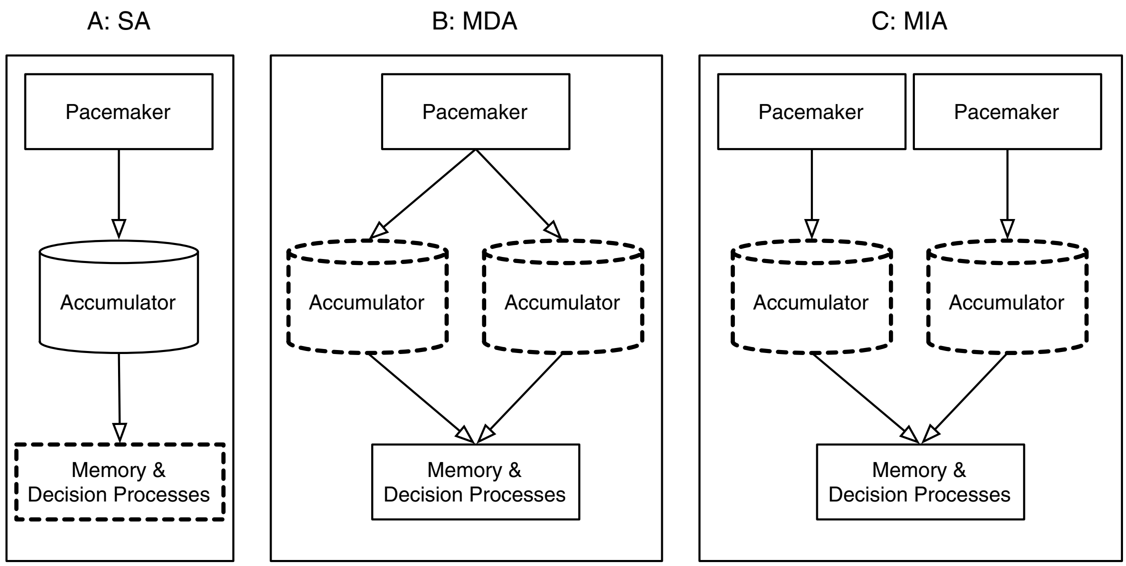

Fig. 1. Three possible systems to account of parallel timing. Panel A depicts a single pacemaker, single accumulator (SA) system, Panel B a multiple dependent accumulators (MDA) system, and Panel C a multiple independent accumulators (MIA) system. The entities with the dashed lines denote the elements of the system that enable parallel time perception.

asynchrony, SOA, here 1.5 s) the start signal for the second interval. For both intervals, participants had to indicate when the presented interval was equal to the previously learned interval. The random SOA between the two start signals prevented fixed timing strategies, and produces a variable overlap between the two intervals. In Experiment 1, Session 1, both intervals were 2 s, while in Experiment 1, Session 2 and Experiment 2 one interval was 2 s and the other interval was 3 s.

Before turning to the discussion of the experiments, we ask: what mechanism could explain performance? We will discuss the three possible mechanisms presented in Fig. 1, and derive predictions (see Table 1) for these mechanisms given either a linear or a nonlinear timescale.

The straightforward explanation for timing both intervals is presented in Fig. 1, Panel C. According to this account, each interval is assigned its own pacemaker–accumulator combination. As both intervals can be reproduced on the basis of the previous learning session (e.g., 2 s equals 17 pulses, regardless of the underlying distribution), there is no scale-based reason why these combinations should produce any decrease in timing accuracy when multiple parallel intervals have to be estimated. A decrease in accuracy, however, can be due to other factors, for example, attention that has to be shared across intervals or dual-tasking costs (e.g., Brown & West, 1990; Rousseau & Rousseau, 1996). For both a linear and a nonlinear scale, increasing overlap increases the estimates, as the sharing of resources results in slower updating of the accumulators (see, for example, Block & Zakay, 1997). In other words, an increase in SOA results in less overlap, and should therefore result in shorter estimates when compared with shorter SOAs.

The strategy presented in Panel B, multiple dependent accumulators (MDA), predicts exactly the same effects as multiple independent accumulators (MIA) when linear timescales are assumed. Whenever a linear timescale is assumed, the SOA does not affect the rate of accumulation. Only the attentional and dual-tasking costs apply, predicting an increase in SOAs to be associated with shorter estimates.

An effect in the opposite direction is expected if we assume a nonlinear timescale: The longer the SOA, the longer the time between the pulses, and the longer it will take before the second pacemaker has reached its critical value. This effect could, of course, partly be cancelled out by the attentional and dual-tasking costs discussed above. As these costs apply to both accumulators, the prediction for the first estimate is similar to the predictions of the multiple independent accumulators account: shorter SOAs result in longer estimates. Because of the single pacemaker, a slow first estimate will affect the second estimate, as slow or fast pulses

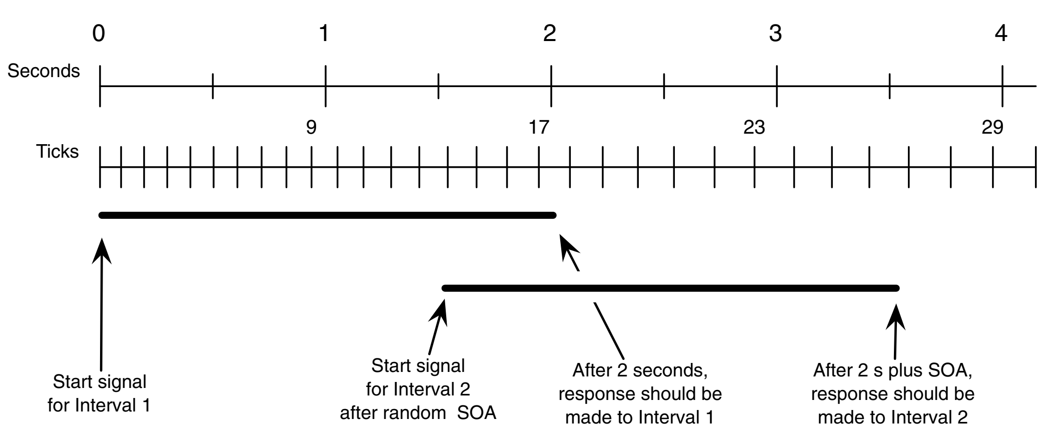

Fig. 2. Experimental paradigm used in the experiments.

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Table 1
Effects of increased SOA on first and second estimates

Timescale	A: SA		B: MDA		C: MIA	
	Linear	Nonlinear	Linear	Nonlinear	Linear	Nonlinear
First interval	None	None	Decrease	Decrease	Decrease	Decrease
Second interval	None	Increase	Decrease	Increase + decrease	Decrease	Decrease

in the overlapping periods influence the estimates of both first and second intervals. To summarize, MDA combined with a nonlinear timescale predicts shorter estimates when the SOA increases for the first interval, and a combination of effects (both increasing and decreasing) for the second interval (Table 1).

The last account, Panel A: single pacemaker, single accumulator (SA) is based on the idea of a single source of time information that can be used strategically by general cognition. To produce the two intervals in Fig. 2, the SOA between the two start signals has to be stored during the production of the first interval. After the response on the first interval has been made, one has to wait for the stored SOA before making the second response. The consequence of this method is that, similarly to MDA, estimates are no longer independent. For example, if the first estimate is too long we also expect the second estimate to be too long. A second consequence of serialization is that a nonlinear timescale will bias the second estimate. The SOA between the onset of interval one and two is internally represented on a pseudo-logarithmic scale, resulting in an internal length of, for example, five pulses. When this internal representation is added to the first interval to estimate the second interval, this length of five pulses represents a longer time than what was perceived originally because the pulses are spaced wider apart. This results in an overestimation of the second interval, which becomes larger as the SOA increases. If a linear timescale is assumed, temporal arithmetic does not induce systematic biases, resulting in the absence of any effects of SOA on the estimates. As this account assumes only a single pacemaker and a single accumulator, there is no reason to assume any attention or dual-tasking costs apart from possible dual-tasking penalties in the memory and decision processes (although, according to ACT-R, these should be absent as long as they do not coincide, see Salvucci & Taatgen, 2008). However, as this task is extremely simple from a memory and decision process stance (cf. Anderson, Taatgen, & Byrne, 2005; Van Maanen & Van Rijn, 2007), no SOA-related effects are to be expected.

Table 1 summarizes the predictions derived from the three accounts.

To test the predictions described above, we ran two experiments. Experiment 1 consisted of two consecutively run sessions. In Session 1, both intervals are 2 s, while in Session 2 one interval equals 2 s and the other interval equals 3 s. For presentation purposes, we will present these two sessions as Experiments 1a and 1b. Given that both sessions were run as a single experiment, learning and transfer effects might have influenced the participants' behavior in Experiment 1b. Therefore, a replication study of Experiment 1b was run, Experiment 2, using a similar setup to Experiment 1b but with naive participants.

We will first discuss Experiment 1a and the cognitive model we constructed to account for the data of Experiment 1a, and then Experiments 1b and 2.

2. Experiment 1a

2.1. Method

2.1.1. Participants

Twenty-six students (12 females, average age 23.6, range 18–33) from Carnegie Mellon University participated and were paid $8 compensation. Five participants were excluded from analysis because they did not adhere to the instructions.

2.1.2. Design, stimuli and procedure

The purpose of the first block (46 trials) was to learn a stable and correct representation of the interval they would be asked to estimate later. Participants were told that the task was to estimate an interval of an unspecified length, and, at the start of each block, were instructed not to count or use any other strategies to measure the passing of time (cf. Penney et al., 2000; Rakitin et al., 1998, Experiment 2). Each trial started with two open circles on both sides of a "!" that served as fixation point. After an interval that was randomly selected from [750, 1250] ms, one of both circles was filled in either blue (left) or green (right). Each circle was selected equally often. The selected circle remained colored for 2000 ms (see Ulbrich, Churan, Fink, & Wittman, 2007, for a discussion on the range of durations where cognitive processes are involved). As soon as the color disappeared, the "!" was replaced by a "∗" to indicate that the reproduction phase started. In the reproduction phase, the circle filled with color again until the participant pressed a key, indicating that they thought the circle had been filled the same amount of time as before. For the left circle the "z" had to be pressed, for the right circle the "/".

Participants received feedback in terms of "too fast", "correct" or "too slow" which remained on the screen for 1500 ms. A response was categorized as correct when it was in the interval 1750–2250 ms, making a response of 2000 ms optimal. This 500 ms range was chosen to achieve a correctness of approximately 50%. In addition, to the feedback, participants were also given 10 points per correct answer. The points awarded for this trial and their total score were presented with the correctness feedback.

After the first block, participants received instructions for the second block. In this second experimental block of 120 trials, participants had to respond to both left and right stimuli in each trial, as illustrated in Fig. 2. Either stimulus appeared first in half of the trials. The stimulus onset asynchrony (SOA) was randomly sampled from the intervals $a = [500, 900]$ ms or $b = [1100, 1500]$ ms. Feedback was given as "correct", "too fast" or "too slow" for both stimuli independently, and 10 points were assigned for each correct response. All other aspects of the task were kept constant.

2.2. Results and discussion

Before further analyses, all responses faster than 500 ms and slower than 5000 ms were removed from the dataset (1.2% rejected cases in Experiments 1a and b combined). At the end of the training block, the average estimate over the last 10 trials was 1930 ms (SD = 383, left first, 1920 ms, vs. right first, 1952 ms, $t(20) = 0.59$, $p > .05$). The observed 58% correct responses are close to the expected 50%, and no accuracy difference was found for left vs. right intervals ($P(C)_{left} = .61$, $P(C)_{right} = .55$, $t(20) = -.50$).

Performance in the experimental block was 45% and 44% correct for the first interval and second interval, respectively (the difference is not significant: $t(20) = .59$), but the average accuracy for the first estimate is significantly lower in the experimental block than the accuracy during training (45% vs. 58%, $t(20) = 2.46$, $p = 0.023$). The average estimates were 1933 ms (SD = 453) and

Table 2
Estimations for the fixed effects of the parameters entered in the linear mixed effect models predicting the second estimate in Experiment 1a

Model	Intercept	Trial number	Starting side	SOA	First estimate
1	402***	−0.944	−22***	0.499***	0.671***
2	1728***	−1.341	−24***	0.496***	
3	903***	−0.991	−21***		0.670***

*** $p < 0.001$.

2128 ms (SD = 478). These estimates differ significantly ($t(20) = -5.4$, $p < 0.001$).

The simplest test related to parallel timing involves the dependency of the two estimates. To test whether the first estimate has an influence on the second estimate, we compared two linear mixed effect (LME, Bates, 2005, and see for a nontechnical introduction, Baayen, Davidson, & Bates, 2008) models shown as Models 1 and 2 in Table 2. The first model entails the second estimate as a function of the fixed effects of trial number, starting side, SOA and first estimate, and a random effect for subjects. The second model has the first estimate removed, but is otherwise identical. The fit of the reduced Model 2 is significantly worse ($\chi^2(1) = 1741$, $p < 0.001$), indicating a significant contribution of the first estimate in the prediction of the second estimate.

Longer first estimates yield longer second estimates ($\beta = .671$, $t(2503) = 50.15$, $p < 0.001$). This is in line with the single accumulator (SA) account, as with a single pacemaker, the second estimate is by definition dependent on the first. However, arguments in favor of dependency can be made in the context of the other two accounts when additional assumptions regarding dual tasking are made.

To assess the contribution of SOA on the second estimate, the stronger test associated with the predictions, we constructed a similar model to the best fitting model described above, but in which SOA was removed (see Table 2, Model 3). The fit of the reduced model is significantly worse ($\chi^2(1) = 664$, $p < 0.001$) compared with the more complex model (Table 2, Model 1), indicating a significant contribution of SOA in the prediction of the second estimate. The estimated effect of SOA in the complex model ($\beta = .499$, $t(2503) = 27.57$, $p < 0.001$) indicates that longer SOAs yield longer second estimates. It is important to note the only account that univocally predicts this effect on the second estimate is the single accumulator account with a nonlinear timescale. At the same time, according to a SA account, SOA should have no influence on the first estimate, whereas according to the hypotheses derived from MDA and MIA, SOA length should influence the first estimate. We compared two models, one with trial number, starting side and SOA as fixed effects and subject as random effect as predictors for the first estimate, and the other model with SOA removed. Model comparisons indicate that the simpler model without SOA is preferred over the complex model ($\chi^2(1) = 0.034$, $p = 0.85$), also arguing in favor of the single accumulator account.

The experiment provides evidence in favor of one pacemaker with a nonlinear scale of temporal estimation for three reasons. First, the first estimate contributes significantly to the second estimate. Second, the estimated SOA effects on the second estimate are significant and have a positive value. Third, no effect is observed for SOA on the first estimate.

3. Cognitive model

3.1. Time estimation

The temporal module in ACT-R (Taatgen et al., 2007) measures time in pulses that start at 100 ms, but become gradually longer, creating a nonlinear representation of time, as illustrated in Fig. 3. This means that in the run shown in Fig. 3 and 2 s corresponds to a total of 17 pulses in the accumulator as the 17th pulse entered the accumulator at about 1.95 s, but 4 s only to 29 pulses instead of 34 (note that because of moment-to-moment noise, different runs can have different associated accumulator values.) The model is presented the same number of training trials as the participants and has, at the start of the experimental block, a reasonably stable internal representation of 2 s (17 pulses). When the start signal for the first interval is given, the timer is started. At some point, the start signal for the second interval is given, prompting the model to store the value of the timer at that moment (in the examples illustrated in Fig. 3, Panel A: 5 and 13 pulses for the upper 0.6 and lower 1.5 SOAs, respectively). When the timer reaches the 17 pulses, corresponding to 2 s, the model will make the first response. It then adds the stored pulse number at the moment of SOA to 17, and waits until the timer reaches that value to make the second response. As Fig. 3, Panel A illustrates, the nonlinear scale introduces a bias in the second response that becomes larger with longer SOAs: The bias for the 0.6 s SOA trial is $2.72 - 2 - .6 = .12$ s, compared to $4.15 - 2 - 1.5 = .65$ s for the longer, 1.5 s SOA trial.

3.2. Representation of the time interval

The model maintains a representation of the time interval in its declarative memory. This representation is based on instance theory (Logan, 1988), which assumes that each experience creates an example in memory. Whenever the model makes a correct estimate, it stores the number of pulses in declarative memory as a successful experience. If the model receives feedback that it is too late, it will subtract one pulse from its estimate on the next trial. If the model is too early, on the other hand, it will add one pulse to its next estimate. Initially, successful examples will be 17 pulses on average. However, once the model has to estimate two overlapping intervals, the nonlinear effect causes the model to be systematically late on the second interval. Based on the average feedback, these experiences cause the model to shorten its representation of 2 s somewhat (to approx. 16 pulses), maximizing the proportion of correct responses.

3.3. Model parameters

In the simulations reported here, the parameters are set to start pulse (t_0) = 100 ms, pulse multiplier (a) = 1.02 and noise (b) = 0.015. Note that both the t_0 and a parameters have been changed from the values reported earlier (Taatgen et al., 2007). The 2007 parameters ($t_0 = 11$ ms, $a = 1.1$) were fit using a least-square optimalization routine on a simple temporal estimation experiment (Rakitin et al., 1998) for which wide ranges of parameters would have fitted well. However, as the experiments described in Taatgen et al. were not concerned with quantitative aspects of the nonlinear scale, the selected parameters sufficed. However, in the current experiment, the absolute values of the nonlinear scale are important, resulting in the parameters presented here. Cross-validation of these parameters on the data reported in Taatgen et al. (2007) shows that none of the fits is negatively affected by these changes. Moreover, the new values are also more in line with a pulse length of 200 ms proposed by Meck, Church, and Gibbon (1985), especially since the length of the pulses in our account increases with the estimate.

3.4. Model results

Fig. 4 shows the distributions of time estimates for the first block in which only a single estimate had to be made (labeled “single”), and the first and second responses in the second block

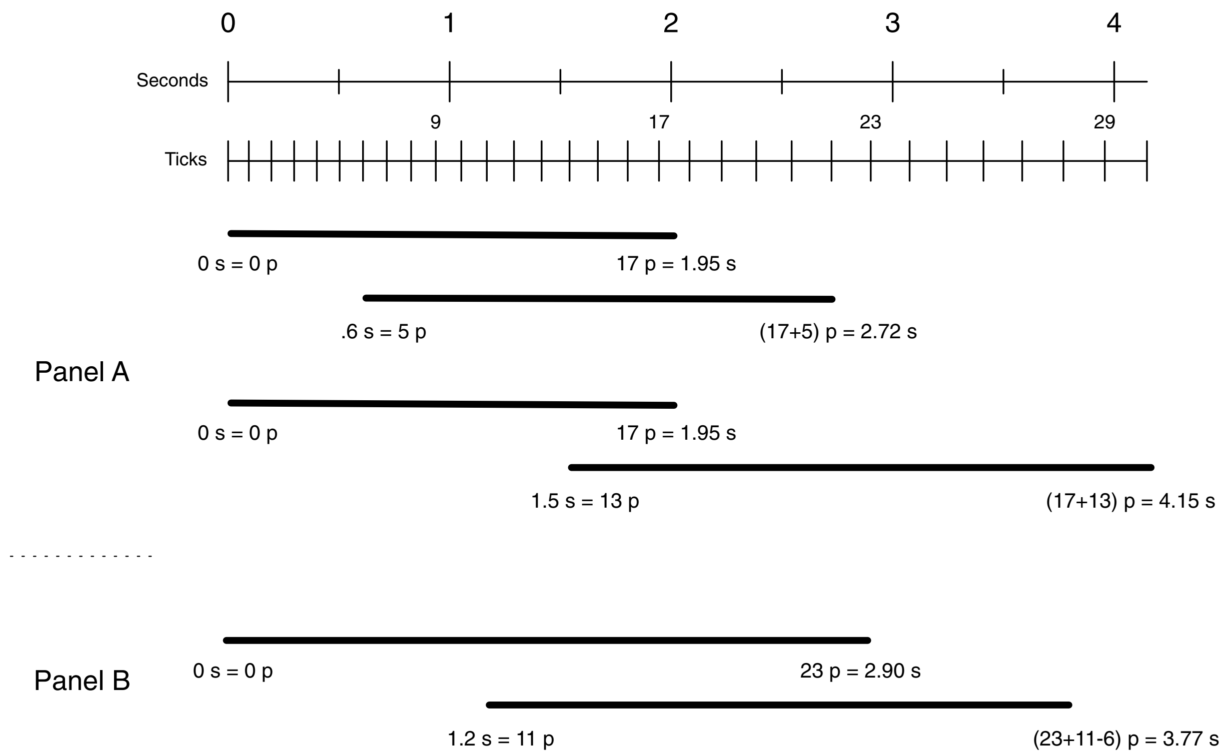

Fig. 3. Panel A shows a visual representation of the estimates as provided by the cognitive model for Experiment 1. Note that the Ticks-axis illustrates the nonlinear increase in between pulse intervals. Panel B depicts the mechanisms underlying the estimates in Experiments 1b and 2: The response for the second interval is produced by adding the SOA (11 pulses) to the 3 s response, and then subtracting the difference between the 2 and 3 s (6 pulses). In this example, the representation for 2 s is 17 pulses and for 3 s is 23 pulses, both learned previously.

(labeled "first" and "second"). It shows that the second responses are generally later than the first responses, which is due to the bias in the scale. It also makes evident that the distribution of the first response is pushed somewhat to the left, corresponding to the above-mentioned 16 pulses, compared to the single task case, to compensate for the second response. This explains the decrease in accuracy on the first interval. Fig. 5 shows the effect of the SOA on the second response, and illustrates the effect of the non-linear scale.

4. Experiment 1b

The empirical results and the model of Experiment 1a support an account of simple temporal arithmetic: after waiting for the

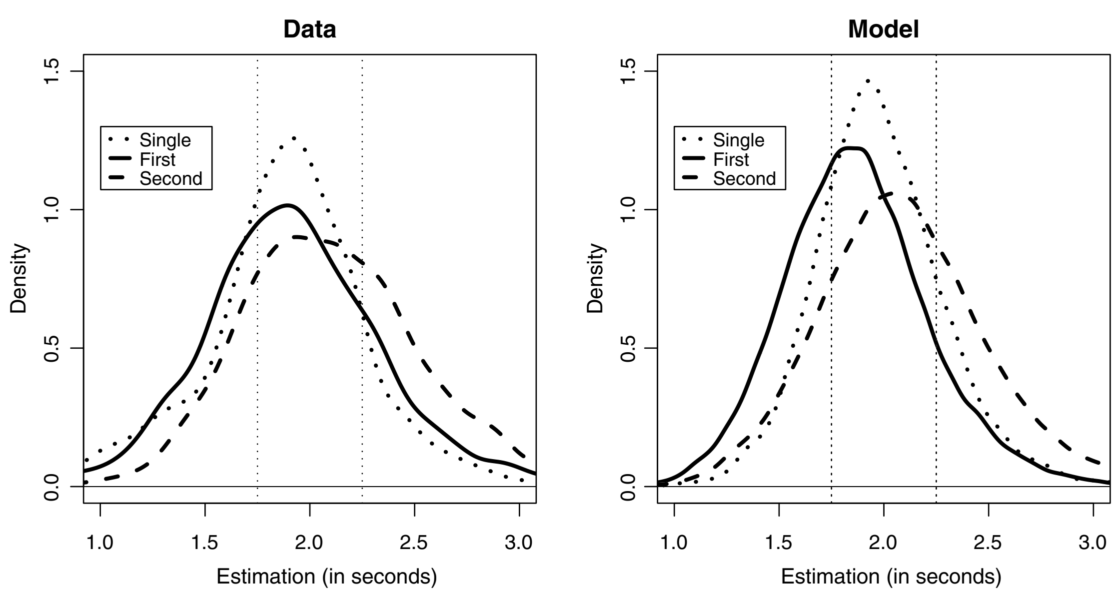

Fig. 4. Distributions of time estimates in Experiment 1a for human participants and the cognitive model for estimates made in the single estimate per trial block and for the first and second estimates made in the dual estimation block.

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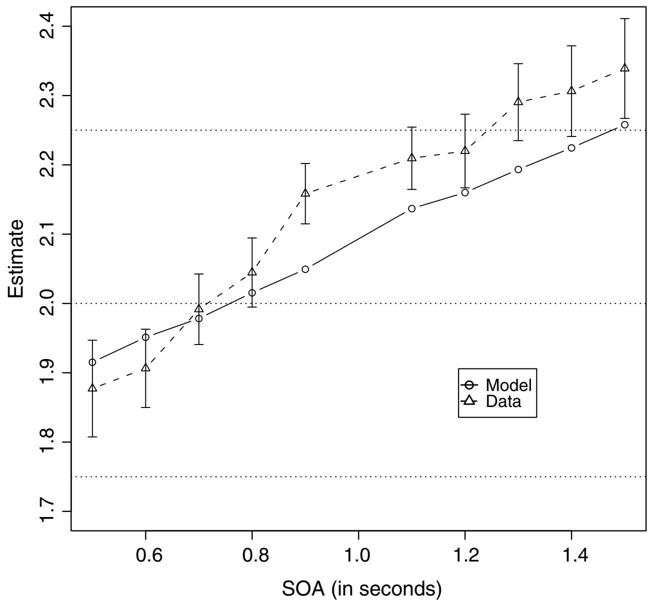

Fig. 5. The effect of the SOA on the second response for both human participants and the cognitive model in Experiment 1a.

duration associated with the first interval, participants wait for another duration similar to the SOA that has just been perceived. In the model, this is accounted for by adding the number of pulses associated with the SOA to the number of pulses associated with the interval duration. However, this does not require actual addition of intervals. A similar effect can be achieved by just putting one interval after the other ("wait for A and then wait for B"), instead of constructing a new temporal representation ("A plus B equals C, so wait for C").

To show that actual temporal arithmetic is used to handle multiple intervals, Experiment 1b involves both addition and subtraction of intervals. Subtraction of time intervals cannot be achieved by the simple strategy of putting one interval after the other, and must involve actual temporal arithmetic. This experiment is the same as Experiment 1a, except that one of the two intervals is increased to 3 s. In the case where a trial starts with a 2 s interval, the 3 s interval has to be constructed by adding the SOA and the difference between the 2 s and the 3 s intervals (i.e., 1 s, or 9 pulses in the model) to the first response. When the trial starts with a 3 s interval, the 2 s interval has to be constructed by adding the SOA, and then subtracting the 1 s interval (Fig. 3, Panel B illustrates the latter case).

4.1. Method

4.1.1. Participants

The same students participated in Experiment 1b as in Experiment 1a.

4.1.2. Design, stimuli and procedure

The same stimuli were used as in Experiment 1a, except the right, blue stimulus was now associated with a 3 s interval. The region marked as correct ranged from 2625 to 3375 ms for this interval. The experiment consisted of two blocks. In the first block the participants learned the 3 s interval. Each trial consisted of just a single interval. The first 10 trials were 3 s intervals, followed by 40 trials randomly selected from 2 and 3 s intervals. In the second block, consisting of 160 experimental trials, participants had to respond to two simultaneous intervals, one of 2 s and the other of 3 s with a stimulus onset asynchrony sampled from [500, 900] ms or [1100, 1500] ms. Half the trials started with the 2 s interval and the other half with the 3 s interval. Note that apart from the increase of the right stimulus from 2 to 3 s, all other aspects were kept constant between Experiments 1a and 1b.

4.2. Results and discussion

The same outlier rejection criteria were applied as in Experiment 1a. The average estimates at the end (last 10 trials) of the training block for the 3 s duration were significantly different from the average estimates for the short, 2 s duration (2894 ms vs. 2131 ms, $t(20) = 12.1$, $p < 0.0001$). It should be noted that although participants had to learn two intervals (2 s vs. 3 s) instead of a single interval, performance as measured by the proportion correct responses did not decrease. At the end of the training block, participants responded correctly to 52% of the short trials and 63% to the long trials. When comparing the short trials with performance on Experiment 1a, no effect was found ($t(20) = -1.18$, $p = 0.25$).

Table 3 shows the average estimates and the proportion correct responses for both the short and long durations per condition. Similar to Experiment 1a, the average accuracy for the first short estimate is significantly lower in the experimental block than the accuracy during training (39% vs. 52%, $t(20) = 3.53$, $p = 0.002$). To test whether both estimates influenced each other, we compared a full LME model (Table 4, Model 1) that expressed the second estimate as a function of condition, trial number, first estimate and SOA as fixed effects and participants as random effect against a model with the first estimate removed (Table 4, Model 2). The full model fits significantly better ($\chi^2(1) = 316.6$, $p < 0.001$).

To test whether increased SOAs influenced the performance on the second estimate, we compared a full LME to one without the effect of SOA (Table 4, Model 3). The full LME model (Table 4, Model 1) fit the data significantly better than a simpler model ($\chi^2(1) = 347.1$, $p < 0.001$). The positive effect of SOA on the second estimate is of most consistent with the one pacemaker, one accumulator account.

At the same time, the first estimate is not influenced by SOA, neither when the trial started with the short estimate ($\chi^2(1) = 0.514$, $p = .47$), nor when the first response had to be made to the first appearing stimulus (i.e., trials that started with the long estimate combined with a long SOA, $\chi^2(1) = 1.169$, $p = .28$).

Still, participants performed relatively accurately regardless of the interval that had to be estimated first. (Accuracy does not differ for 2 or 3 s intervals, first responses: $P(C, \text{left}) = .39$, $P(C, \text{right}) = .39$, $t(20) = 0.20$, second responses: $P(C, \text{left}) = .49$, $P(C, \text{right}) = .43$, $t(20) = 1.24$, $p = .23$).

Table 3
Average estimates and proportion correct responses (in parentheses) per condition in Experiment 1b

	Observed duration and proportion correct for	
	Short interval	Long interval
Short interval first	2193 ms (.39)	2877 ms (.49)
Long interval first	2236 ms (.43)	2571 ms (.39)

Table 4
Estimations for the fixed effects of the parameters entered in the linear mixed effect models predicting the second estimate in Experiment 1b

Model	Intercept	Trial number	Starting side	SOA	First estimate
1	1764^{***}	−0.042	-751^{***}	0.494^{***}	0.284^{***}
2	2424^{***}	0.038	-644^{***}	0.456^{***}	
3	2306^{***}	−0.038	-740^{***}		0.260^{***}

*** $p < 0.001$.

The similar response pattern in both conditions and the combination of no effect of SOA on the first estimate and a positive correlation between SOA and second estimate suggests that a single procedure is utilized for the estimation of the durations. As the condition in which the long interval is presented first cannot be accounted for by a pure reset-based mechanism, temporal arithmetic seems the most likely candidate for explaining the observed behavior.

4.3. Model results

The model for Experiment 1b is similar in setup to the model for Experiment 1a with a few extensions to account for the different intervals. In fact, before going through Experiment 1b, the model runs through Experiment 1a to create the same starting point that the participants were in. The model handles the trials that start with the shorter 2 s interval as in Fig. 3a, except that the model will add the difference between the two intervals to the second response. In the 600 ms SOA example, this would mean that the second response is made at 17 (estimate of 2 s) + 5 (estimate of the SOA) + 6 (difference between 3 and 2 s = 23 − 17 = 6) = 28 pulses, or after 3.77 s. When the trial starts with the long, 3 s, interval, the difference between the two intervals is *subtracted* to obtain the right estimate for the 2 s interval (see Fig. 3b for an example). As in the first model, the successes and failures of the model will push most of the estimates downwards because of the systematic overestimations of the second interval. However, the 3 s interval is more susceptible to this, because the 2 s interval has been practiced throughout Experiment 1a, and therefore has a firmer representation in memory. Fig. 6 shows the distributions of the responses for the trials that start with the short interval and the trials that start with the long interval. The downward adjustment is visible when Fig. 6 is compared with Fig. 4: the peak of the first estimates is earlier in Fig. 6 than in Fig. 4.

In both cases, the nonlinear timescale creates a bias to overestimate the second interval. As a consequence, if the short interval is presented first it pushes both estimates further apart (because it extends the long interval), but when the long interval is presented first both estimates are closer together (because the short interval is extended). Note that this effect is additive to the earlier

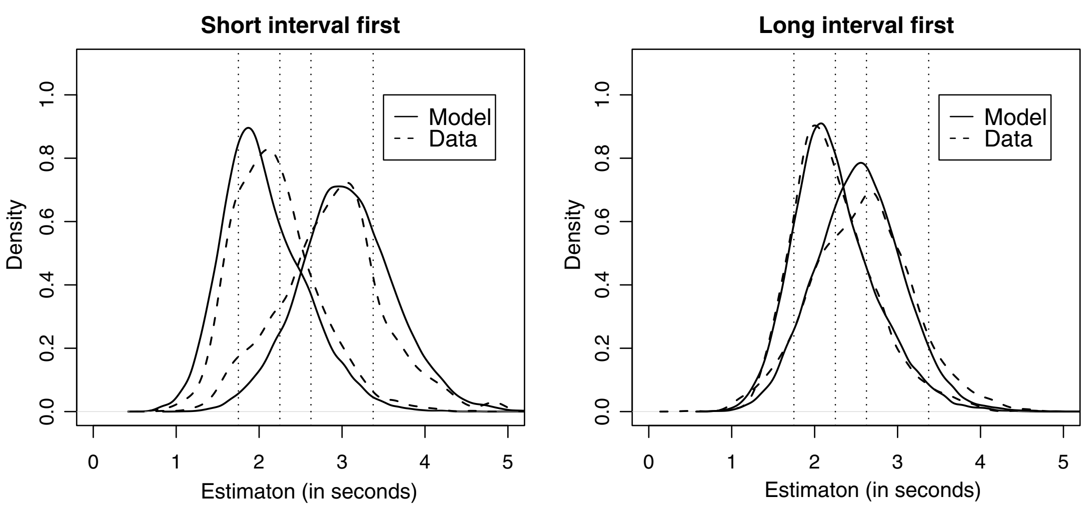

Fig. 6. Distributions of time estimates in Experiment 1b for human participants and the cognitive model for the short and long durations (the left and right distributions in each panel), separated for trials that started with the short interval vs. the long interval. Vertical dashed lines indicate the intervals in which the estimate was considered "Correct".

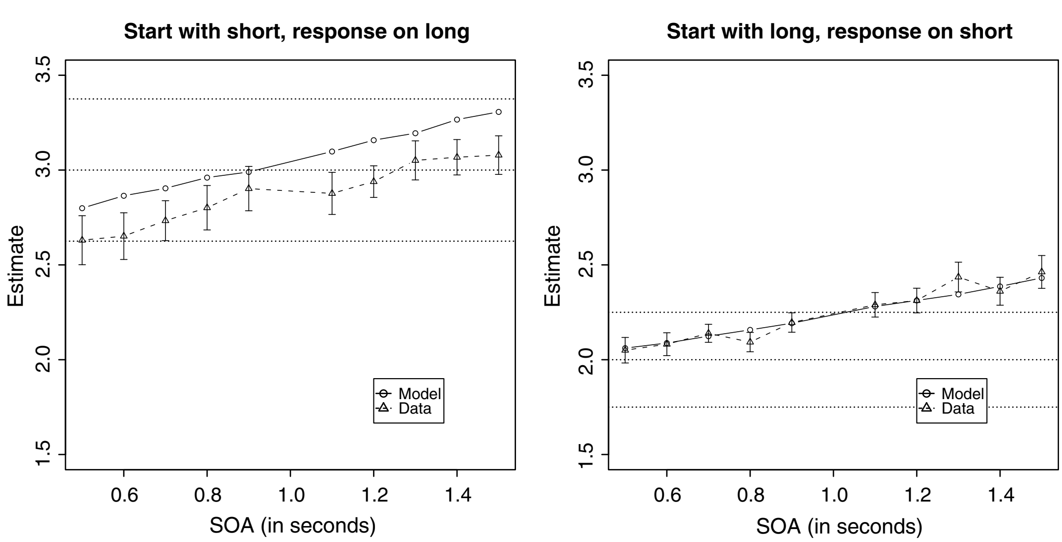

Fig. 7. The effect of the SOA on the response associated with the second interval for both human participants and the cognitive model in Experiment 1b, separated for trials that started with the short interval vs. the long interval.

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Table 5
Average estimates and proportion correct responses (in parentheses) per condition in Experiment 2

	Observed duration and correctness for	
	Short interval	Long interval
Short interval first	2039 ms (.50)	3332 ms (.39)
Long interval first	2343 ms (.50)	2773 ms (.49)

Table 6
Estimations for the fixed effects of the parameters entered in the linear mixed effect models predicting the second estimate in Experiment 2

Model	Intercept	Trial number	Starting side	SOA	First estimate
1	2358***	−0.499	−1271***	0.223***	0.384***
2	3254***	−0.670	−989***	0.120**	
3	2641***	−0.581	−1251***		0.356***

** $p < 0.005$.
*** $p < 0.001$.

mentioned downward adjustment of the intervals. This also becomes evident in the effects of SOA on the second estimate as a function of the duration of the first estimate, an effect that is nicely captured by the model (Fig. 7).

However, as the participants in Experiment 1b also participated in Experiment 1a, the results might be influenced by the training the participants had in Experiment 1a. Therefore, we ran Experiment 2 to answer the question whether participants are able to estimate parallel but unequal time intervals without prior training. It also enables assessing how robust the model is when the experiment is run in a new setting with naïve participants.

5. Experiment 2

5.1. Method

5.1.1. Participants

Fourteen students of the University of Groningen (three females, average age 21.2, range 19–25) participated in this experiment in exchange for course credits. Data of two students were removed because they did not adhere to the instructions.

5.1.2. Design, stimuli and procedure

The same stimuli were used as in Experiment 1b. Participants were presented two blocks, one of 40 trials to learn the 2 and 3 s intervals, and one block consisting of 120 experimental trials. Apart from translating the instructions into Dutch, the procedure of Experiment 2 was identical to Experiment 1b.

5.2. Results and discussion

Applying the same outlier criteria as for Experiment 1 resulted in the removal of 0.5% of data points. The average estimate at the end (last 10 trials) of the training block was 2648 ms (SD = 418) for the 3 s duration, and 1980 ms (SD = 373) for the short, 2 s duration. Like in Experiment 1, performance measured in proportion correct responses did not decrease when compared with the end of the training block. At the end of the training block, participants responded correctly to 60% of the short trials and 63% to the long trials (in Experiment 1a, performance was 58% correct).

Table 5 shows the average estimates and the proportion of correct responses for both the short and long durations per condition. The average accuracy for the first short estimate does not significantly differ between the experimental block and training if tested with a paired t-test ($t(11) = 1.56$, $p = 0.147$). However, inspection of the data showed that this was partly due to one participant still needing the last trials in the training block to familiarize themselves with the experiment. This notion was supported by the results of an exact binomial test (10/12, $p = 0.0386$), indicating that the lack of effect is due to the extreme scores of a single participant[2].

As in the prior experiments, the full model (Table 6, Model 1) fit the data better than simpler models with either first estimate (Table 6, Model 2) or SOA (Table 6, Model 3) removed ($\chi^2(1) = 231$, $p < 0.001$, $\chi^2(1) = 37.6$, $p < 0.001$, respectively). The first estimate is not influenced by SOA, neither when the trial started with the short estimate ($\chi^2(1) = 0.061$, $p = .81$), nor when the first response had to be made to the first appearing stimulus ($\chi^2(1) = 0.243$, $p = .62$). And again, accuracy does not differ for 2 s or 3 s intervals, first responses: $P(C, \text{left}) = .50$, $P(C, \text{right}) = .49$, $t(12) = 2.5$, $p = 0.24$, second responses: $P(C, \text{left}) = .50$, $P(C, \text{right}) = .39$, $t(12) = 0.57$).

In sum, these results illustrate that the effects found for Experiment 1b were not due to practice or spillover effects from Experiment 1a. All analyses show the same patterns for Experiments 1b and 2, often with very similar statistics.

5.3. Model results

Before analyzing the results of Experiment 2, we predicted the outcomes of this Experiment using the model of Experiment 1b (cf. Salvucci & Macuga, 2002; Taatgen & Anderson, 2008). The only difference between the runs simulating Experiments 1b and 2 was that the runs for Experiment 1b started out with experience gained in Experiment 1a, whereas Experiment 2 commences without any task relevant information. However, Experiment 1b contained a specific training session to balance the experience between 2 and 3 s intervals, and as the analyses reported for Experiment 1b show, there was no significant difference between both intervals. This results in a model prediction for Experiment 2, shown in Fig. 8 that is very similar to the model fit for Experiment 1b. The main deviation is that the human participants in Experiment 2 have a more distinct representation of the 3 s interval than the model. This is not only a difference between the model runs simulating Experiment 2 and the human participants, but also between the human data for Experiments 1b and 2 (Welch two sample t-test, short interval first: 2571 ms vs. 2773 ms, $t(29.7) = -2.35$, $p = 0.026$, long interval first: 2879 ms vs. 3332 ms, $t(28.1) = -4.13$, $p = 0.0003$). This might indicate that participants in Experiment 1b were more likely to confuse both intervals than participants in Experiment 2, which might be due to the stronger representation of the 2 s interval in Experiment 1b. Instead of adjusting the model to more precisely account for the data found in Experiment 2, we present the model predictions to illustrate the possibilities of the proposed system to predict quantitative data.

6. General conclusions

Do multiple sources of temporal information drive parallel time estimates, or do we strategically use the output of a single time source for parallel timing? Here, we presented a study that provides evidence for the latter account. In the introduction, we discussed three different information-processing proposals that could account for parallel timing. Although predictions can be derived for different measures, the most interesting prediction is the effect of the stimulus onset asynchrony on the estimates. As discussed earlier, the effect of SOA depends on the timescale underlying temporal processing. If it is assumed that the underlying timescale is linear, simple temporal arithmetic can be performed

[2] The performance of this participant is within normal ranges in the experimental phase.

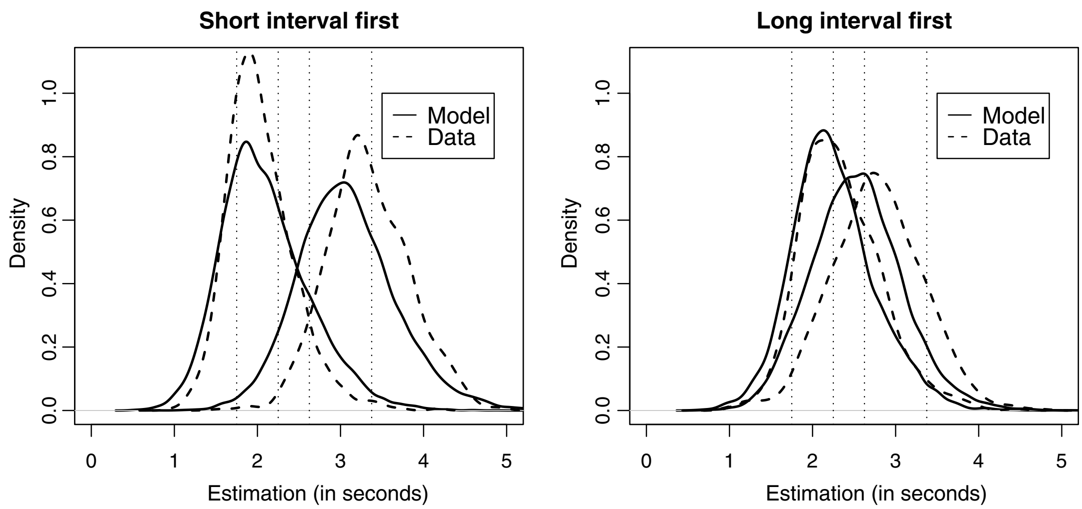

Fig. 8. Distributions of time estimates in Experiment 2 for human participants and the cognitive model for the short and long durations (the left and right distributions in each panel), separated for trials that started with the short interval vs. the long interval. Vertical dashed lines indicate the intervals in which the estimate was considered "Correct".

without systematic biases. However, when time is internally represented on a nonlinear scale, effects of the nonlinear scale should be visible in the estimates.

In all the three experiments reported in this paper, SOA does not have an effect on the estimate of the first interval, as predicted by all the accounts we have contrasted. The predicted effects of SOA on the second estimate are more pronounced. According to the multiple independent accumulators account, the second estimate should decrease with increasing SOA, because a smaller overlap (longer SOA) leads to shorter estimates. According to a multiple dependent accumulators account, and assuming a nonlinear timescale, the effect of SOA depends on the effect associated with the nonlinearity (which predicts an increase because of the wider spaced pulses associated with longer SOAs) and the effect of shared attention (which predicts a decrease because of less overlap). The single accumulator proposal combined with a nonlinear timescale predicts an increase in estimate because of the wider spaced pulses. When a linear timescale would be assumed, the SA proposal predicts no effect of SOA and the MDA and MIA proposals would both predict a decrease in performance because of shared attention. The results of all the three experiments show a significant positive effect of SOA magnitude on estimated duration, being in line with the prediction of the combination of a single accumulator and a nonlinear timescale. Note that the multiple dependent accumulators combined with a nonlinear timescale could theoretically also predict an increase in estimated duration for the second interval, but that would still leave the lack of fit between prediction and found data for the first estimate. To sum up, the results can be explained best by assuming a mechanism that strategically uses the output of a single internal nonlinear time generator, consistent with Taatgen et al. (2007) and Staddon and Higa (2006), but contrary to Gibbon (1977).

The lower accuracy of the first estimate in the dual-timing phase compared to the single-timing phase cannot be explained by a theoretical analysis of the single accumulator account. According to the single accumulator account, performance of the first estimate in dual-timing conditions should be equal to performance in single-timing conditions, as both processes should be completely equal (i.e., the processing of the second estimate takes place only after the first estimate is given). The computational model gives an elegant explanation of this effect. Each time a response is made, the model is presented feedback on the correctness of the response. The wider spaced pulses for the second estimate cause the model to be late relatively often. Thus, because the nonlinear scale biases responses towards late responses, the model will shorten its estimate of both intervals, yielding a lower accuracy for the first estimate in dual-time estimations than during single-time estimation.

An issue that is often raised in timing literature is whether explicit timing strategies such as counting should be prevented. In the experiments reported here, participants were instructed not to count or use any other explicit strategies to measure the temporal intervals. This is in line with the previous work on human time perception (e.g., Penney et al., 2000), and it has been shown that although explicitly instructing participants to count decreases the variance, it does not influence the accuracy of the estimations (Rakitin et al., 1998, Experiment 2). Furthermore, counting is not straightforward in the experimental conditions where at random SOAs a second interval started. Assuming relative slow counting (e.g., in the order of seconds or half-seconds), this would either predict inaccurate second estimates or suggest parallel counting.

Nevertheless, even if participants could have accounted for parallel counting and did count because no secondary task was given, this does not negate the results as a higher accuracy would have made it less likely to have found the reported results.

Do the results of our experiment rule out parallel clocks? In the experiments reported in this paper, we did not find any evidence of parallel clocks. To the contrary, all evidence found points towards a single source of temporal information that is used by the cognitive system to account of the estimation of partly overlapping intervals. However, it still might be the case that although humans can recruit multiple time clocks, participants in these experiments decided to only use a single time source for efficiency reasons. If this is the case, the conclusion has to be that multiple clocks can be recruited, but that even conditions where using a single clock requires participants to subtract two intervals that are not complex enough to warrant recruiting a second clock. In other words, the cost of recruiting a secondary clock is such that most tasks should be accounted for assuming the use of only a single clock.

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