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How are overlapping time intervals perceived? Evidence for a weighted sum of segments model

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1. Introduction

How people perceive short intervals of time and then recreate these intervals or compare them to other short intervals has been the focus of research for many years (François, 1927; Hoagland, 1933). This type of timing is called prospective interval timing, because the participants know in advance that they should attend to time. The most commonly used cognitive models of prospective interval timing are pacemaker-accumulator models (Church, 1984; Creelman, 1962; Rammsayer & Ulrich, 2001; Treisman, 1963; Zakay & Block, 1997). These models posit that an internal pacemaker emits pulses which pass through a switch and are stored by an accumulator. The number of pulses can be stored for a short time in working memory, or for a longer time in reference memory, to facilitate comparisons. The rate at which these pulses are emitted is debated (van Rijn & Taatgen, 2008; Wearden & Jones, 2007); it could be constant (i.e. the gaps between pulses are always the same, producing a linear timescale), or the rate of pulses could decrease with real time (i.e. the gaps between pulses increase, resulting in a nonlinear timescale). According to these models, in order to reproduce a previously perceived interval, the participant simply ceases the reproduction when the same number of pulses has been accumulated as were perceived. In order to compare two intervals, the number of pulses in working memory is compared to the number of pulses collected in relation to the second interval.

Simple interval timing can be achieved in a fairly straightforward manner using the pacemaker-accumulator model. However, what is less well understood is how people time intervals that overlap. Such intervals could in fact be more representative of the timing that people require in everyday situations. This skill could be particularly important, for instance, in order to judge one's own performance in a multi-tasking situation where the processing of two tasks overlaps (Bryce & Bratzke, 2014; Corallo, Sackur, Dehaene, & Sigman, 2008; Marti, Sackur, Sigman, & Dehaene, 2010). There is some evidence from animal studies for the existence of different pacemakers that are used for intervals of different durations (Buhusi & Meck, 2005). However, even if it is possible for humans to use more than one pacemaker and accumulator, it remains unknown exactly how participants behave in a multiple timing context. Certainly, the few studies that have directly investigated multiple timing in humans have shown it to be an effortful process that leads to deterioration in timing performance (Brown, Stubbs, & West, 1992; Brown & West, 1990; Gamache & Grondin, 2010; Grondin, 2010).

Most multiple timing studies have considered the effects of increasing the number of to-be-timed intervals, rather than the degree

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of simultaneity of two intervals. One previous study (van Rijn & Taatgen, 2008) has addressed the simultaneity issue by examining how accurately people produce pre-learned intervals when they overlap with one another. That is, participants learned to produce specific intervals (2 or 3 s), and then had to indicate when that period of time had elapsed after two separate start signals. There was a stimulus onset asynchrony (SOA) between the two start signals that resulted in the two intervals overlapping by varying degrees. van Rijn and Taatgen (2008) found that as the two intervals became more temporally separated (i.e. SOA increased), participants' estimates of the second interval increased, whereas the estimate of the first interval was unchanged. Further, they found that the two estimates were not independent. That is, on a trial-by-trial basis, longer estimates for the first stimulus were associated with longer estimates for the second stimulus. The authors concluded that a single pacemaker, single accumulator model with a nonlinear pseudo-logarithmic timescale (see also Taatgen, van Rijn, & Anderson, 2007) best explained their data. That is, in order to perform this task when both intervals were 2 s, participants first of all stored the number (x) of pulses accumulated during the SOA (i.e. between the two start signals), then indicated the end point of the first interval after timing it fairly accurately, and then waited until x pulses had passed again before indicating the end of the second interval. Under this model, only a nonlinear timescale would predict an increase in the estimate of the second interval with increasing SOA. This is because the number of pulses collected during the first SOA contributes to the second estimate and this represents a longer period of real time as the nonlinear scale progresses (i.e. with increasing SOA).

1.1. The present study

In their study, van Rijn and Taatgen (2008) investigated multiple timing in interval production. That is, these experiments examined how participants produce pre-learned intervals in an overlapping context. In contrast, in the present study, we were interested in how people perceive the durations of two overlapping intervals. To this end, we presented participants with two stimuli (S1 and S2) of the same duration (2 s), with variable SOAs. Increasing the SOA had the effect of decreasing the degree of temporal overlap between the two stimuli. Participants reported the perceived duration of each stimulus separately (estimates 1 and 2; E1 and E2).

We applied timing models already described in the literature to the overlapping interval perception context, derived predictions, and compared our results to these. We started with the same three structural constraints that were tested in van Rijn and Taatgen (2008). These structural constraints can be distinguished by the number of pacemakers and accumulators available to the timing system. When only a single pacemaker and single accumulator are available, a calculation is required in order to estimate the intervals. Another timing model described in the literature, the weighted sum of segments model (Matthews, 2013), suggests that there may be an additional constraint in such a single pacemaker single accumulator structure, in the form of a weighting which is applied in the calculation process. The weighted sum of segments model was originally proposed to describe how people judge sequences that are composed of different segments. It posits that in order to estimate an entire sequence length, each segment is timed, a weight is applied to each segment depending on its distance from the end of the sequence (further away receives less weighting), and these weighted segments are summed. Thus, under the structural constraints of a single pacemaker and single accumulator, there are two possible timing models — a simple version and a weighted version.

Two other structures were considered — the single pacemaker, multiple accumulators structure, and the multiple pacemakers, multiple accumulators structure. A calculation is not required for these models, thus a weighted version was not modelled. Theoretically, these two models could have as many accumulators as required, and the multiple pacemakers, multiple accumulators model could have as many pacemakers as required, based on the number of intervals to be timed. However, in this case participants must only time two intervals so we consider models with two accumulators and/or pacemakers. Importantly, when more than one accumulator must operate simultaneously, estimates suffer from dual-task costs. Specifically, according to van Rijn and Taatgen (2008), dual-task costs are assumed to result from the accumulators being slower to update (and therefore missing pulses) when two accumulators operate simultaneously.

Details of how these models were applied to the experimental context of the present study, and the resulting predictions, are described next. Full details of Monte Carlo data simulations are provided in Appendix A.

1.2. Predictions

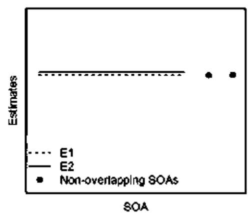
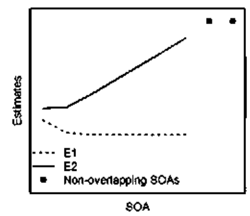
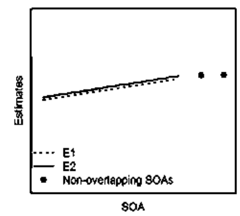
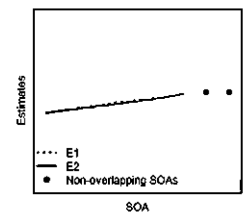
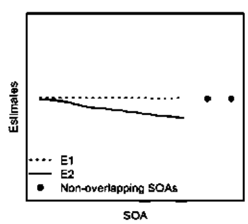
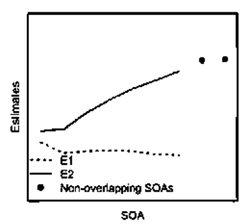
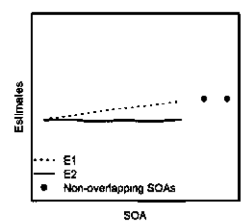
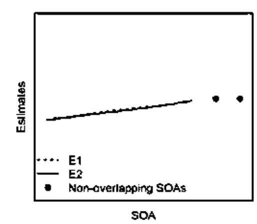
In applying the models to the experimental context we tested, three assumptions were made. First, because participants reported each perceived interval separately (i.e. not in an overlapping fashion, as in the study by van Rijn & Taatgen), the pacemaker was assumed to be reset for reporting the perception of the second interval. Second, for models in which there is only one accumulator, it was assumed that the three segments of the overlapping intervals would be timed separately, and then combined (in different ways depending on the model) to produce estimates 1 and 2 (E1 and E2). The three segments are: (1) from the start of S1 until the start of S2 (i.e. the SOA), (2) from the start of S2 until the end of S1 (i.e. the overlap, or interval 1 − SOA), and (3) from the end of S1 until the end of S2 (i.e. in this case, this is again the SOA as each interval was 2 s). Third, for models in which there were dual-task costs these were assumed to affect estimates of both intervals (E1 and E2) equally. Table 1 summarizes the four models and their predictions, and Fig. 1 illustrates how the models would function when a nonlinear timescale is assumed. A nonlinear timescale is used for the illustration because in most of the models, a nonlinear timescale predicts the greatest effects of SOA on estimates. However, as previously mentioned, the important issue of whether time is represented linearly or nonlinearly in the mind is not yet settled.

If the timing system is constrained structurally by having only one pacemaker and one accumulator (SPSA, referred to as the single accumulator model in van Rijn & Taatgen, 2008), in order to complete the task in the present experiments, the most likely strategy is that the three segments are timed, the number of pulses is stored, and then calculations are performed to produce E1 and E2. E1 would be calculated as the sum of segment 1 and segment 2; E2 would be calculated as the sum of segment 2 and segment 3 (this is the simple application of the SPSA structure, named $SPSA_{simple}$; see Fig. 1A). If time is represented by a linear timescale, these calculations would be similarly accurate across SOAs. However, if time is represented nonlinearly, E1 would remain unchanged by SOA, while E2 would decrease with increasing SOA. This is because the pulses become more spaced out as the entire sequence lengthens, primarily affecting segment 3. This would result in fewer pulses being collected during segment 3 than segment 1 of the same objective length, as SOA increases. This model posits that timed intervals are not subject to dual-task costs because there is only one accumulator. Thus, there is no competition between two accumulators operating simultaneously.

In the weighted application of the SPSA structure ($SPSA_{weighted}$), based on the weighted sum of segments model (Matthews, 2013), a calculation is also performed in order to produce estimates. However, the $SPSA_{weighted}$ model assumes that the pacemaker is reset for each segment[1], that time is represented nonlinearly, and that in calculating

[1] While Matthews (2013) noted the similarities between the structural constraints of his model and a single pacemaker single accumulator timing model, he did not explicitly define the number of pacemakers and accumulators involved. Instead, the weighted sum of segments model assumes that each segment is represented by "a separate negatively-accelerated function of its duration". However, whether this would be generated by one pacemaker which restarts, or separate pacemakers for each segment, is largely academic.

Table 1
Summary of the distinguishing features of each model and predicted data patterns for each model and timescale.

	Single pacemaker single accumulator simple	Single pacemaker single accumulator weighted	Single pacemaker multiple accumulators	Multiple pacemakers multiple accumulators
Model features				
Pacemakers	1	1	1	2
Accumulators	1	1	2	2
DT cost?	No	No	Yes	Yes
Calculation?	Yes	Yes	No	No
Recency weight?	No	Yes	No	No
Linear timescale predictions				
Mean estimates				
E1 E2 relationship	Yes, weakens with SOA	Yes, weakens with SOA	Yes, weakens with SOA	No
Nonlinear timescale predictions				
Mean estimates				
E1 E2 relationship	Yes, weakens with SOA	Yes, weakens with SOA	Yes, weakens with SOA	No

Note: DT = dual-task; E1 = estimate of the first interval; E2 = estimate of the second interval; SOA = stimulus onset asynchrony.

E1 and E2 the different segments receive different weighting. That is, the further a segment is from the end of the whole sequence, the less weighting it receives in computing the estimates (i.e. a recency weighting is applied; see Fig. 1B). For example, in a short SOA condition (where there is a large overlap), segment 2 is the largest part of the first interval, and is not far from the end of the whole sequence, so it would receive a relatively large weight in calculating E1; in contrast, at a long SOA, segment 1 is the largest part of the first interval but it is relatively

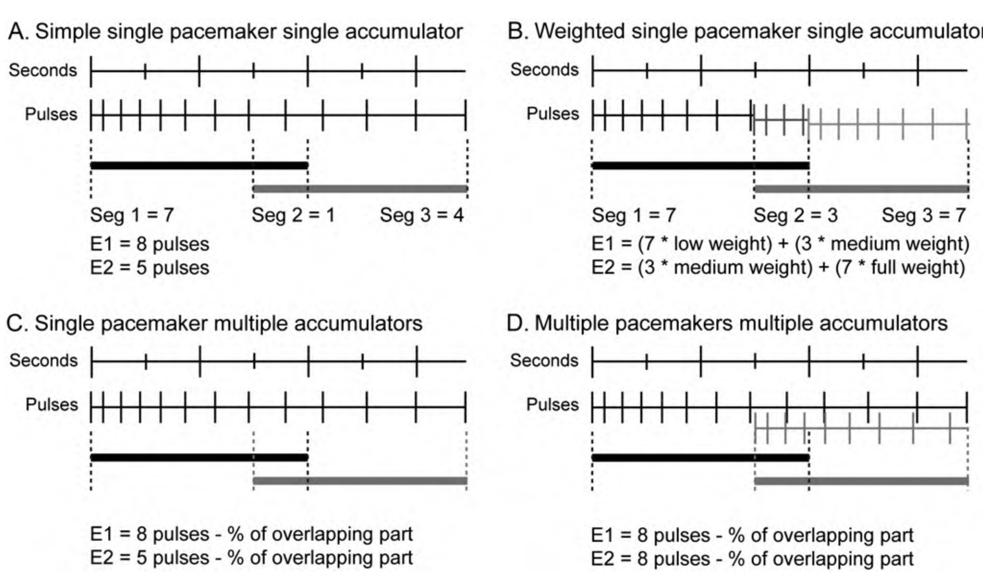


Fig. 1. An illustration of how each of the models would provide estimates of two overlapping time intervals, when a nonlinear timescale is assumed, in one relatively long SOA condition. The thick black line represents the first interval, and the thick grey line represents the second interval. Within the nonlinear timescale, each vertical line represents one pulse, and the inter-pulse interval increases as time proceeds. The same approach would be applied with a linear timescale; the only difference being that the pulses would be emitted at a constant rate. Note: E1 = estimate of the first interval; E2 = estimate of the second interval; Seg = segment.

far from the end of the whole sequence, so it would receive a small weight in calculating E1. Therefore, E1 would decrease and E2 would increase with increasing SOA. Additionally, E2 would be longer than E1 (as segment 3, which always receives full weighting, is included in E2). It should be noted that the effect of SOA would be more pronounced on E2 than on E1, again because the last segment (segment 3) always receives full weighting and is always included in E2. Further, the two estimates would deviate from one another with increasing SOA. In the original description of the weighted sum of segments model, only a nonlinear timescale was modelled (Matthews, 2013). However, a very similar pattern would be predicted for both types of timescale.

According to the single pacemaker multiple accumulators model (SPMA; referred to as the multiple dependent accumulators model in van Rijn & Taatgen, 2008), there is only one pacemaker and the pulses in relation to each interval are collected in two separate accumulators (see Fig. 1C). This model makes the same predictions as the $SPSA_{simple}$ model, except that timed intervals are also subject to dual-task costs. As described by van Rijn and Taatgen (2008), dual-task costs are assumed to result from the accumulators being slower to update when two accumulators are operating simultaneously, and therefore some pulses are missed during the overlapping period. Consequently, more pulses are missed when there is greater overlap. Therefore, when time is represented linearly the SPMA model would predict an increase in both E1 and E2 with increasing SOA (due to dual-task costs). If time is represented on a nonlinear scale, an increase in E1 with increasing SOA is predicted due to dual-task costs. However, E2 would be subject to two influences across SOA — a decrease due to the nonlinear scale and an increase due to dual-task costs. Depending on the strength of the dual-task costs and the specific features of the nonlinear timescale, this could manifest as a small increase, a small decrease or no change in E2 with increasing SOA (see also van Rijn & Taatgen, 2008).

The multiple pacemakers multiple accumulators model (MPMA; referred to as the multiple independent accumulators model in van Rijn & Taatgen, 2008) posits that there are separate pacemakers and separate accumulators for each interval to be timed. Thus, each interval is timed separately, with its own pacemaker being reset from the start (see Fig. 1D). This model makes very similar predictions as the SPMA model; here, E1 and E2 would both increase with increasing SOA regardless of timescale, due to dual-task costs. If the representation of time adheres to a nonlinear timescale, E2 would be shorter than E1 because more pulses would be lost from the second interval than from the first in the overlapping period, due to dual-task costs. This is because the overlapping period represents the end of interval 1 (when pulses are spaced out, see the black timescale in Fig. 1D), and the beginning of interval 2 (when pulses are close together, see the grey timescale in Fig. 1D). This difference between E1 and E2 should also increase with increasing SOA, as the effects of the nonlinear timescale become more pronounced. These effects are barely visible in the predicted mean estimate figures in Table 1, as they depend on the features of the nonlinear timescale and the severity of the dual-task costs. In contrast to the SPMA model, the MPMA model always predicts an increase in both estimates with increasing SOA.

One prediction shared by the three timing models with only one pacemaker (the $SPSA_{simple}$, $SPSA_{weighted}$ and SPMA models) is that the two estimates should be related to each other on a trial-by-trial basis. These models assume that the number of pulses emitted during the overlapping part of the two intervals (referred to as segment 2 for the $SPSA_{simple}$ and $SPSA_{weighted}$ models) are common to each estimate. As the size of the overlapping part decreases with increasing SOA, these three models predict that the relationship between E1 and E2 will weaken with increasing SOA. In contrast, the MPMA model employs a new independent pacemaker for the onset of the second interval. Therefore, the pulses collected for the two intervals are independent of each other, and this model predicts that E1 is not related to E2.

In each of the following experiments, we also included two SOA conditions which produced scenarios in which the two stimuli did not overlap. For these non-overlapping SOA conditions, three of the four models make the same prediction. That is, the $SPSA_{weighted}$, SPMA and MPMA models predict that both estimates would be longer in non-overlapping SOA conditions than in overlapping SOA conditions. In non-overlapping conditions, it is assumed that the intervals would be timed independently and the pacemaker would be reset at the beginning of each interval. Therefore, we posit that in the $SPSA_{weighted}$ model there would be no weighting of segments according to recency as the intervals would be timed separately and these estimates stored in memory until they are reported (i.e. no summing is required so both intervals get full weighting). The SPMA and MPMA models would no longer suffer from dual-task costs, as only one accumulator would be collecting pulses at one time. In contrast, the $SPSA_{simple}$ model predicts that estimates in non-overlapping SOA conditions would be no different from the estimates in overlapping SOA conditions, as there were no dual-task costs in the overlapping contexts and estimates were produced by simply summing relevant segments (with no weighting of segments).

In summary, a range of predictions were made by the different timing models regarding the effect of SOA on E1 and E2 (see Table 1). Experiment 1 was a unimodal version (two visual stimuli) of this experiment using either visual analogue scales (VASs; Experiment 1a) or reproduction (Experiment 1b) as the reporting methodology.[2] In order to investigate whether the results of Experiment 1 were specific to the unimodal context, Experiment 2 was a bimodal version (one visual and one auditory stimulus) of the same task employing the VASs of Experiment 1a.

2. Experiment 1a

2.1. Method

2.1.1. Participants

Fifteen females and five males, aged between 20 and 35 years ($M =$ 23.6 years) participated in one 1 h session. Participants reported normal or corrected-to-normal vision, and received either course credit or payment. Fourteen participants were right-handed, and six were left-handed.

2.1.2. Apparatus and stimuli

The experiment was run in a sound-attenuated, dimly illuminated room. The experiment was programmed in Matlab® using the Psychophysics Toolbox extension (Brainard, 1997) version 3.0.10 and run on an iMac with OS X. Visual stimuli were presented via the built-in LCD monitor (60 Hz). The stimuli were two circles with diameters of 1.75 cm each, presented to the left and the right of a central fixation point (square) of 0.26 cm^2. The two circles were separated by a gap of 2.6 cm. At an approximate viewing distance of 50 cm this results in visual angles of 2°, 0.3°, and 3° respectively.

2.1.3. Procedure and design

Each trial began with the presentation of a fixation point in the centre of two unfilled circles. After 1 s, one of the circles was filled black. After a stimulus onset asynchrony (SOA), the other circle was filled black. There were 9 SOAs: 250, 500, 750, 1000, 1250, 1500, 1750, 2000 and 2250 ms. Each filled circle returned to being unfilled 2 s after it became filled, regardless of SOA. 500 ms after the second circle was again unfilled, estimates of the first and second intervals were collected from the participant (always in that order). Interval estimates

[2] When subjective durations are reported via the method of reproduction, not only perception but also the reproduction may be influenced by the timescale (linear vs. nonlinear). Additional simulations incorporating the influence of each timescale on reproductions were conducted, and produced data patterns that were virtually identical to those generated by the original simulations. For the nonlinear timescale, however, estimates were overall slightly longer.

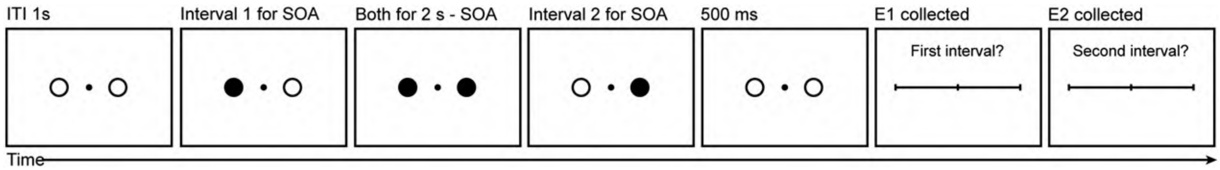


Fig. 2. Trial structure of Experiment 1a. This figure illustrates only SOA conditions that would produce overlapping intervals. In the non-overlapping conditions, the third screen would be two unfilled circles for the duration *SOA − 2 s*. Note: ITI = inter-trial interval; SOA = stimulus onset asynchrony; E1 = estimate of the first interval; E2 = estimate of the second interval.

were given by a mouse click on a horizontal visual analogue scale (VAS; see Bryce & Bratzke, 2014; Corallo et al., 2008; Marti et al., 2010) ranging from 1 to 3 s. The marker of the first estimate remained on the screen for the second estimate. After a 1 s pause, the next trial began (see Fig. 2). Every combination of stimuli was presented once in each block: 9 SOA × 2 Start Sides (left or right), resulting in 18 experimental trials per block. Trials were presented in random order. First, participants completed a practice block, and then ten experimental blocks.

2.1.4. Analysis

E1 and E2 were analyzed in SOA (7) × Start Side (2) repeated measures ANOVAs (only the 7 SOAs that produced overlapping intervals were included in these analyses). The Greenhouse–Geisser correction was used to adjust *p*-values where appropriate. Post hoc Tukey-HSD tests were used to examine ANOVA contrasts. Standard errors for within-subjects designs were calculated according to Cousineau (2005). E1 and E2 in the longer non-overlapping SOAs (2000 and 2250 ms) were also compared to E1 and E2 in each overlapping SOA using post hoc Tukey-HSD tests. As some models predicted that the mean difference between E1 and E2 would increase with SOA, an additional ANOVA was conducted which treated Stimulus (S1 vs. S2) as a factor (a SOA × Stimulus repeated measures ANOVA) and Estimate as the dependent variable. To directly assess the relationship between E1 and E2, Pearson product–moment correlations were calculated within each participant and SOA. Separate one sample *t*-tests were performed on the correlations for each SOA to test whether they differed from zero. As most of the timing models predict that this relationship between E1 and E2 weakens with increasing SOA, we additionally conducted linear mixed effect (LME) models to examine this relationship. Data from single trials (of overlapping SOA conditions only) were used to create two LME models, one with E1 as the dependent variable, and the other with E2. Each model contained the fixed effects of SOA, 'Other' estimate, Start Side, and the SOA × Other estimate interaction, and the random effect of participant. As there was evidence of collinearity in the models (the collinearity diagnostic $\kappa = 55.4$ when E1 was the dependent variable, and $\kappa = 57.9$ when E2 was the dependent variable), the data were centred by subtracting the overall mean from each value. After centering, kappa values were reduced to $\kappa = 1.3$ and $\kappa = 1.2$, and the intercept then reflected the value of the dependent variable when all predictors were set to their means (Jaeger, 2011; Knoblauch & Maloney, 2012).

2.2. Results

The mean estimate results of Experiment 1a can be seen in Fig. 3A. There was no significant effect of SOA on E1, $F(6, 114) = 1.68$, $p = .131$, although the data showed a slightly U-shaped pattern across SOAs. The side at which the first stimulus appeared also did not significantly affect E1, $F(1, 19) = 0.93$, $p = .347$. E1 was significantly longer at long non-overlapping SOAs (2000 and 2250 ms), than at most overlapping SOAs (250, 500, 750, 1000, 1250 and 1500; all $ps < .001$).

E2 increased across the 7 overlapping SOAs, $F(6, 114) = 8.21$, $p < .001$. Post hoc tests indicated that E2 at the 250, 500 and 750 ms SOAs was shorter than at the 1250, 1500 and 1750 ms SOAs, and that E2 at the 1000 ms SOA was shorter than at the 1500 and 1750 ms SOAs (all $ps < .001$). Again, there was no effect of Start Side on E2, $F(1, 19) = 0.97$, $p = .336$. E2 was significantly longer in non-overlapping SOA conditions (2000 and 2250 ms SOAs) than in the four overlapping conditions with the most overlap (SOAs of 250, 500, 750 and 1000 ms, $ps < .001$).

The SOA × Stimulus ANOVA indicated that E2 was longer than E1, $F(1, 19) = 12.35$, $p < .001$, and the difference between E1 and E2 increased with increasing SOA, $F(6, 114) = 11.12$, $p < .001$.

The results of the LME model with E1 as the dependent variable indicated that SOA made a small negative contribution ($\beta = -0.04$, $SE = 0.008$, $p < .001$). This result is in contrast to the non-significant SOA main effect elicited in the ANOVA and probably due to the inclusion of E2 as a predictor, which also made a significant contribution to E1 ($\beta = 0.62$, $SE = 0.01$, $p < .001$). There was also a very small but significant negative estimate associated with the SOA × E2 interaction ($\beta = -0.0002$, $SE = 0.00002$, $p < .001$) which can be interpreted as showing that with increasing SOA, the contribution of E2 to E1 decreases. This is consistent with the correlation analyses indicating that while the correlation between E1 and E2 was significantly greater than zero at all SOAs (all $ps < .001$), it appears to weaken with increasing SOA (Fig. 3B). The other independent variable entered into the model, Start Side, did not make a significant contribution to E1 ($\beta = -5.67$, $SE = 7.45$, $p = .45$). The LME model with E2 as the dependent variable indicated that both SOA ($\beta = 0.09$, $SE = 0.008$, $p < .001$), and E1 ($\beta = 0.61$, $SE = 0.02$, $p < .001$) made positive contributions to E2. The SOA × E1 interaction made a negative contribution ($\beta = -0.00006$, $SE = 0.00002$, $p = .01$), again indicating that the relationship between E1 and E2 weakened with increasing SOA. Start Side made no significant contribution to E2 ($\beta = -1.80$, $SE = 7.56$, $p = .81$).

2.3. Discussion

The results of Experiment 1a can be summarized as follows. First, estimates of the first interval were unaffected (according to the ANOVA), or even slightly negatively affected (according to the LME model), by the degree of overlap between the two intervals (i.e. increasing SOA). Second, the estimate of the second interval increased as the two intervals were more temporally separated (i.e. as SOA increased). Third, both intervals were estimated to be longer in the non-overlapping SOA conditions than in most of the overlapping conditions, and fourth, E2 was longer than E1, an effect that increased with increasing SOA. Fifth, on a trial-by-trial basis, the relationship between the two estimates decreased with increasing SOA, a finding that offers support for a single pacemaker structure ($SPSA_{simple}$, $SPSA_{weighted}$ and SPMA models). That is, single pacemaker models predict that the two estimates are related because the estimates have the overlapping section (between the onset of the second and the offset of the first interval) in common. In contrast, models in which a second pacemaker starts anew at the onset of the second interval, such as the MPMA model, predict that each estimate is independent. Therefore, the correlation and LME results pose a considerable challenge for a structure involving multiple pacemakers.

Of the models with a single pacemaker, the $SPSA_{simple}$ model is the least consistent with the observed data. While it correctly predicted that mean E1 would be unaffected by SOA, and that the relationship between E1 and E2 would decrease across SOAs, the other three predictions from the $SPSA_{simple}$ model were not evidenced in the data. It falsely

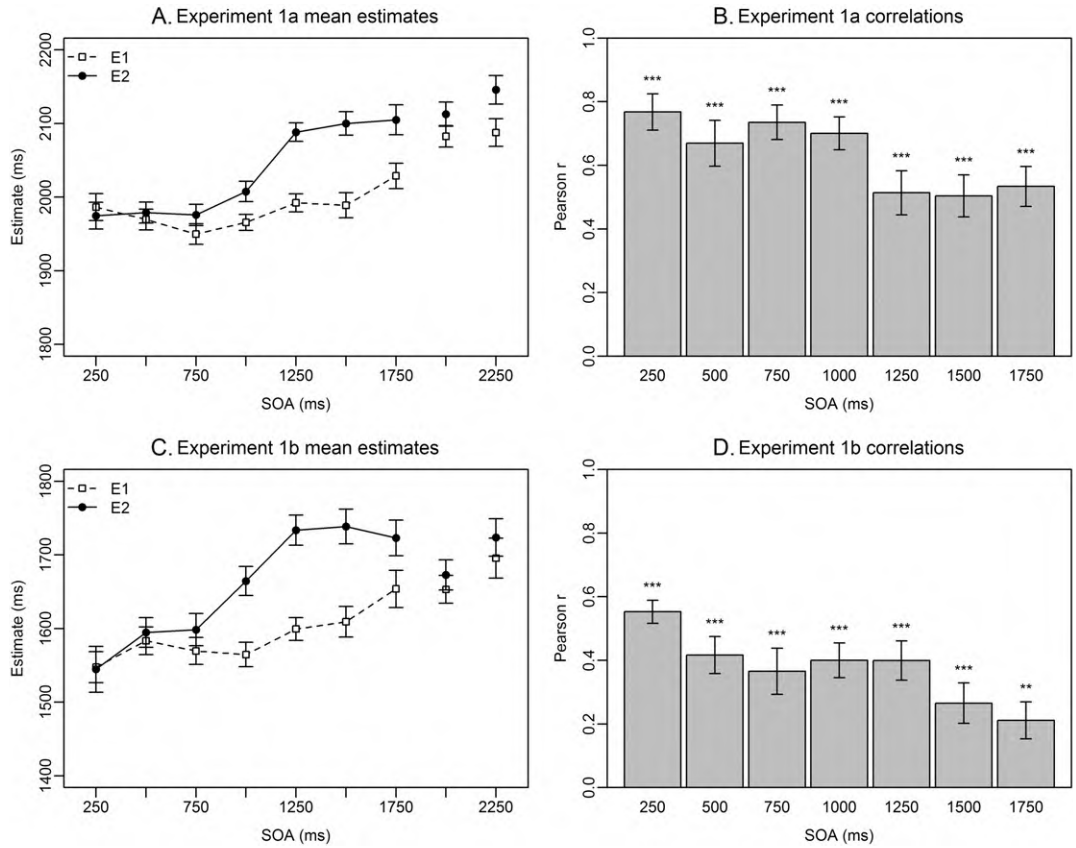


Fig. 3. Results from Experiment 1a (A–B) and Experiment 1b (C–D). Mean estimates of the first (E1) and second (E2) interval as a function of stimulus onset asynchrony (SOA), averaged across Start Side (A and C). Error bars represent ±1 within-subjects SE. The connected points represent the data from overlapping SOA conditions, and the separate points represent the data from the non-overlapping SOA conditions. Note: The absolute values of the axes are different, but they represent the same scale. Mean E1–E2 correlation coefficients as a function of SOA (B and D). $^{**}p < .01$; $^{***}p < .001$.

predicted that E2 would either be unaffected by SOA (linear timescale) or decrease with increasing SOA (nonlinear timescale), that estimates would be no different in non-overlapping and overlapping SOA conditions, and that the two estimates would either be of a similar level (linear timescale) or E1 would be greater than E2 (nonlinear timescale).

The other two models that feature a single pacemaker (the $\text{SPSA}_{\text{weighted}}$ and SPMA models), however, are more consistent with the results. First, they both correctly predicted the increase in E2 with SOA, either due to the more recent segments receiving greater weighting (in the $\text{SPSA}_{\text{weighted}}$ model), or due to decreased dual-task costs when there was less overlap (in the SPMA model). Second, both models correctly predicted that estimates would be longer in non-overlapping conditions than in overlapping conditions, either due to the recency weighting only being applied in overlapping situations (in the $\text{SPSA}_{\text{weighted}}$ model) or due to dual-task costs only applying in overlapping conditions (in the SPMA model).

However, the ambiguous findings regarding the effect of SOA on E1 could be in conflict with both the $\text{SPSA}_{\text{weighted}}$ and SPMA models. The $\text{SPSA}_{\text{weighted}}$ model predicted a slight decrease in E1 with increasing SOA, while the SPMA model predicted an increase. While the ANOVA results are inconsistent with both of these predictions, the LME model results are consistent with the $\text{SPSA}_{\text{weighted}}$ model predictions. Additionally, the finding that E2 was longer than E1 raises further doubts about the SPMA model, as this finding is not consistent with the assumptions regarding dual-task costs. That is, if dual-task costs are caused by losing pulses from the overlapping time-period, either the same number of pulses should be lost from both estimates (linear timescales) or more pulses should be lost from E2 than E1 (nonlinear timescales). In contrast, the $\text{SPSA}_{\text{weighted}}$ model is the only one that correctly predicted that E2 would be longer than E1 and that the difference between the estimates would increase with SOA.

In summary, our data from Experiment 1a do not conclusively support any of the aforementioned models as none of the models were entirely consistent with the pattern of results. Nevertheless, the SPMA and $\text{SPSA}_{\text{weighted}}$ models appeared to be more successful at explaining the data pattern than the $\text{SPSA}_{\text{simple}}$ and MPMA models. Comparing the SPMA and $\text{SPSA}_{\text{weighted}}$ models, the finding that E2 was longer than E1 could be considered evidence in favour of the $\text{SPSA}_{\text{weighted}}$ model. However, it is possible that the use of a VAS in this experiment biased participants' reports and caused E2 to be longer than E1. That is, perhaps there is an inclination to treat the VAS as a timeline, especially as the mental timeline goes from left to right (Santiago, Lupiáñez, Pérez, & Funes, 2007; Ulrich & Maienborn, 2010); in this case, participants could be reluctant to place E2 before E1 (as it came later in the series of events). This could have been reinforced by the E1 marker remaining on the VAS while the participants gave E2. Thus, it is unclear whether the finding that E2 is longer than E1 truly reflects participants' subjective experiences or merely reflects a bias caused by the use of the VAS. Therefore, in Experiment 1b we replicated Experiment 1a using interval reproduction as the reporting method, rather than a VAS.

3. Experiment 1b

3.1. Method

3.1.1. Participants

Fourteen females and six males, aged between 20 and 44 years ($M = 24.95$ years) participated in one 1 h session. Participants reported normal or corrected-to-normal vision, and received either course credit or payment. Eighteen participants were right-handed, and two were left-handed. None of these participants had previously participated in Experiment 1a.

3.1.2. Apparatus and stimuli

The apparatus and stimuli were identical as in Experiment 1a.

3.1.3. Procedure and design

The trial was exactly as in Experiment 1a. After the trial one unfilled circle (the one to be reproduced) was presented again in the same position on the screen (left or right), with a prompt, "how long was the first/second stimulus?" Participants gave their interval reproductions by pressing the space-bar for the desired amount of time, and for the duration of the reproduction the circle was filled black. The participants always reproduced the first, and then the second interval, regardless of which side was first. While participants' perceptions of each interval are now 'reproductions', in the interests of consistency we still label these E1 and E2. As in Experiment 1a, participants completed a practice block (18 trials), and then ten experimental blocks (18 trials each).

3.1.4. Analysis

As the reproduction interval was not limited in any way, trials with extremely long or short reproductions were rejected. That is, within each participant, trials with an E1 (or E2) further than 3 standard deviations from that participant's mean E1 (or E2) were rejected (0.02% of all trials). Otherwise, data analysis was conducted in the same manner as in Experiment 1a. In building the LME models, there was again evidence of collinearity in the models which was reduced when variables were centred (with E1 as the dependent variable, κ reduced from 31.4 to 1.3; with E2 as the dependent variable, κ reduced from 34.2 to 1.2).

3.2. Results

The results of Experiment 1b are depicted in Fig. 3C. E1 was again unaffected by SOA, $F(6, 114) = 2.05$, $p = .12$. E1 was reproduced as 26 ms longer when it was presented on the left than when it was presented on the right, $F(1, 19) = 6.64$, $p = .018$. Comparing E1 at non-overlapping and overlapping SOAs, only the contrasts between the 2250 ms SOA and the 250, 750 and 1000 ms SOAs were significant (all $ps < .05$).

The increase in E2 across the 7 overlapping SOAs was significant, $F(6, 114) = 6.65$, $p = .002$. Post hoc tests indicated that E2 was longer at the 1250, 1500 and 1750 ms SOAs than at the 250 and 500 ms SOAs, and also longer at the 1250 and 1500 ms SOAs than at the 750 ms SOA (all $ps < .05$). The difference between E2 at long non-overlapping SOAs and overlapping SOAs was less distinct than in Experiment 1a. The only significant comparison was between the 2250 ms SOA and the 250 ms SOA conditions ($p < .001$).

In contrast to Experiment 1a, E2 was not significantly longer than E1 in Experiment 1b, $F(1, 19) = 2.67$, $p = .119$. However, the difference between E1 and E2 did increase with increasing SOA, $F(6, 114) = 3.70$, $p = .016$.

The LME model with E1 as the dependent variable showed that E2 made a positive contribution ($\beta = 0.32$, SE $= 0.02$, $p < .001$) and the SOA $\times$ E2 interaction made a negative contribution ($\beta = -0.0001$, SE $= 0.00002$, $p < .001$) to E1, while neither SOA ($\beta = 0.01$, SE $= 0.01$, $p = .38$) nor Start Side ($\beta = -22.52$, SE $= 12.97$, $p = .08$) did. With E2 as the dependent variable, the LME model indicated a positive influence of SOA ($\beta = 0.11$, SE $= 0.02$, $p < .001$), and E1 ($\beta = 0.45$, SE $= 0.02$, $p < .001$), no effect of Start Side ($\beta = -0.69$, SE $= 1.23$, $p = .96$), and a negative influence of the SOA $\times$ E1 interaction ($\beta = -0.0001$, SE $= 0.00003$, $p = .001$) on E2. As in Experiment 1a, the negative estimates for the SOA $\times$ 'Other' estimate in each model indicate that the relationship between the two estimates weakens with increasing SOA, as illustrated by the correlation results (Fig. 3D).

3.3. Discussion

The findings of Experiment 1b largely replicated those of Experiment 1a, indicating that these results are stable regardless of the method used to collect estimates. The reproductions of the first interval did not change across SOAs, while reproductions of the second interval increased with increasing SOA. While the effects of SOA on the two estimates/reproductions were very similar in Experiments 1a and 1b, there were also some differences in the results. First, the absolute values of the estimates were different. Participants largely underestimated both intervals when they reproduced them, while their estimates via VASs were close to the objective interval duration. However, the estimates in Experiment 1a were possibly influenced by the VAS being labelled with a midpoint reflecting the objective interval duration. Also, underestimation is a common finding in interval reproduction (e.g. Droit-Volet, 2010; Wackermann & Ehm, 2006). Second, even though in both experiments participants seemed to perceive the second interval as longer than the first, in Experiment 1b this effect did not reach statistical significance. Therefore it is possible that the use of VASs in Experiment 1a may have contributed somewhat to this effect. Importantly, as in Experiment 1a, the finding that the difference between E1 and E2 increased with increasing SOA was only predicted by the $\text{SPSA}_{\text{weighted}}$ model.

As in Experiment 1a, participants' reproductions of each interval were related on a trial-by-trial basis and this relationship weakened with increasing SOA, as indicated by the correlation analyses and LME model results. This result offers strong support for a single pacemaker structure, as the two estimates appear to have in common the number of pulses in the overlapping part. Therefore, the results of both experiments suggest that the $\text{SPSA}_{\text{weighted}}$ (with one accumulator and a weighted summing of segments) and SPMA (with two accumulators and dual-task costs) models are the most likely to reflect how participants perceive and estimate two overlapping intervals.

However, as referred to in the discussion of Experiment 1a, the findings that mean E1 did not change across SOAs and that SOA did not contribute to E1 in LME model analyses are in conflict with the predictions of both of these models. It is possible that a null effect on E1 is nevertheless consistent with the $\text{SPSA}_{\text{weighted}}$ model, as the $\text{SPSA}_{\text{weighted}}$ model predicted only a small decrease in E1 across SOAs. Alternatively, an asymmetrical version of the SPMA model (linear timescale) could also explain these results—that is, one in which only the timing of the second interval suffered from dual-task costs. Such models would of course predict that E1 is unaffected by SOA and that E2 increases with increasing SOA. However, as dual-tasks costs are thought to result from the accumulators missing pulses during the overlapping period, it follows that E2 should be shorter than E1. This is contrary to what was observed. Indeed, the recency weighting element of the $\text{SPSA}_{\text{weighted}}$ model is the only feature of any model that predicts such an increase in E2 with increasing SOA as well as the deviation of E2 from E1. Hence, on balance, the results of Experiment 1b again provide more evidence in favour of the $\text{SPSA}_{\text{weighted}}$ model than the other two models.

It seems that when people must estimate the durations of two visual stimuli overlapping in time, they split the entire sequence into segments and then sum the relevant segments applying a recency weighting. What is not clear is how participants would perform such a task if the stimuli were presented in different modalities. The unimodal case requires participants to first time the duration of one visual stimulus and then to shift their attention to the position of the other stimulus when it begins. Perhaps this encourages participants to time each segment separately. It is reasonable to suppose that a different approach might be taken if the visual attention demands were reduced, as in a bimodal context where one stimulus is visual and the other is auditory. Indeed, it could be that separate pacemakers or accumulators can function for separate modalities, in which case the MPMA or SPMA models may best explain timing in a bimodal multiple timing task. Therefore, in Experiment 2 we conducted a bimodal version of the overlapping intervals experiment.

4. Experiment 2

4.1. Method

4.1.1. Participants

Forty participants[3] (31 females and 9 males) aged between 18 and 41 years ($M = 21.7$ years) took part in one 1 h session. Participants reported normal hearing and normal or corrected-to-normal vision, and received either course credit or payment. Thirty-six participants were right-handed, and four were left-handed.

4.1.2. Apparatus and stimuli

The visual stimulus was a circle with a diameter of 1.75 cm presented in the centre of the screen. Assuming a viewing distance of 50 cm, this resulted in a visual angle of 2°. Distance from the screen was not fixed, so this visual angle is approximate. The auditory stimulus was white noise presented for a duration of 2 s via headphones.

4.1.3. Procedure and design

Each trial began with the presentation of an unfilled circle in the centre of the screen. After 1 s, in the 'visual first' condition, the circle was filled black. After a stimulus onset asynchrony (SOA), the auditory stimulus was presented. As in Experiments 1a and 1b, there were 9 SOAs: 250, 500, 750, 1000, 1250, 1500, 1750, 2000 and 2250 ms. The filled circle returned to being unfilled, and the auditory stimulus ended, 2 s after each was presented. In the 'auditory first' condition, the presentation order was reversed. 500 ms after the second stimulus ended, interval estimates of the first and second stimulus were collected from the participant (always in this order) via a VAS as in Experiment 1a. After a 1 s pause, the next trial began. Every combination of stimuli was presented once in each block: 9 SOA × 2 Order (auditory–visual or visual–auditory), resulting in 18 experimental trials per block. As before, trials were presented in random order. First, participants completed a practice block, and then ten experimental blocks.

4.1.4. Analyses

As before, only the 7 SOAs that produced overlapping intervals were included in ANOVAs and the longer SOAs (2000 and 2250 ms) were examined separately via post hoc tests. Consequently, E1 and E2 were analyzed in SOA (7) × Order (2: auditory–visual/visual–auditory) repeated measures ANOVAs. The Greenhouse–Geisser correction was used to adjust p-values where appropriate. Post hoc Tukey-HSD tests were used to examine ANOVA contrasts. Standard errors for within-subjects designs were calculated according to Cousineau (2005). As there were significant SOA × Order interaction effects on E1 when all the data were analyzed together, $F(6, 234) = 7.192$, $p < .001$, for the main analyses the data were split according to stimulus presentation order, and a one-way ANOVA with the factor SOA was conducted in each. As before, an ANOVA that treated Stimulus as a factor (a SOA × Stimulus repeated measures ANOVA) was also conducted within each order condition, as well as E1–E2 correlation analyses as a function of SOA. The LME model analyses were also conducted in the same manner as in Experiments 1a and 1b, but without Start Side as a fixed effect. As before, there was evidence of collinearity in the models which was successfully reduced after variables were centred (AV condition: with E1 as the dependent variable, κ reduced from 56.6 to 1.2; with E2 as the dependent variable, κ reduced from 64.4 to 1.1; VA condition: with E1 as the dependent variable, κ reduced from 57.1 to 1.1; with E2 as the dependent variable, κ reduced from 54.4 to 1.3). First, we present the results for the order auditory–visual (AV), and then for the order visual–auditory (VA).

4.2. Results

4.2.1. Auditory–visual order

Fig. 4A depicts the results of the AV order condition. There was only a marginally significant effect of SOA on E1 (auditory), $F(6, 234) = 2.20$, $p = .065$. On closer examination this trend seems to be due to the E1 being longer in the 1750 ms SOA than in the other overlapping SOA conditions. E1 was longer in the non-overlapping SOA conditions (SOAs of 2000 and 2250 ms), than in all overlapping SOA conditions (all $ps < .001$).

E2 (visual) increased with increasing SOA, $F(6, 234) = 3.26$, $p = .012$, and post hoc tests indicated that E2 was significantly longer at the longest overlapping SOA (1750 ms) than at the 250 and 750 ms SOAs ($ps < .05$). Further, E2 was significantly longer in non-overlapping SOA conditions (2000 and 2250 ms) than in all overlapping SOA conditions (all $ps < .001$).

E1 was longer than E2, $F(1, 39) = 19.35$, $p < .001$, but this difference did not change across SOAs.

The results of the LME models for the AV condition were similar to those in Experiment 1b. That is, E2 made a positive contribution ($\beta = 0.34$, SE $= 0.02$, $p < .001$), and the SOA × E2 interaction made a negative contribution ($\beta = -0.00009$, SE $= 0.00003$, $p = .001$) to E1, whereas SOA made no contribution ($\beta = 0.009$, SE $= 0.01$, $p = .35$). When E2 was the dependent variable, SOA ($\beta = 0.04$, SE $= 0.009$, $p < .001$) and E1 ($\beta = 0.33$, SE $= 0.02$, $p < .001$) both had positive estimates, while the estimate for the SOA × E1 interaction was negative ($\beta = -0.00007$, SE $= 0.00003$, $p = .015$). These results are consistent with both the ANOVA and correlation analyses (Fig. 4B). All correlation coefficients were significantly greater than zero (all $ps < .001$) and the relationship between the estimates appeared to weaken with SOA.

4.2.2. Visual–auditory order

Fig. 4C depicts the results of the VA order condition. In contrast to all previous results, when the first stimulus was visual in the bimodal context, E1 decreased with increasing SOA, $F(6, 234) = 8.93$, $p < .001$. Post hoc tests indicated that E1 in the shortest SOA condition (250 ms) was longer than when SOA was 750 ms or greater (all $ps < .001$). Further, E1 was longer in the 500 ms SOA than in the 1000, 1250, or 1500 ms SOA conditions ($ps < .05$). E1 in the longest non-overlapping condition (SOA of 2250 ms) was longer than in five of the overlapping conditions (750, 1000, 1250, 1500 and 1750 ms SOAs, $ps < .001$) and E1 in the 2000 ms SOA condition was longer than in the 1250 and 1500 ms SOA conditions ($ps < .001$).

As in all previous experimental conditions, E2 (auditory) increased with increasing SOA, $F(6, 234) = 2.91$, $p = .018$. Post hoc tests indicated that the only significant contrast was between the 1750 and 1000 ms SOAs ($p = .042$). E2 was longer in non-overlapping conditions (2000 and 2250 ms SOAs) than in all overlapping conditions (all $ps < .05$, except for the 2000–1750 ms comparison which was only marginally significant with $p = .092$).

In contrast to the AV order, and similar to Experiments 1a and 1b, when the first stimulus was visual, the difference between E1 and E2 increased with increasing SOA, $F(6, 234) = 10.86$, $p < .001$.

As one would expect, the LME model results in the VA condition are slightly different to all previous LME model results. In this case, SOA made a negative contribution ($\beta = -0.09$, SE $= 0.01$, $p < .001$), E2 made a positive contribution ($\beta = 0.32$, SE $= 0.02$, $p < .001$), and the SOA × E2 interaction made a negative contribution ($\beta = -0.00007$, SE $= 0.00003$, $p = .015$) to E1. E2 was positively predicted by SOA ($\beta = 0.06$, SE $= 0.01$, $p < .001$) and E1 ($\beta = 0.29$, SE $= 0.002$, $p < .001$), and negatively predicted by the SOA × E1 interaction ($\beta = -0.00008$, SE $= 0.00003$, $p = .003$). These results were again completely consistent with the ANOVA and correlation analyses. The correlation results

[3] The sample size was doubled for Experiment 2 in order to maintain the same statistical power as the previous two experiments, as the two order conditions were analyzed separately.

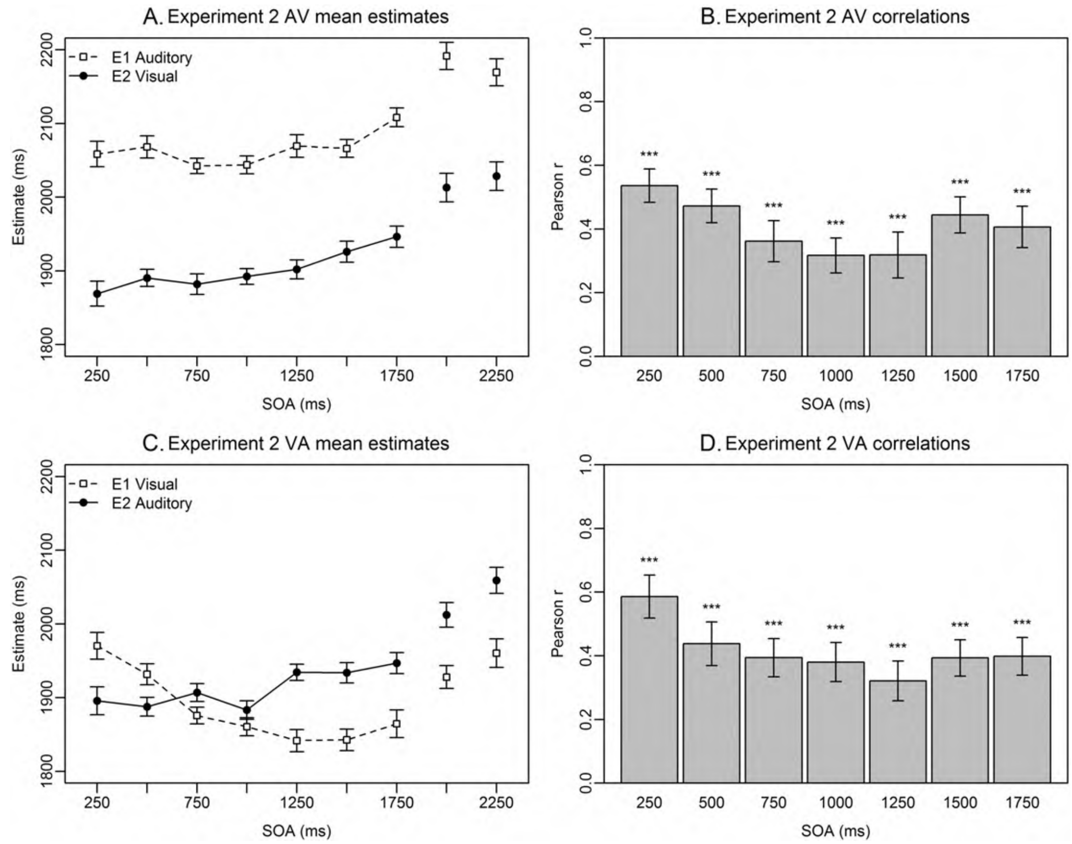


Fig. 4. Results from Experiment 2, split by stimulus presentation order; auditory then visual order (A–B) and visual then auditory order (C–D). Mean estimates of the first (E1) and second (E2) interval as a function of stimulus onset asynchrony (SOA), averaged across Start Side (A and C). Error bars represent ± 1 within-subjects SE. The connected points represent the data from overlapping SOA conditions, and the separate points represent the data from the non-overlapping SOA conditions. Mean E1–E2 correlation coefficients as a function of SOA (B and D). $^{**}p < .01$; $^{***}p < .001$.

indicated that E1 and E2 were significantly correlated at all SOAs (Fig. 4D; all $ps < .001$) and the results from the LME models confirm that this relationship weakened with increasing SOA.

4.3. Discussion

In this bimodal experiment, interval estimates were differently affected by SOA depending on the order of stimulus presentation. When stimuli were presented in the order 'first auditory then visual' (AV), the results were largely the same as in the unimodal visual–visual context (Experiments 1a and 1b). That is, there was no change in E1 across SOA, E2 increased with increasing SOA, both estimates were longer in non-overlapping than overlapping intervals, and the relationship between E1 and E2 weakened with increasing SOA. As such, these results can also be partially explained by the $SPSA_{weighted}$ and SPMA models. However, in contrast to the results of Experiments 1a and 1b, E1 was longer than E2. This is in line with previous findings that auditory intervals are estimated to be longer than visual intervals (e.g., Goldstone & Lhamon, 1972; Wearden, Edwards, Fakhri, & Percival, 1998; Wearden, Todd, & Jones, 2006). Within pacemaker-accumulator models, it has been proposed that auditory interval estimates are longer and more accurate than visual interval estimates because the pacemaker emits pulses at a higher rate for auditory intervals than for visual or vibrotactile intervals (Jones, Poliakoff, & Wells, 2009; Occelli, Spence, & Zampini, 2011; Wearden et al., 1998). Such effects could be explained by both the $SPSA_{weighted}$ model and an asymmetric SPMA model with some minor adjustments. Indeed, in his model Matthews (2013) included a parameter to account for differences in the perceived duration of an auditory segment depending on tone frequency (higher tones are perceived as longer). In the current context, such a parameter could be included to account for modality effects on perceived duration.

In contrast to all the previous experimental conditions, in the 'first visual then auditory' (VA) condition, E1 decreased with increasing SOA. The $SPSA_{weighted}$ model is the only model that is consistent with such a decrease in E1 across SOAs. Therefore, in the VA condition, the results are fully consistent with the predictions of the $SPSA_{weighted}$ model. This raises the question, why does the result pattern change when the order of stimulus presentation changes? More specifically, why is there a different effect of SOA on the first estimate when the stimulus presentation order is VA or AV? It is unlikely to be a pre-planned strategy effect, as the trials were intermixed and participants did not know until the first stimulus onset which modality would be presented first. Instead, it is more likely to reflect a complex set of rules that determine in which modality the time intervals are represented. This idea will be elaborated upon in the General discussion section.

5. General discussion

The present experiments aimed to investigate how people perceive and give estimates of two overlapping intervals. Predictions were made from four models that were proposed in previous related research, and current findings were compared to these. The unimodal visual experiments (Experiments 1a and 1b) as well as the AV order condition in Experiment 2 showed a similar result pattern — the estimate of the first interval was mostly unchanged by the degree of overlap of the two intervals, whereas the second estimate increased with decreasing temporal overlap (i.e., increasing SOA). Also, in the unimodal visual experiments, the estimate of the second interval was longer than that of the first interval, and the two estimates diverged with increasing SOA. A different pattern of results was observed in the VA order condition of Experiment 2. In this condition, the degree of overlap affected both estimates. Estimates of the first interval decreased whereas estimates of the second interval increased with decreasing temporal overlap (i.e., increasing SOA). Across all experimental contexts there was a trend for the non-overlapping intervals to be estimated as longer than the overlapping intervals, with the exception of a few data points in Experiment 1b and the VA order condition of Experiment 2. Further, across all experimental contexts, the two estimates were related on a trial-by-trial basis and this relationship generally weakened with decreasing temporal overlap.

Overall, the results are inconsistent with both the simple calculation version of the single pacemaker, single accumulator model ($\text{SPSA}_{\text{simple}}$), and the structure containing multiple pacemakers and accumulators (the MPMA model) in which a second pacemaker starts at the onset of the second interval. Specifically, the consistent finding that the second estimate increased with decreasing temporal overlap cannot be reconciled with the $\text{SPSA}_{\text{simple}}$ model. The positive relationship between the two estimates strongly argues against a multiple pacemaker model. However, the results can be largely explained by the other two single pacemaker models — one of which incorporates only one accumulator and applies a recency weighting when segments are summed (the $\text{SPSA}_{\text{weighted}}$ model), the other of which incorporates more than one accumulator (the SPMA model). Nevertheless, both models predicted an effect of SOA on the estimate of the first interval, a finding that was only observed in the LME model results of Experiment 1a and the VA order condition of Experiment 2. That is, SOA made a negative contribution to E1 (Experiment 1a), and estimates of the first interval decreased with increasing SOA (Experiment 2 VA). Importantly, these results are completely consistent with the $\text{SPSA}_{\text{weighted}}$ model but not with the SPMA model. Thus, the $\text{SPSA}_{\text{weighted}}$ model is most successful (although not flawless) at explaining the data patterns across the range of contexts investigated in the present study.

The difference between the two single pacemaker, single accumulator models is that the $\text{SPSA}_{\text{weighted}}$ model, based on the weighted sum of segments model (Matthews, 2013), has a recency weighting applied to the calculations. That is, the more time that passes after the end of a segment, the less it contributes to the estimate of the entire sequence. A similar idea is proposed by fading-trace theories which posit that the more time passes, the more the memory of an interval fades (i.e. pulses are lost). Such fading-trace theories (Schab & Crowder, 1988; Wackermann & Ehm, 2006; Wearden & Ferrara, 1993) were proposed to account for the negative time order effect (TOE), a common finding in interval comparison studies whereby the second of two intervals is judged to be longer than the first (Woodrow, 1935; see also Schab & Crowder, 1988 for evidence of a negative TOE with the method of interval reproduction). While there is strong conceptual overlap between the weighted sum of segments model and fading-trace theories, there are also some important differences between them. Most importantly, the weighted sum of segments model is specifically a model of how people estimate the length of a sequence composed of continuous segments (i.e. without gaps), whereas fading-trace theories are used to explain the negative TOE observed with temporally separated intervals. Matthews (2013) in fact states that the recency weighting is applied when the segments are summed, implying that no such weighting would affect the estimates of two separate intervals; this is why we predicted that the non-overlapping SOA conditions would elicit the longest estimates. Indeed, in the current experiments estimates were either longer in the non-overlapping than in the overlapping SOA conditions, or there was no difference between these conditions. A strict application of a fading trace theory would predict that E1 should be shortest at the longest SOA (as it is furthest from the time when the estimate is given), which was certainly not the case.

The model that best explains our findings and the model that best explained van Rijn and Taatgen's (2008) data both have a single pacemaker and single accumulator structure. However, in order to explain our data, we must apply an additional weighting to the calculation. Further, the data patterns observed by van Rijn and Taatgen (2008) and in our experiments are surprisingly similar – no effect of SOA on E1 and an increase in E2 with increasing SOA – even though applying the simple calculation (the $\text{SPSA}_{\text{simple}}$ model) to our time perception context would predict a different pattern (see Table 1). Indeed, it is possible to also apply the principles of the weighted sum of segments model to the context of interval production. van Rijn and Taatgen (2008) suggested that in order to produce the second of two overlapping intervals, participants add their representation of SOA to the end of the first interval. This representation might be subject to a recency weighting based on the time passed since the end of SOA (in this case, interval 2 onset). Such a weighted calculation would make the same predictions as were made by the simple calculation model supported by van Rijn and Taatgen (2008) – no effect of SOA on E1, and an increase in E2 with increasing SOA – albeit for different reasons. That is, in the simple calculation model the nonlinear timescale is responsible for the effect of SOA on E2, whereas in the weighted calculation model the crucial feature is the weighting rather than the properties of the timescale.

An interesting feature of the present study's data pattern is that the E2-SOA functions appear to be nonlinear. There appears to be a change in E2 around the 1000 ms SOA, which could be described as a step function (e.g. in Experiment 1a and Experiment 2 VA order), or as the estimates reaching an asymptote (e.g. in Experiment 1b). Of course, the 1000 ms SOA condition represents a special case in which each segment is 1000 ms (Matthews, 2013, refers to such conditions as constant rate sequences). Therefore, the shape of E2 could reflect the influence of a changing temporal structure (accelerating, decelerating and constant rate sequences) which is a feature of the weighted sum of segments model. Note that van Rijn and Taatgen (2008) did not include the 1000 ms SOA as a condition in their experiments, so we do not know whether such a change of the E2 function across SOAs would have also occurred at the midpoint in their context.

Neither the $\text{SPSA}_{\text{weighted}}$ model nor any of the other described models can explain why a different pattern of results was observed when the stimuli presentation order changed in the bimodal case (Experiment 2). In multimodal timing contexts, the way in which time intervals of different modalities are encoded and represented in working memory or the reference memory is still an unresolved issue. The specific context might determine whether the timing system represents time intervals in the same modality as they are presented, in a common 'amodal' code (Filippopoulos, Hallworth, Lee, & Wearden, 2013), or transforms them into the other modality. There is some evidence that temporal information is primarily encoded in the auditory system and that visual temporal structures (rhythms) or intervals are automatically transformed into an auditory representation (cross-modal encoding; Bratzke, Seifried, & Ulrich, 2012; Guttman, Gilroy, & Blake, 2005; Kanai, Lloyd, Bueti, & Walsh, 2011). The present data are clearly not consistent with such a strict version of cross-modal encoding, which would predict similar result patterns across all experiments irrespective of input modalities and presentation order. However, it has also been suggested that whether or not such cross-modal encoding occurs might depend on the timing context (Takahashi & Watanabe, 2012). Thus, the likelihood of cross-modal encoding occurring during timing of overlapping intervals in a bimodal context (as in Experiment 2) may depend on, for instance, the order in which the different stimuli are presented and the durations of the to-be-timed intervals or segments. Additionally, how the timing system represents the overlapping segment is unclear — it could retain two separate representations (one visual, one auditory), compute one averaged (visual–auditory) representation, or use only the auditory representation. Which of these options is applied might depend on the same contextual factors as above (see Walker & Scott, 1981, for evidence of contextual effects in auditory–visual timing). There is also evidence that long-term representations in reference memory can interfere with one another when multiple representations of different durations and/or modalities must be maintained across trials (memory mixing; Penney, Allan, Meck, & Gibbon, 1998; Ogden, Wearden, & Jones, 2008). While such memory mixing may generally contribute to estimates in the present study, it is unlikely that it can account for the modality order effects of Experiment 2.

Some possible methodological limitations of the present study deserve to be mentioned. First, using a VAS to collect interval estimates is not typical in timing research. However, it is not unlike the common method of verbal estimation (where participants verbally report interval duration using units such as milliseconds or seconds) and VASs have been used in other studies to collect time estimates (Bryce & Bratzke, 2014; Corallo et al., 2008; Marti et al., 2010). One drawback is that the estimates' absolute values cannot be interpreted using this method, as they are probably influenced by the labelling of the scale. In its favour, collecting time estimates via a VAS is quicker than other methods such as interval reproduction. Further, interval reproduction also has disadvantages, such as motoric limitations which are particularly problematic when participants must reproduce short time intervals. It is clear that all methods have specific strengths and weaknesses, but we are confident in the reliability of our results as the same data pattern was observed with both the VAS and the reproduction methods (see also Bryce & Bratzke, in press). Another issue that may apply to both methods is that participants always reported their perception of the first and then the second interval. Further research is needed to establish whether and if so how the order of reporting might affect estimates.

In conclusion, the present results support the notion that two overlapping intervals cannot be timed independently. An application of the weighted sum of segments model ($SPSA_{weighted}$) to this situation can best account for the present results. Accordingly, the timing system appears to be constrained by a single pacemaker and a single accumulator structure. When timing multiple overlapping intervals, it appears to treat these as a sequence of non-overlapping and overlapping segments which are then summed in order to estimate each interval. Because these segments are weighted according to their recency, interval estimates vary with the degree of overlap. Furthermore, we found that in a bimodal context, timing of each interval also depended on the stimulus presentation order. Any comprehensive model of interval timing should therefore consider not only the modalities of the to-be-timed intervals but also the order in which stimuli of different modalities are presented.

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Appendix A. Data simulations

This appendix describes how the four timing models for overlapping interval perception were modelled and data from each were generated. First, the method of generating the nonlinear and linear timescales is described, followed by how each model used these timescales to provide estimates of the two intervals.

A.1. Timescales

The nonlinear timescale was created in the same way as described in van Rijn and Taatgen (2008) and in Taatgen et al. (2007). Accordingly, each pulse was separated from the previous pulse by an interval amounting to 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 was added to this interval. The interval between the first two pulses t_0 was set to 100 ms and the parameters a and b were set to $a = 1.02$, and $b = 0.015$. The linear timescale was created in the same way as the nonlinear timescale, with the exception that $a = 1$, so that the intervals between the pulses did not increase over time.

The subjective durations were calculated as follows. First, the intervals between the pulses were cumulated to create a function of objective time values T_{obj}. This function describes the points in time when each pulse was emitted. Second, the number of pulses n generated during a particular interval I (e.g., SOA) was derived from the empirical cumulative distribution function of T_{obj} at the endpoint of I. Finally, to compute the subjective duration E of the interval I, the number of pulses n was multiplied by a fixed subjective inter-pulse interval t of 100 ms.

A.2. Monte Carlo simulations

For each timescale (nonlinear and linear) and each of the seven overlapping SOAs (250, 500, 750, 1000, 1250, 1500, 1750 ms) and two non-overlapping SOAs (2000, 2250 ms), 500 trials per SOA were simulated. Estimates of interval 1 and interval 2 (*E1* and *E2*) were generated according to the four timing models. When a single pacemaker was reset or a second pacemaker was utilized, a new timescale was generated. This ensured that the random noise was unique to each timescale. Since in the present study both intervals had the same duration (2000 ms), they are denoted *Interval*. Below, we describe the steps in data simulation for each model regardless of timescale; however, data was generated for each model for both nonlinear and linear timescales.

A.3. Simple single pacemaker single accumulator model

The simulated estimates for each interval (*E1* and *E2*) were generated according to the $SPSA_{simple}$ model as follows.

Step 1: Generate a timescale.
Step 2: *If SOA* < *Interval* {overlapping interval condition}
$E1 = E(Interval)$
$E2 = E(SOA + Interval) - E(SOA)$
Else {non-overlapping interval condition}
$E1 = E(Interval)$
Step 3: Generate a new timescale.
$E2 = E(Interval)$
End
Stop

A.4. Weighted single pacemaker single accumulator model

There were two possible methods for calculating the estimates according to the weighted single pacemaker single accumulator ($SPSA_{weighted}$) model — either using the timescales generated according to van Rijn and Taatgen (and described above), or according to the original method described in Matthews (2013). Matthews calculated a subjective duration as a negatively-accelerated function of an objective duration. It is important to note that defining a subjective duration as a negatively-accelerated function of an interval has the same effect as generating a timescale with pulses that are increasingly spaced out. We report both methods for completeness, but they generated very similar patterns across SOAs. Table 1 in the main manuscript shows the predictions for the $SPSA_{weighted}$ model using the timescales as in van Rijn and Taatgen.

A.4.1. $SPSA_{weighted}$ model using the van Rijn and Taatgen timescales

According to the $SPSA_{weighted}$ model, two overlapping intervals are perceived as three segments (denoted Seg_1, Seg_2, and Seg_3) which are then combined to estimate the two intervals. The $SPSA_{weighted}$ model was applied to the overlapping SOA context as follows. First, the subjective duration of each segment was modelled. Next, the subjective duration of each segment was multiplied by a weight (denoted w_1, w_2, w_3) which was determined by the elapsed time since the end of that segment. According to Matthews (2013), the segment weights decay exponentially as the time since the end of that segment increases, from a maximum of $w + 1$ to a minimum of w. As in the study of Matthews, the weights were calculated as the exponential of the time passed since the end of that segment subtracted from a constant, w (here, $w = 1$). The exponential decay parameter, r, took the same value as in the original paper, $r = 0.0075$. Finally, the relevant weighted segments were summed to provide *E1* and *E2*.

Step 1: Generate a timescale. Generate weights (w_1, w_2, w_3) for each segment.

$$w_1 = w + \exp(-r \cdot Interval)$$
$$w_2 = w + \exp(-r \cdot SOA)$$
$$w_3 = w + 1$$

Step 2: *If SOA < Interval* {overlapping interval condition}

$$E(Seg_1) = E(SOA)$$

Step 3: Generate a new timescale.

$$E(Seg_2) = E(Interval - SOA)$$

Step 4: Generate a new timescale.

$$E(Seg_3) = E(SOA)$$
$$E1 = E(Seg_1) \cdot w_1 + E(Seg_2) \cdot w_2$$
$$E2 = E(Seg_2) \cdot w_2 + E(Seg_3) \cdot w_3$$

Else {non-overlapping interval condition}

$$E1 = E(Interval) \cdot (w + 1)$$

Step 3: Generate a new timescale.

$$E2 = E(Interval) \cdot (w + 1)$$

End

Stop

A.4.2. SPSA$_{weighted}$ model according to the Matthews (2013) method

In order to simulate data according to the original approach described in Matthews (2013), the only difference from the previous method described was how subjective durations were calculated. As previously mentioned, the original weighted sum of segments model calculated the subjective duration of each segment ($E(Seg_1)$, $E(Seg_2)$, etc.) as a negatively-accelerated function of its objective duration:

$$E(Seg_1) = a \cdot {Seg_1}^b.$$

The values of a and b varied depending on whether we were modelling a linear or a nonlinear timescale. In the Matthews study, $a = u \times v \ln(fi)$, where fi was a multiplier determined by the frequency of the auditory stimulus, and b varied across experiments between 0.22 and 0.45. We chose values of a and b with the aim of generating a timescale which was as similar as possible to that in van Rijn and Taatgen (2008). Therefore, for the nonlinear timescale, $a = 4$, and b was randomly selected from a normal distribution with a mean of 0.8 and a standard deviation of 0.02. For the linear timescale, $a = 1$, and b was randomly selected from a normal distribution with a mean of 1 and a standard deviation of 0.025. The segment intervals were then computed as follows.

Step 1: Generate weights (w_1, w_2, w_3) for each segment.

$$w_1 = w + \exp(-r \cdot Interval)$$
$$w_2 = w + \exp(-r \cdot SOA)$$
$$w_3 = w + 1$$

Step 2: *If SOA < Interval* {overlapping interval condition}

$$E(Seg_1) = a \cdot SOA^b$$
$$E(Seg_2) = a \cdot (Interval - SOA)^b$$
$$E(Seg_3) = a \cdot SOA^b$$
$$E1 = E(Seg_1) \cdot w_1 + E(Seg_2) \cdot w_2$$
$$E2 = E(Seg_2) \cdot w_2 + E(Seg_3) \cdot w_3$$

Else {non-overlapping interval condition}

$$E1 = (a \cdot Interval^b) \cdot (w + 1)$$
$$E2 = (a \cdot Interval^b) \cdot (w + 1)$$

End

Stop

A.5. Single pacemaker multiple accumulators model

The SPMA model was modelled similarly to the SPSA$_{simple}$ model, but with the addition of dual-task costs (*DTCost*). Dual-task costs are operationalized as the loss of 25% of pulses in the overlapping period (when both accumulators are active). There are no dual-task costs in the non-overlapping SOA conditions.

Step 1: Generate a timescale.

Step 2: *If SOA < Interval* {overlapping interval condition}

$$DTCost = 0.25 \cdot (E(Interval) - E(SOA))$$
$$E1 = E(Interval) - DTCost$$
$$E2 = E(SOA + Interval) - E(SOA) - DTCost$$

Else {non-overlapping interval condition}

$$E1 = E(Interval)$$

Step 3: Generate a new timescale.

$$E2 = E(Interval)$$

End

Stop

A.6. Multiple pacemakers multiple accumulators model

The MPMA model has a second pacemaker that starts at the onset of the second interval, and estimates also suffer from dual-task costs as the two accumulators operate simultaneously. Dual-task costs for each estimate were calculated differently, as the overlapping period represents a different number of pulses for the first and second intervals.

Step 1: Generate a timescale.

Step 2: *If SOA < Interval* {overlapping interval condition}

$$DTCost1 = 0.25 \cdot (E(Interval) - E(SOA))$$
$$E1 = E(Interval) - DTCost1$$

Step 3: Generate a new timescale.

$$DTCost2 = 0.25 \cdot E(SOA)$$
$$E2 = E(Interval) - DTCost2$$

Else {non-overlapping interval condition}

$$E1 = E(Interval)$$

Step 3: Generate a new timescale.

$$E2 = E(Interval)$$

End

Stop

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