How to minimize time distortions

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4 Abstract

5 Humans perceptually distort (dilate/shrink) time when discriminating the duration of
6 successive events. This so called “Time order error” is a powerful window into the de-
7 terminants of subjective perception. We hypothesized that optimal temporal processing
8 would occur when stimulus duration falls within the boundaries of rhythmic attention
9 (4-8 Hz, theta band). In three experiments, we searched for a ‘temporal sweet spot’ by
10 increasing the duration of a Standard from 120-ms, corresponding to an 8.33 Hz rhythmic
11 attentive window, to 160 ms (6.25 Hz), to 200 ms (5 Hz). We found that time distortions
12 disappear for 200 ms events, highlighting the theta band as an optimal processing spot.
13 In contrast, for shorter events, temporal attention, which we parametrized as the interval
14 size between Standard and Comparison events (400 to 2000 ms), governs the process
15 to reduce time distortions. Our results highlight a flexible use of attentive functions in
16 subjective time perception.

Introduction

The processing of temporal information on the scale of milliseconds is essential to successfully navigate and survive our sensory environment (Merchant and De-Lafuente, 2014). One core capacity is interval timing, that is the ability to discriminate the duration of events (Van Wassenhove, 2016). Interval timing is a critical ingredient of complex motor and sensory phenomena such as speech recognition and motion processing (Mauk and Buonomano, 2004; Buhusi and Meck, 2005). One way to test this ability in a simple, parametric and quantitative manner is to use a two-interval forced choice (2IFC) paradigm in which a first event (the Standard event S) is followed by a second event (the Comparison event C), separated by an Inter-stimulus Interval (ISI).

In a 2IFC test, two parameters are used to measure individual temporal performance: sensory precision and perceived event duration, indexed via the Weber fraction (WF) and the Constant error (CE), respectively (Grondin et al., 2001; Grondin, 2008). The WF is a dimensionless measure of sensory precision, *i.e.* temporal resolution, and is calculated by the ratio of the just noticeable difference (JND) to the duration of the Standard stimulus. The CE tracks instead a subjective judgement in duration estimation, and is derived as the difference of the Point of Subjective Equality (PSE) and the duration of the S stimulus.

Distortions of perceived event duration are inherent to 2IFC test behavior. When participants are asked to discriminate which of two events is longer (or shorter), they tend to dilate/shrink the second event relative to the first. Subjective time distortions — termed “Time order error”, and indexed by the CE — are a ubiquitous, well-documented but poorly understood phenomenon (Allan and Gibbon, 1994).

Understanding how the human brain minimizes time distortions offers a unique opportunity to unveil key determinants of the subjective component of temporal perception. Nakajima and colleagues found a systematic shrinking illusion using sequences of successive empty intervals marked by light flashes: for example, in order to subjectively equate a 50-ms Standard duration, participants required the Comparison duration to be about 50% longer, leading to a large, positive CE (Nakajima et al., 1991; Nakajima et al., 1992; Ten Hoopen et al., 2008). Insightfully, Grondin reported that the magnitude of the CE was markedly reduced if an ISI of about 1.5 seconds was used between Standard and Comparison (Grondin, 2001). In the auditory domain, Buonomano and colleagues tested short (250 ms) and long (750 to 1000 ms) ISIs, and showed that for a 100-ms auditory Standard temporal precision increases with long ISIs, but time distortions remained unaffected (Buonomano et al., 2009).

Building on these findings, we hypothesized that long ISIs would reduce time distortions by increasing the deployment of attention in time, improving detection accuracy (Nobre et al., 2007). Indeed, beneficial effects of the temporal orienting of attention - also termed foreperiod or waiting-time effects - on accuracy and response times have been documented for other tasks/sensory modalities (Cravo et al., 2013; Stefanics et al., 2010). To finely map how variations in temporal attention modulate subjective times distortions, we parametrically varied the ISI between Standard and Comparison from sub-second to supra-second intervals: 400, 800, 1600, and 2000 ms.

However, Grondin’s work also hints at the existence of another, perhaps more relevant if underestimated variable: The duration of the Standard stimulus (Grondin, 2001). In 2IFC experiments, the Comparison stimulus is generated by systematically adding or subtracting small fractions Δt to the Standard duration. Grondin showed that, without an ISI intervening between Standard and Comparison, the Constant Error was significant for a 150-ms Standard, but tended to be suppressed for a 300-ms Standard. This qualitative change suggests the possibility of an optimal interval duration that, *per se*, would be sufficient to minimize time distortions.

To detect said temporal sweet spot, we drew upon a rhythmic model of attention, modulated by perceptual cycles (Lakatos et al., 2009; Landau and Fries, 2012; Zoefel and VanRullen, 2017). The central tenet of rhythmic attention is that intrinsic neuronal oscillations facilitate the processing of task-relevant information, avoiding sensory overflow and interference. Support for rhythmic attention comes from a rich behavioral and electrophysiological literature — in both human and non-human primates — showing that rhythmic attention gates in and out sensory information according to the phase of a neural oscillator (Landau and Fries, 2012; Fiebelkorn and Kastner, 2019; VanRullen and Koch, 2003; VanRullen et al., 2007; VanRullen, 2016). An internal oscillator would mechanistically determine a sweet spot for optimal processing.

Fiebelkorn and Kastner (Fiebelkorn and Kastner, 2019) proposed that rhythmic attention uses theta band activity (4-8 Hz) to temporally organize sensory and motor functions in the attention network. We thus set out to map visual interval timing onto the theta band range by parametrizing the duration of the Standard event from 120 to 160 and 200 ms, which would correspond to attentive frequencies of 8.33, 6.25, and 5 Hz, respectively. The 120-ms duration lies just outside the theta band, the 160-ms duration occupies its high portion, while the 200-ms lies in its core region. If rhythmic attention is pivotal in optimizing stimulus processing, then group-wise behavioral performance should be at ceiling for durations within the theta band - maximally reducing time distortions regardless of any additional benefit that may come from temporal attention. Conversely,

temporal attention would be of the essence when moving outside of the oscillatory sweet spot.

Results

In three behavioral experiments, participants sampled Standard (S) and Comparison (C) empty visual durations, each defined by two successive flashes, and determined which duration was longer (see **Fig. 1a**). In the first experiment S lasted 120 ms, while for the second and third experiment S lasted 160 and 200 ms, respectively. Responses were modeled using a psychometric function, from which we obtained two indices of performance: an indicator of temporal sensitivity (Weber Fraction, WF), derived by dividing the Just Noticeable Difference (JND) by the Standard duration, and a measure of subjective time distortion (Constant Error, CE; **Fig. 1b**), derived by subtracting the Standard duration from the Point of Subjective Equality, PSE (Grondin, 2005; Grondin, 2014). The CE is positive when participants internally underestimate the perceived duration of the C event relative to the S event, and need a longer C to match the S. The CE is negative when the Comparison's duration is overestimated. The WF helps isolating the CE effect to internal timer estimates, unconfounded by differences in sensory resolution.

To test the effects of the orienting of attention in time, for each experiment a repeated measures (RM) ANOVA was implemented for both the WF and the CE, across ISI levels (400, 800, 1600 and 2000 ms). To characterize the strength of evidence in favor of the alternative model M_{ISI} (using the ISI factor as predictor) vs. the null model M_0 (no difference among ISI levels), we implemented a Bayes factor approach to ANOVA by applying Bayesian Model Comparison (Wagenmakers, 2007; Rouder et al., 2016; Rouder et al., 2017).

Goodness of fit (R^2)

Participants were able to successfully discriminate between S and C durations in all experimental condition: The goodness-of-fit of the psychometric function was high, making inferences on mental processes reliable. In experiment 1 (S = 120 ms; 8.33 Hz), the mean R^2 values for the 400-ms, 800-ms, 1600-ms, and 2000-ms ISIs were 0.95, 0.97, 0.98, and 0.98 respectively. In experiment 2 (S = 160 ms; 6.25 Hz), the mean R^2 values for

Figure 1: **Experimental paradigm and response model.** **a)** Sequence of events in the 2IFC temporal-discrimination task. In each trial, participants judged whether the standard (S) or the comparison event (C) lasted longer. In order to assess the effects of temporal attention on temporal processing, we parametrized the inter-stimulus interval (ISI) to four levels: 400, 800, 1600, and 2000 ms. To test whether rhythmic attention plays a role in time distortions, we parametrized the duration of S: 120, 160 and 200 ms, which correspond to attentive frequencies of 8.33, 6.25 and 5 Hz, respectively. **b)** Example of response model fit for one participant in each ISI level of experiment 1: The six C durations are plotted on the x -axis and the probability of responding “C longer than S” on the y -axis. Black dots interpolated at the 50% value on the y -axis correspond to the points of subjective equality (PSE) for each condition. The just noticeable difference (JND) is obtained from the slope β of each curve.

were 0.98, 0.98, 0.98, and 0.98. For experiment 3 ($S = 200$ ms; 5 Hz), the mean R^2 values were 0.97, 0.98, 0.98, and 0.98.

Weber Fraction (Sensory precision)

In experiment 1, the mean WF values for the 400-ms, 800-ms, 1600-ms, and 2000-ms ISIs conditions were: 0.23 (SD = 0.12), 0.17 (SD = 0.07), 0.17 (SD = 0.08), and 0.16 (SD = 0.08). We found statistically significant differences among the four ISI levels ($F(2.65, 101.03) = 8.98$, $p < 0.001$, $\eta_p^2 = 0.19$, Huynh-Feldt correction). Post hoc comparisons showed that sensory precision in the ISI_{400} was lower than in the rest of the conditions: ISI_{800} , ISI_{1600} , and ISI_{2000} (all $ts \geq 3.69$, all $ps \leq 0.002$, Bonferroni-corrected; **Fig. 2a**). The Bayes Factor yielded decisive evidence in favor of the M_{ISI} model ($BF_{10} = 935$). That is, the data were 935 times more likely under the model that includes the ISI as a predictor, compared to the null model. (See annotated .jasp files with results of the Frequentist and Bayesian analysis at Open Science Framework: osf.io/583vg/).

130 In experiment 2, the mean WF values were: 0.15 (SD = 0.05), 0.13 (SD = 0.04), 0.14
 131 (SD = 0.04), and 0.13 (SD = 0.04), for the 400-ms, 800-ms, 1600-ms, and 2000-ms ISIs
 132 conditions, respectively. The increase of 40 ms in S duration resulted in non-significant
 133 differences between ISI levels ($F(3, 117) = 1.81$, $p = 0.148$, $\eta_p^2 = 0.04$; **Fig. 2b**). Con-
 134 gruently, the Bayes factor showed that the data were best explained by the M_0 model
 135 ($BF_{10} = 0.28$).

136 In Experiment 3 we again found no significant differences between ISI levels ($F(3, 114)$
 137 $= 1.44$, $p = 0.235$, $\eta_p^2 = 0.03$; **Fig. 2c**). The mean WF values for the ISI levels were:
 138 $ISI_{400} = 0.13$ (SD = 0.05), $ISI_{800} = 0.12$ (SD = 0.06), $ISI_{1600} = 0.12$ (SD = 0.04), and
 139 $ISI_{2000} = 0.12$ (SD = 0.04). As before, the Bayes factor showed that the data were best
 140 explained by the M_0 model ($BF_{10} = 0.18$).

Figure 2: **Sensory precision stabilizes with longer Standard events.** Box-and-whisker plots show the distribution of the Weber fractions (WF) for each ISI level in experiments 1, 2 and 3. The bottom and top edges indicate the interquartile range (IQR), whereas the median is represented by the horizontal line. The extension of the whiskers is 1.5 times the IQR. Boxplots are overlaid with data of each participant. **a)** Results of experiment 1 showed a significant effect of the orienting of attention in time: Temporal sensitivity increased for waiting time windows $\geq$ to 800 ms, as reflected by lower WF values in the ISI_{800} , ISI_{1600} , and ISI_{2000} conditions. **b)** In experiment 2, the effects of temporal orienting disappeared. **c)** The same was true for experiment 3, as no changes between ISI levels were detected. (***) = p -value < 0.001 ; ** = a p -value < 0.01 ; and ‘n.s.’ = a non-significant result with a p -value ≥ 0.05).

Constant Error (Time distortions)

In experiment 1, the mean CE values were: $ISI_{400} = 11.21$ (SD = 16.56), $ISI_{800} = 7.63$ (SD = 13.91), $ISI_{1600} = 2.35$ (SD = 12.52), and $ISI_{2000} = -2.67$ (SD = 11.37). We first tested the presence of time distortions by running a series of two-sided, one-sample t -test for each ISI level (Bonferroni corrected). We found a significant CE for both sub-second conditions, but not for the supra-second conditions (ISI_{400} and ISI_{800} : $ts(38) \geq 3.42$, $ps \leq 0.001$; ISI_{1600} and ISI_{2000} : $ts(38) \leq 1.17$, $ps \geq 0.151$; respectively). Congruently, the RM ANOVA showed a statistically significant difference between ISI levels ($F(3, 114) = 12.44$, $p < 0.001$, $\eta_p^2 = 0.24$), specifically between sub-second and supra-second conditions: ISI_{400} vs ISI_{1600} ; ISI_{400} vs ISI_{2000} ; and ISI_{800} vs ISI_{2000} (all $ts \geq 3.63$, all $ps \leq 0.003$; Bonferroni-corrected; **Fig. 3a**). In line with these results, the Bayes factor revealed decisive evidence in favor of the M_{ISI} model ($BF_{10} = 41134$; **Fig. 3d**).

In experiment 2, the mean CE values for the ISI levels were: $ISI_{400} = 10.53$ (SD = 13.12), $ISI_{800} = 1.96$ (SD = 9.91), $ISI_{1600} = -0.13$ (SD = 10.03), and $ISI_{2000} = -3.37$ (SD = 7.33). One-sample t -tests showed that the ISI_{400} and ISI_{2000} conditions were significant, while the ISI_{800} and ISI_{1600} conditions were non-significant ($ts(39) \geq -2.9$, $p \leq 0.006$; $ts(39) \geq -0.085$, $p \geq 0.217$; respectively). We found again significant differences between ISI levels: $F(2.21, 86.29) = 19.35$, $p < 0.001$, $\eta_p^2 = 0.33$, Huynh-Feldt Correction. Post hoc analyses (Bonferroni correction) revealed that the ISI_{400} differed from all the remaining conditions (ISI_{800} , ISI_{1600} , and ISI_{2000}), and that the ISI_{800} differed from the ISI_{2000} condition (all $ts \geq 3.55$, all $ps \leq 0.006$, **Fig. 3b**). As in experiment 1, the Bayes factor reported decisive evidence in favor of the M_{ISI} model ($BF_{10} = 5.54 * 10^7$; **Fig. 3e**).

In experiment 3, the mean CE values for the ISI levels were: $ISI_{400} = 1.28$ (SD = 13.38), $ISI_{800} = 2.30$ (SD = 11.98), $ISI_{1600} = -3.02$ (SD = 10.48), and $ISI_{2000} = -1.54$ (SD = 10.35). One-sample t -tests found non-significant CE effects in all ISI conditions (all $ts(38) \geq -1.79$, all $ps \geq 0.119$). The RM ANOVA confirmed these results: $F(2.64, 100.42) = 2.21$, $p = 0.099$, $\eta_p^2 = 0.05$ (**Fig. 3c**). Congruently, Bayesian analyses showed that the data were best explained by the M_0 model ($BF_{10} = 0.48$; **Fig. 3f**).

Taken together, these results show that setting the Standard duration to 200 ms minimizes subjective time distortions in the context of high sensory precision, regardless of temporal orienting of attention.

Figure 3: Time distortions are suppressed for longer Standard events. a-c) Box-and-whisker plots show the distribution of the Constant error (CE) for each ISI level in experiments 1, 2 and 3. **a)** In experiment 1, with a 120-ms Standard (corresponding to an 8.33 Hz attentive rhythm) we observed a decrease of the CE as a function of orienting of attention in time: waiting times longer than ISI_{800} decreased subjective distortions of the Comparison event. **b)** The temporal attention effect was still present for a 160-ms Standard event (corresponding to a 6.25 Hz attentive rhythm), but this time limited to ISI_{400} level. **c)** The effects of temporal attention disappeared for a 200-ms Standard event (5 Hz attentive rhythm): No differences in CE among ISI levels were observed, and performance was group-wise not different from zero. That is to say, for a 200-ms S event the duration of the C event was optimally perceived, independently of temporal attention. **d-f)** Results of the Bayesian ANOVA. Plots show the model-averaged posterior distributions (horizontal bars show the 95% credible intervals around the median). **d)** In experiment 1, posterior distributions showed a clear effect of temporal orienting. This effect is best expressed by the contrasting distributions of the two extreme levels: ISI_{400} vs ISI_{2000} . **e)** Posterior distributions in experiment 2 showed again a clear separation between the ISI_{400} distribution and the rest of the conditions, which means that the beneficial effect of temporal attention is still present. **f)** Results of experiment 3 revealed no effect of temporal orienting, as the overlap in posterior distributions visually confirms. (** = p -value < 0.01; *** = p -value < 0.001; and ‘n.s.’ = a non-significant result with a p -value ≥ 0.05).

Decomposing optimality

So far, we determined that a 200-ms duration for S optimizes stimulus processing, as it substantially minimized subjective distortions of interval duration independently of the beneficial effects of temporal attention. How is optimality obtained? To find out, we asked which comparison step - $\pm\Delta$, i.e. the physical difference between Standard and Comparison durations - was specifically affected by extending the S duration from 120 to 200 ms. For that, we analyzed the percentage of responses “C longer than S” for each comparison step between S and C, and applied a robust linear regression for each individual participant across the four ISI levels (Theil, 1992). Notice that the magnitude of comparison steps was constant across experiments, allowing for unbiased contrasts: $\pm\Delta 20$, $\pm\Delta 60$, and $\pm\Delta 100$ ms.

We applied a linear fit separately to each $\pm\Delta$, obtaining individual slope values as a synoptic measure of the impact of waiting time on accuracy. Negative slopes would suggest that temporal attention did influence accuracy in determining whether S or C was longer. We analyzed slopes with a series of between-subjects ANOVA with Experiment - that is, the duration of the Standard - as factor, as well as Bayesian Model Comparison. This time we build the M_E model (using the slopes as dependent variable) and compared it to the M_0 model (no effect effect of Standard duration).

We found significant differences for the $-\Delta 100$, $-\Delta 20$, and $+\Delta 20$ durations ($F(2, 115) = 4.35$, $p = 0.015$, $F(2, 115) = 3.07$, $p = 0.050$, $F(2, 115) = 7.75$, $p < 0.001$; respectively). Post hoc analyses (all Bonferroni-corrected) showed significant differences between the slopes of experiment 1 and experiment 3 ($t = -2.87$, $p = 0.014$) in the $-\Delta 100$ condition (**Fig. 4a-b**). For the $-\Delta 20$ condition, we found significant differences between the slopes of experiment 2 and experiment 3 ($t = 2.47$, $p = 0.044$). For the $+\Delta 20$, post hoc analyses yielded significant differences between the slopes of experiment 3 vs experiments 1 and 2 ($t = 3.86$, $p < 0.001$; $t = 2.58$, $p = 0.033$; respectively).

However, Bayesian Model Comparison revealed that for the $-\Delta 100$ condition the evidence in favor of the M_E model was only anecdotal ($BF_{10} = 2.8$; **Fig. 4c**), while for the $-\Delta 20$ condition the evidence was neither in favor of the M_E nor for the M_0 model ($BF_{01} = 1.0$). Solely for the $+\Delta 20$ condition was the evidence in favor of the M_E very strong ($BF_{10} = 41.92$). Following these results, we analyzed the three slopes of $+\Delta 20$ condition by using one-sample t -tests (Bonferroni correction). Results revealed statistically significant slopes for experiments 1 and 2 (both $t_s \geq 5.49$, both $p_s < 0.001$; two-sided), but a non-significant slope for Experiment 3 ($t = 1.53$, $p = 0.134$; two-sided). We conclude that extending the S duration from 120 to 200 ms affected the $+\Delta 20$ discrimination step.

207 Hence, optimality in time processing results not from a generic improvement of accuracy
208 across the board, but from a specific increase in performance for small sensory differences.

209 Conversely, for the $-\Delta 60$, $+\Delta 60$ and $+\Delta 100$ steps, we found no significant effect of
210 Standard duration: ($F(2, 115) = 0.63$, $p = 0.533$; $F(2, 115) = 0.01$, $p = 0.987$; $F(2,$
211 $115) = 0.02$, $p = 0.972$). Congruently, the Bayes factor reveled that the data were best
212 explained by the M_0 model ($\text{BF}_{10} = 0.13$; $\text{BF}_{10} = 0.08$; $\text{BF}_{10} = 0.08$; respectively). This
213 is because, when sensory evidence is strong enough, time distortions do not arise.

Figure 4: **Finding the source of optimality in time processing.** **a-b)** Box-and-whisker plots show the distribution of the regression slopes for each of the Standard-Comparison differences. The effects of increasing S duration can be observed on the $-\Delta 100$ and $\pm\Delta 20$ conditions. These differences indicate that an increase in S results in an increase in accuracy for correctly identifying the longer stimulus. For the rest of the conditions no significant differences were present. **c)** Results of the Bayesian models for the $-\Delta 100$ and $\pm\Delta 20$ conditions. Plots show the model-averaged posterior distributions. The overlapping distributions on the $-\Delta 100$ and $-\Delta 20$ conditions show a lack of support for significant differences between different S levels. Indeed, the Bayes Factor (BF) revealed that only for the $+\Delta 20$ condition, the evidence in favor of the M_E model was very strong. This can be visually confirmed by the separation of the posterior distributions. ($*** = p\text{-value} < 0.001$; $*$ = a $p\text{-value} < 0.05$; and 'n.s.' = a non-significant result with a $p\text{-value} \geq 0.05$).

Discussion

Interval timing is an essential feature of human behavior, which depends on sensory precision and stimulus encoding fidelity. Sensory precision pertains to the resolution of the

sensory system, in our case vision. Fidelity in stimulus encoding has been relatively less investigated, although it is known that humans tend to subjectively distort the perception of successive interval durations (Allan and Gibbon, 1994; Grondin, 2001). We parametrically manipulated two experimental features: The size of the inter-stimulus interval between Standard and Comparison as a proxy for the linear increase in orienting attention in time, (Nobre et al., 2007; Cravo et al., 2013), and the fit of Standard duration, which determines Comparison duration, to rhythmic attentive sampling within the theta band (Fiebelkorn and Kastner, 2019; Landau and Fries, 2012; Zoefel and VanRullen, 2017).

As for the first function of attention, Buonomano and colleagues observed that increasing ISI from 250 to 750 or 1000 ms with a 100-ms auditory Standard significantly improved sensory precision, measured as the percentage difference in stimulus duration that is just noticeable (Buonomano et al., 2009). Although they used auditory intervals and we used visual intervals, we expected to see an improvement in temporal sensitivity with longer ISIs. This prediction was borne out in experiment 1 (Standard = 120 ms). As soon as the Standard was extended to 160 ms, sensory precision was at ceiling regardless of temporal orienting of attention. Hence, we conclude that sensory precision in duration discrimination is first and foremost a function of Standard duration, as the beneficial effects of ISI lengthening only appeared for very short Standard durations. Notice that the absence of a temporal attention effect on sensory precision for 160-ms and 200-ms Standards, is not a sufficient proof of optimal stimulus processing, as it could simply reflect a ceiling effect due to other factors, such as the use of empty intervals (Grondin et al., 1998). Rather, optimality is obtained when the Comparison stimulus is faithfully encoded. On this note, the work of Grondin suggests that an ISI of 1500 ms leads to a reduction of time distortions (Grondin, 2001). In That prediction was borne out in experiments 1 and 2, as 1600-ms and 2000-ms ISIs benefited Comparison duration encoding, minimizing time distortions. Finally, in experiment 3, with a 200-ms Standard corresponding to a 5-Hz attentive rhythm, optimal fidelity in Comparison stimulus encoding was obtained regardless of temporal attention, as no significant time distortions were found across ISI levels.

Importantly, we found very strong evidence suggesting that for 120-ms and a 160-ms Standard stimuli, increasing temporal attention primarily contributed to discriminate a $+\Delta 20$ Comparison stimulus. For the same difference step, accuracy was at ceiling for 200-ms long Standard stimulus. According to the scalar expectancy theory, or Weber law (Gibbon, 1977; Grondin et al., 2001), discriminating $+\Delta 20$ for a 200-ms standard duration (that is, a 10% increase) should be more difficult - and therefore benefit more

253 from temporal attention - than discriminating $+\Delta 20$ for a 120-ms standard duration
254 (a 16.6% increase). However, the opposite result occurred, confirming that a 200-ms
255 standard event, corresponding to a 5-Hz rhythmic attentive rate, *per se* optimizes time
256 processing.

257 Taken together, the results from experiments 1-3 suggest the novel perspective that the
258 human brain relies on different attentive functions depending on the characteristics of the
259 stimulus to be encoded. Orienting attention in time captures an important but partial
260 picture of how attention benefits sensory processing (Nobre et al., 2007; Cravo et al.,
261 2013). Rather, sensory fidelity seems to depend on how well incoming stimulus dura-
262 tion matches a participant’s internal attentive rhythm, centered on the theta band of the
263 oscillatory spectrum. The linear effects of waiting time can be deemed a backup mech-
264 anism, kicking in for small discrimination steps when stimulus durations are suboptimal
265 for rhythmic attentive sampling functions.

266 Our behavioral results are in line with the existence of an oscillatory mechanism running
267 at about 5 Hz and driving the attentive sampling of visual information. In our experiment,
268 the onset of the first flash would signal the opening of a temporal integration window,
269 which would be closed by the onset of the second flash. Electrophysiological results in
270 animal research signal that the theta band would help segmenting sensory information
271 in chunks amenable to processing (Kepecs et al., 2005; Gupta et al., 2012; Colgin, 2013)
272 Moreover, the theta rhythm appears to exert a general facilitatory function in internally
273 representing complex events across perceptual domains, such as continuous speech (Ding
274 et al., 2017; Luo and Poeppel, 2007).

275 The 200-ms duration/5 Hz rhythm may be hitting on a sweet spot specific for the faithful
276 internal processing of stimuli that need to be remembered, or a general sweet spot for
277 time encoding. Alternatively, the 200-ms could represent the emergence of a plateau in
278 performance, with all stimuli equal to or longer than 200 ms being optimally processed.
279 Settling this issue will require further research. If true, it would suggest that optimality
280 in duration processing extends into the delta band (1-4 Hz), too.

281 We proved that the duration of the Standard event has a direct, un-confounded effect
282 on the quality of Comparison duration perception. While this result sits well within
283 the rhythmic attention framework, it is not informative as to whether the underlying
284 mechanism can be better described as the alignment of a neural oscillation with stimulus
285 onset, or a phase adjustment process, triggered by phase reset due to flash onset. The
286 visual system might be more prone than the auditory system to continuous adjustments
287 to time-varying sensory input (Zoefel and VanRullen, 2017). This point, too, shall await

neurophysiological data analysis for a satisfactory answer.

In conclusion, we proved that stimulus duration is optimally processed at ~ 200 ms/5 Hz rhythmic attention cycle, with maximal fidelity in subjective time representation and sensory precision. Orienting attention in time kicks in to help, once we move away from that processing window.

Materials and Methods

Ethics statement. The studies were approved by the Ethics Committee of the Max Planck Society. Written informed consent was obtained from all participants previous to the experiment.

Participants. Experiment 1. Fifty-two participants (34 female; ages: 18-33; mean age: 24.42) participated in experiment 1. For each participant we computed the goodness-of-fit of the psychometric function (R^2). Participants with a R^2 value lower than two standard deviations of the mean were removed. We applied the same procedure in each experiment. Six participants were removed from analysis following this procedure. In both dependent variables, WF and CE, we discarded outliers. We identified outliers by establishing an upper (UT) and a lower threshold (LT): $UT = Q1 - 1.5 * IQR$; and $LT = Q3 + 1.5 * IQR$, where IQR is the Interquartile Range, Q1 and Q3 the first and third quartile respectively. We implemented the same procedure in each experiment. Seven participants were discarded for being marked as outlier in experiment 1. Therefore, the final analysis included the data from thirty-nine participants (24 female; ages: 18-33; mean: 24.07). Experiment 2. Fifty-three participants (42 female; ages: 18-34; mean age: 24.71) participated in experiment 2. Five participants were removed from analysis due to their low R^2 values. Eight participants were discarded for being marked as outliers. Therefore, the final analysis included the data from forty participants (31 female; ages: 19-34; mean: 25.47). Experiment 3. Fifty participants (40 female; ages: 18-35; mean age: 24.54) participated in experiment 3. Two participants were removed from analysis due to their low R^2 values. Nine participants were discarded for being marked as outliers. Therefore, the final analysis included the data from thirty-nine participants (32 female; ages: 18-31; mean: 23.94). In total, we report on the behavior of 118 participants.

Individuals were recruited through online advertisements. Participants self-reported normal or corrected vision and had no history of neurological disorders. Up to three participants were tested simultaneously at computer workstations with identical configurations. They received 10 euros per hour for their participation.

Design. We used a 2IFC experiment in a classical interval discrimination task (Mauk and Buonomano, 2004). Subjects were presented with both an S and an C visual duration defined by two successive flashes on each trial. Participants judged whether the S or C stimulus was the longer duration, and responded by pressing one of two buttons on an RB-740 Cedrus Response Pad (cedrus.com, response time jitter < 1 ms, measured with an oscilloscope). They were provided with immediate feedback on each trial.

S was either 120 ms (experiment 1), 160 ms (experiment 2), or 200 ms (experiment 3) and was always displayed in the first position. In all experiments, we used three magnitudes for duration difference (Δt) between S and C: 20, 60, and 100 ms. The durations of the C stimuli were derived as $S \pm \Delta t$. Thus, C durations were 20, 60, 100, 140, 180, and 220 ms for experiment 1. For experiment 2, they were 60, 100, 140, 180, 220 and 260 ms. For experiment 3 they were 100, 140, 180, 220, 260, and 300 ms (Table 1). Across experiments, we used the same four different ISIs: 400, 800, 1600, and 2000 ms. For each trial, the inter-trial interval (ITI) was randomly chosen from a uniform distribution between 1 and 3 seconds.

S durations (ms)	C durations (ms)					
120	20	60	100	140	180	220
160	60	100	140	180	220	260
200	100	140	180	220	260	300

Table 1: Standard (S) and Comparison (C) durations for the 2IFC temporal-discrimination task.

Stimuli and Apparatus. Stimulus duration was determined as a succession of two blue disks with a diameter of 1.5° presented on a gray screen. Empty stimuli were used in order to ensure that participants were focused on the temporal properties of the stimuli (Grondin et al., 1998). All stimuli were created in MATLAB R2018b (mathworks.com), using the Psychophysics Toolbox extension (Brainard, 1997; Pelli, 1997). Visual stimuli were displayed on an ASUS monitor (model: VG248QE; resolution: 1,920 x 1,080; refresh rate: 144 Hz; size: 24 in) at a viewing distance of 60 cm.

Protocol (Task). The experiment was run in a single session of 70 minutes. Participants completed a practice set of four blocks (18 trials in each block). All experiments consisted of the presentation of four blocks, one for each ISI duration. Each block was composed of 120 trials and presented in random order. In order to avoid fatigue, participants always had a break after 60 trials. Each trial began with a black fixation cross (diameter: 0.1°) displayed in the center of a gray screen. Its duration was randomly selected from a

distribution between 400 and 800 ms. After a blank interval of 500 ms, S was displayed and followed by C after one of the ISI durations.

Participants were instructed to compare the durations of the two stimuli by pressing the key “left”, if S was perceived to have lasted longer, and the key “right” if C was perceived to have lasted longer. After responding, they were provided with a feedback: the fixation cross color changed to green when the response was correct, and to red when the response was incorrect.

Data analysis

The data analysis was implemented with Python 3.7 (python.org) using the libraries Pandas ([The pandas development team, 2020](https://pandas.pydata.org)), Seaborn ([Waskom, 2021](https://seaborn.pydata.org)), Pingouin ([Vallat, 2018](https://pingouin-stats.org)), and the ecosystem SciPy (scipy.org). Frequentist statistical analyses were executed in Pingouin. Bayesian statistical analyses were implemented using the BayesFactor package for R ([Morey and Rouder, 2018](https://cran.r-project.org/web/packages/BayesFactor/index.html)). All data and statistical analyses were performed in Jupyter Lab (jupyter.org).

To endorse open science practices and transparency on statistical analyses ([Klein et al., 2018](https://doi.org/10.1016/j.jasp.2018.01.001)), we used JASP (jasp-stats.org) for providing statistical results (data, plots, distributions, tables and post hoc analyses) of both Frequentist and Bayesian analyses in a graphical user-friendly interface ([JASP Team, 2020](https://jasp-stats.org)). These results can be consulted at Open Science Framework as annotated .jasp files (osf.io/583vg/). As JASP uses the BayesFactor package ([Morey and Rouder, 2018](https://cran.r-project.org/web/packages/BayesFactor/index.html)) as a backend engine, the default prior distributions of the BayesFactor package were the same for JASP.

Psychometric curves

A 6-point psychometric function was fitted to data of each participant, plotting the six Comparison durations on the x -axis and the probability of responding “C longer than S” on the y -axis. We modeled the psychometric function ψ with a logistic function f , with parameters α and β , so that:

$$\psi(x, \alpha, \beta) = f(x) = \frac{1}{1 + e^{-(x-\alpha)/\beta}}$$

where x is the magnitude of the C stimulus, α is the location parameter, and β reflects

the slope of the curve (Lapid et al., 2008). Fitting of the logistic function was done in Python using the nonlinear least-squares fit (Wegrzyn et al., 2017). Two indices of performance were extracted from each psychometric function: one for the perceived duration of the intervals, and another one for the discrimination sensitivity (Grondin, 2005). The perceived duration was measured on the basis of the PSE, which is the point value on the x -axis corresponding to the 50% value on the y -axis (α in the logistic function). To normalize results, we obtained the CE as the difference between the PSE and the physical magnitude ϕ_s of the S stimulus ($CE = \alpha - \phi_s$). An increase in the CE indicates that the duration of the C duration has to be increased in order to become perceptually equal to the S duration (Gescheider, 1997; Grondin, 2001). In other words, positive values indicate that participants perceive the C duration as shorter than the S duration.

We obtained the sensitivity for discriminating intervals by computing the JND, which is traditionally defined as being half the interquartile range of the fitted function: $JND = \frac{x_{.75} - x_{.25}}{2}$, where $x_{.75}$ and $x_{.25}$ denote the point values on the y -axis that output 25% and 75% “longer” responses (Gescheider, 1997; Bush, 1963). The smaller the JND, the higher the discrimination sensitivity of the observer. In order to compare the JND between experiments we obtained the WF as the ratio between the JND and the ϕ_s : $WF = \frac{JND}{\phi_s}$ (Lapid et al., 2008).

Statistical analyses

Frequentist analyses. For frequentist analyses we set the level of statistical significance to reject the null hypothesis to $\alpha = 0.05$. In each experiment we applied a repeated measures ANOVA across ISI levels to test for significant changes in both dependent variables (i.e., the WF and the CE).

Bayesian Model Comparison. Bayesian Model Comparison was implemented to apply a Bayes factor approach to ANOVA (Rouder et al., 2016; Rouder et al., 2017; Wagenmakers et al., 2017). To do that, we implemented Bayes’s rule (Jeffreys, 1961; Lee and Wagenmakers, 2009) for obtaining the posterior distribution $p(\theta | Y)$, where Y express the observed data. Under the model specification M_1 , the $p(\theta | Y)$ is given by

$$p(\theta | Y, M_1) = \frac{p(Y | \theta, M_1) p(\theta | M_1)}{p(Y | M_1)}$$

where $p(Y | \theta, M_1)$ denotes the likelihood, $p(\theta | M_1)$ express the prior distribution,

and the marginal likelihood is expressed by $p(Y | M_1)$. In model comparison, we evaluate the predictive performance of two models. Thus, to evaluate the relative probability of the data under competing models, we estimated the Bayes factor (BF): Let BF_{10} express the the Bayes factor between a null model M_0 versus an alternative model M_1 . The predictive performance of these models is given by the probability ratio obtained by dividing the marginal likelihoods of both models:

$$BF_{10} = \frac{p(Y | M_1)}{p(Y | M_0)}$$

In this case, BF_{10} express to which extent the data support the model M_1 over M_0 , whereas BF_{01} indicates the Bayes factor in favor M_0 over M_1 . BF values < 0 give support to M_0 , whereas $BF > 1$ support the M_1 model (Rouder et al., 2012). A BF of 1 reveals that both models predicted the data equally well (Van Doorn et al., 2020). For our analysis of the dependent variables, we build an alternative model M_{ISI} that includes the ISI as predictor, and compared it to the null model M_0 (no difference among ISI levels). The prior model probability $p(M)$ of each model was set to be equal, *i.e.*, prior model odds of 0.5. For all our analyses we used the default prior values for Bayes factor ANOVA, which are also the default values in the BayesFactor package and JASP (Rouder et al., 2012; Rouder et al., 2017).

For the CE, we performed a series of Bonferroni-corrected ($\frac{\alpha}{4}$) one sample t -tests to zero to ascertain the presence of a significant effect at each ISI, in each experiment. To analyze the effects of S durations/rhythms on the percentages of detection accuracy, we implemented individual linear regression model fits for each C duration ($\pm\Delta 20$, $\pm\Delta 60$, and $\pm\Delta 100$) across ISI levels. To do this, we resorted to a robust regression analysis using a Theil-Sein estimator (Theil, 1992), which computes all possible linear relationships across all pairs of values in a dataset and extracts the median slope and intercept values. We compared the experiment's slopes in each C duration by performing both Frequentist and Bayesian ANOVA. This time we build the model M_E (using slopes of each experiment as predictor), and compared it to the M_0 model.

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Competing interests

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