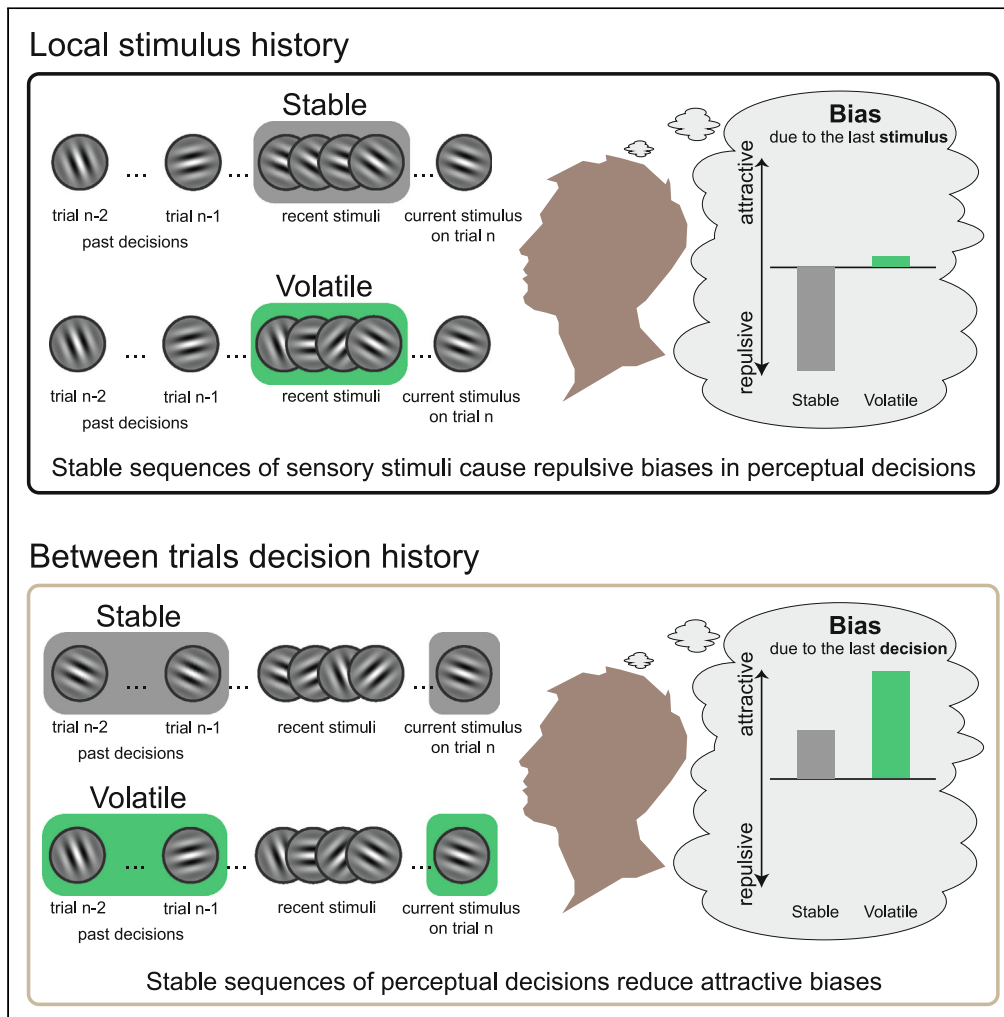


Article

Tuning perception and decisions to temporal context



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Highlights

True temporal correlations reduce serial dependence in perceptual decisions

Stable visual input induces repulsive biases

Broader temporal context is crucial for perception and decision-making

Our results challenge the idea that serial dependence reflects a stability prior



Article

Tuning perception and decisions to temporal context

Philippe Blondé,^{1,3,*} Árni Kristjánsson,¹ and David Pascucci²

SUMMARY

Recent work suggests that serial dependence, where perceptual decisions are biased toward previous stimuli, arises from the prior that sensory input is temporally correlated. However, existing studies have mostly used random stimulus sequences that do not involve such temporal consistencies. Here, we manipulated the temporal statistics of visual stimuli to examine the role of true temporal correlations in serial dependence. In two experiments, observers reproduced the orientation of the last stimulus in a sequence, while we varied temporal correlations in the stimulus features at two timescales: stimulus history within the trial and decision history across trials. We found a clear dissociation: increasing temporal correlation in the stimulus history led to adaptation-like repulsive biases, whereas increasing temporal correlation in the decision history reduced attractive biases. Thus, we suggest that temporal correlation enhances the discriminative ability of the visual system, revealing the fundamental role of the broader temporal context.

INTRODUCTION

From the swaying leaves of a tree to passing clouds, our visual world is in perpetual change. Our eyes are in constant motion as well, with frequent saccades and blinks, resulting in a discontinuous and ever-changing input to the retina. Despite this, the brain is able to maintain a continuous and stable representation of the visual world.

Recent studies suggest that to maintain continuous visual representations, the brain integrates prior and current stimuli based on the temporal and spatial characteristics of sensory events.^{1–3} For instance, when similar visual features occur in close temporal and spatial proximity, they are integrated into a unified and continuous percept of a constant object. This idea, a tenet of several recent models of vision,^{2,4–7} is largely inspired by the behavioral phenomenon of *serial dependence*, in which perceptual decisions are biased toward stimuli seen in the recent past.^{1,8} A classic example is the bias observed when two similarly oriented stimuli are shown one after the other, with the second orientation being judged as more similar to the first than it truly is. Similar effects can be found in almost all visual tasks, ranging from those involving elementary features^{1,6,9–16} to more complex and abstract ones,^{17–22} suggesting that the dependence on prior events is a pervasive and general aspect of perceptual decision-making²³ that cannot be overcome even in situations where it is non-adaptive.²⁴

Serial dependence is believed to be rooted in the strong temporal correlation of natural statistics.^{2,3,25,26} It has been proposed that exposure to such correlations has shaped our internal “priors” about the stability and continuity of visual objects, thus, leading us to interpret current sensory input as similar to the immediate past. This notion, closely linked to Bayesian and predictive theories of the brain,^{5,27–32} rests on the assumption that there is a true correlation between recent perceptual input and the present input.

If the visual system relies on Bayesian inference to update its representation of the current state of the environment, then the transition probabilities in a sequence of items should be a determining factor in the mechanisms responsible for serial dependence.³¹ Interestingly, nearly all available evidence of serial dependence, comes from studies where transition probabilities are uniform and temporal correlation is disrupted by design—i.e., by presenting *random* sequences of sensory signals. This puts into question the assumption that serial dependence in such a context represents an integration of previous stimuli based on stability priors, and leaves an explanatory gap in the understanding of these phenomena, as the conditions under which serial dependence is observed do not necessarily reflect the context in which it is expected to emerge. In principle, combining the present and the past can be an adaptive strategy in the context of static or slowly changing visual input.³³ However, it has no clear advantage in the presence of large moment-to-moment changes, such as radical changes in the orientation or direction of motion of a stimulus,^{1,12} as well as changes in the identity or gender of a face,¹⁸ to name some examples. These latter types of stimulus presentation, typically used in many experiments on serial dependence, involve a highly volatile, non-ecological visual context where prior stimuli are highly unlikely to be constant from one moment to the next.

Moreover, the timescale of these effects also matters. For instance, a small change over several seconds might indicate a negligible fluctuation in the sensory input. The same change over a short timescale may signal the beginning of a transition leading to a fundamental

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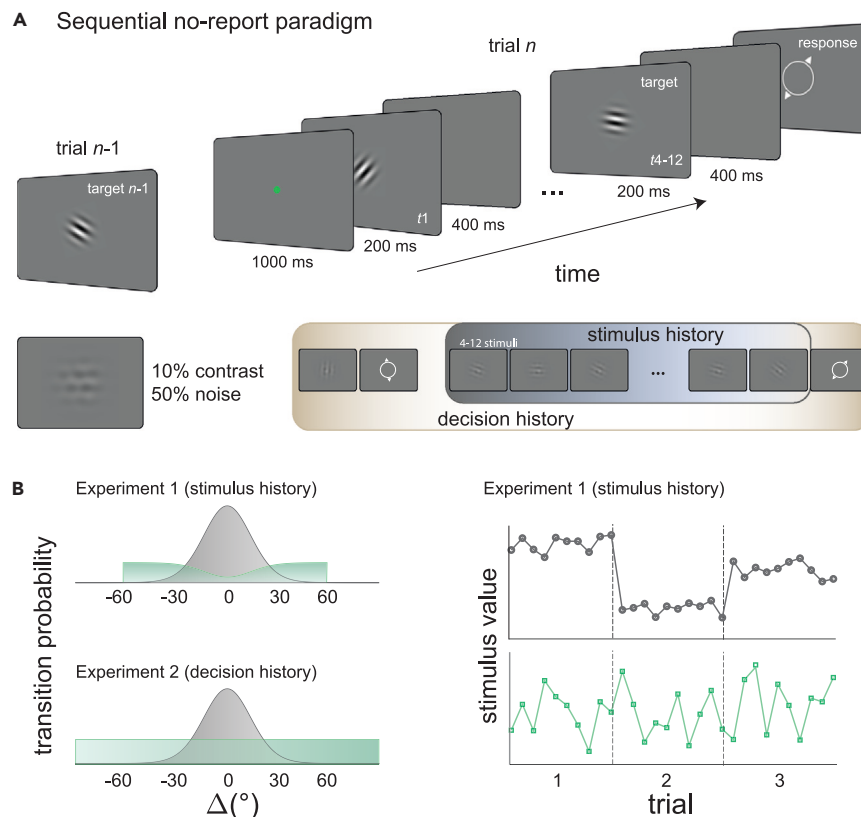


Figure 1. The sequence of events on a single trial

(A) In the sequential no-report paradigm, each trial contains a sequence of stimuli (here from 4 to 12 oriented Gabor patches). Participants reproduce the orientation of the last one using a response tool. To minimize after-images and aftereffects, the stimulus is shown with a low-contrast and embedded in visual noise (see STAR Methods). The stimulus history refers to the effect of the second-to-last stimulus shown within the trial sequence. The decision history refers to the effect of the orientation reproduced on the preceding trial.

(B) Manipulating the orientation transition probability within the trial sequence (Experiment 1) or across trials (Experiment 2) allows us to vary temporal statistics in the stimulus and decision history, respectively. The two probability functions in the left-top plot depict the stable (narrow gray function) and volatile (green function) conditions of Experiment 1, where we manipulated the stimulus history. The distributions below depict the two conditions of Experiment 2, where a similar manipulation was applied at the level of the decision history, while keeping the stimulus history random (see STAR Methods). As shown in the right-side plot, in Experiment 1 the orientations were highly similar within each trial of the stable condition (gray dots and line in the right-side plot) and highly dissimilar in the volatile condition (green squares and line in the right-side plot). Note that orientation changes across trials (e.g., decision history) in the stable condition of Experiment 1 were completely random, thus, dissociated from local stimulus history.

change. Similarly, the same change may have a completely different impact depending on the overall rate of changes in the stimulus stream. Only by taking these aspects into account can we draw conclusions about the mechanisms behind the temporal integration of sensory events and their relation to natural statistics.

An additional argument for examining temporal statistics in perception is the occurrence of a repulsive after-effect in a highly stable context. Classic studies on visual adaptation demonstrate that stable visual input repels perception away from recent stimuli, increasing the sensitivity to small changes, an effect opposite to attractive serial dependence.^{34–37} Several studies over the past decade have indicated that repulsive and attractive history effects originate from different mechanisms, and even at different processing stages, reflecting the constant need to strike a balance between discriminating changes and maintaining continuity.^{5–7,38–42} Most of the research in recent years has strived to disentangle the nature of these two effects, often linking repulsion to early sensory processes and attraction to later processing stages, such as decision-making and working memory.⁸ However, this work has typically relied on standard paradigms with randomized sequences of stimuli, which tells us nothing about how these history effects operate within more realistic temporal sequences. It remains unclear, therefore, whether these mechanisms operate at different time scales and how they depend on the actual temporal statistics, when temporal statistics change.

Here, we investigate the effect of temporal statistics on serial dependence by manipulating the transition probability distribution of stimulus sequences in an orientation adjustment task. In two experiments, observers performed a sequential no-report paradigm in which each trial contained a sequence of visual features of varying lengths.^{6,43} The task required them to monitor the entire sequence and to reproduce the orientation of the last stimulus (see Figure 1). We manipulated the temporal statistics at two levels: the sequence itself (stimulus history) and the

consecutive trials (decision history, Figure 1), with the idea that the two may tap into serial dependence at different processing stages, namely, a stage of perception versus a post-perceptual processing one. In Experiment 1, we made the stimulus history stable (high similarity between the stimuli) or volatile (low similarity between the stimuli), while in Experiment 2, we applied the same manipulation to decision history.

We hypothesized that if stability priors become more prominent in the presence of a true temporal correlation, then attractive serial dependence should be stronger under stable temporal statistics compared to volatile ones. Manipulating temporal statistics should also impact stimulus and decision history effects in different ways, in line with models assuming repulsion and attraction at the two different levels of processing. In line with this, we found a clear double dissociation. Temporal statistics at the stimulus level affected serial dependence due to prior stimuli but not prior decisions. Conversely, temporal statistics at the decision level affected serial dependence due to prior decisions but not prior stimuli. The resulting pattern points to two separate and largely independent phenomena. On the one hand, increased stability at the short-term timescale of stimulus history led to the build-up of adaptation-like repulsive effects. On the other hand, decision history at longer time scales always induced an attractive effect. However, this effect was surprisingly reduced rather than increased when temporal stability in decision history increased.

Taken together, our results provide evidence for a complex interdependency between temporal statistics and serial dependence, in which the effects of prior history depend not only on the temporal statistics of sensory input, but also on the level of processing at which temporal statistics act. Crucially, similar stimuli are judged as more different under stable temporal statistics, revealing a previously unknown contextual effect in serial dependence which suggests that in the presence of temporal correlation in sensory input, the brain increases sensitivity to changes.

RESULTS

Experiment 1

To investigate the effect of temporal statistics on serial dependence, we used the sequential no-report paradigm.^{6,43} On each trial, participants were shown a sequence of stimuli and asked to reproduce the orientation of the last one. A crucial aspect of this paradigm is that it allowed us to assess serial dependence at two levels: *stimulus history* and *decision history*. Stimulus history refers to the effect of the second-to-last stimulus in the sequence, which is never reproduced and therefore requires no active decision. Decision history refers to the effect of the stimulus reproduced on the previous trial, which is always associated with a decision and a response (see STAR Methods and Figure 1).

In this experiment, we manipulated the temporal statistics at the level of the stimulus history. We used two transition probability functions that created either a stable or volatile condition (Figure 1B). In the stable condition, the orientations of stimuli were highly similar within each trial, while in the volatile condition, they were highly different (see STAR Methods). We hypothesized that if participants internalize these patterns and form priors to guide their perception of the next stimulus, we would observe stronger attractive serial dependence from stimulus history in the stable condition, where temporal correlation is high.

First, we analyzed performance in the adjustment task by comparing the error standard deviation in the stable ($8.62 \pm 1.29^\circ$) and volatile conditions ($8.63 \pm 1.41^\circ$). The analysis revealed no significant difference between the two ($t(19) = 0.11$, $p = 0.912$).

To analyze serial dependence, we measured the bias due to the stimulus and the decision history with model-based ($\delta\sigma_G$) and model-free analyses (see STAR Methods). Both approaches involve estimating the error bias as a function of the difference between the previous and current orientation (Δ). When errors and Δ have the same sign (e.g., when both the previous orientation and the current error are clockwise or counter-clockwise to the current stimulus orientation), serial dependence is attractive: the current stimulus is reproduced as similar to the previous. Conversely, when the sign of errors and Δ is opposite, serial dependence is repulsive. The direction of the errors with respect to Δ is quantified by both the half-amplitude parameter α of the $\delta\sigma_G$ curve in the model-based analysis and by the “bias” metric in the model-free analysis (see STAR Methods).

The $\delta\sigma_G$ fit for the effect of the stimulus history revealed significant repulsive serial dependence in the stable condition (see Figure 2A), with a negative α of -1.44° ($p_{\text{perm}} < 0.001$). In the volatile condition, the estimated α was 0.75° ($p_{\text{perm}} = 0.023$), indicating an attractive bias. The direction of the bias was significantly different between the two conditions (volatile vs. stable, difference in $\alpha = 2.19^\circ$, $p_{\text{perm}} < 0.001$). The model-free analysis confirmed these results, revealing a large effect size of the difference in the bias between the two conditions (volatile vs. stable, $t(19) = 5.21$, $p < 0.001$, Cohen’s $d' = 1.17$).

We repeated the same analysis, but now considering the orientation of the stimulus reported on the preceding trial—i.e., the decision history. The $\delta\sigma_G$ fit revealed attractive serial dependence in both the stable ($\alpha = 0.80^\circ$, $p_{\text{perm}} = 0.027$) and volatile conditions ($\alpha = 0.87^\circ$, $p_{\text{perm}} = 0.019$), with no difference between the two, according to both the model-based (volatile vs. stable, difference in $\alpha = 0.07^\circ$, $p_{\text{perm}} = 0.445$) and model-free statistics (volatile vs. stable, $t(19) = -0.32$, $p = 0.750$, $d' = -0.07$). Hence, while the manipulation of the stimulus history led to opposite effects, with a strong repulsive bias in the stable condition, the effect of decision history was always attractive.

In our paradigm, the longer the sequence of stimuli the larger the number of samples characterizing the temporal statistics. To further assess the time course of these biases as a function of the sequence length, we ran a series of linear regressions, modeling the strength of the model-free bias as a function of the number of stimuli shown on each trial (from 4 to 12). Two linear models were run separately for the effect of stimulus and decision history. In the analysis of the stimulus history, the linear model included the sequence length, the condition (volatile vs. stable), and their interaction as the main predictors. In this model, the bias due to the second-to-last stimulus in the sequence was the dependent variable. We found a significant linear regression ($F(4; 356) = 22.9$, $p < 0.001$, $R^2 = 0.16$), indicating a negative slope of the effect of sequence length ($\beta = -0.26$, $p = 0.048$), with a significant main effect of the stimulus history condition ($\beta = -1.77$, $p = 0.047$), and a trend toward a significant interaction ($\beta = -0.35$, $p = 0.061$). As shown in Figure 2B, the interaction trend was mostly driven by the more pronounced

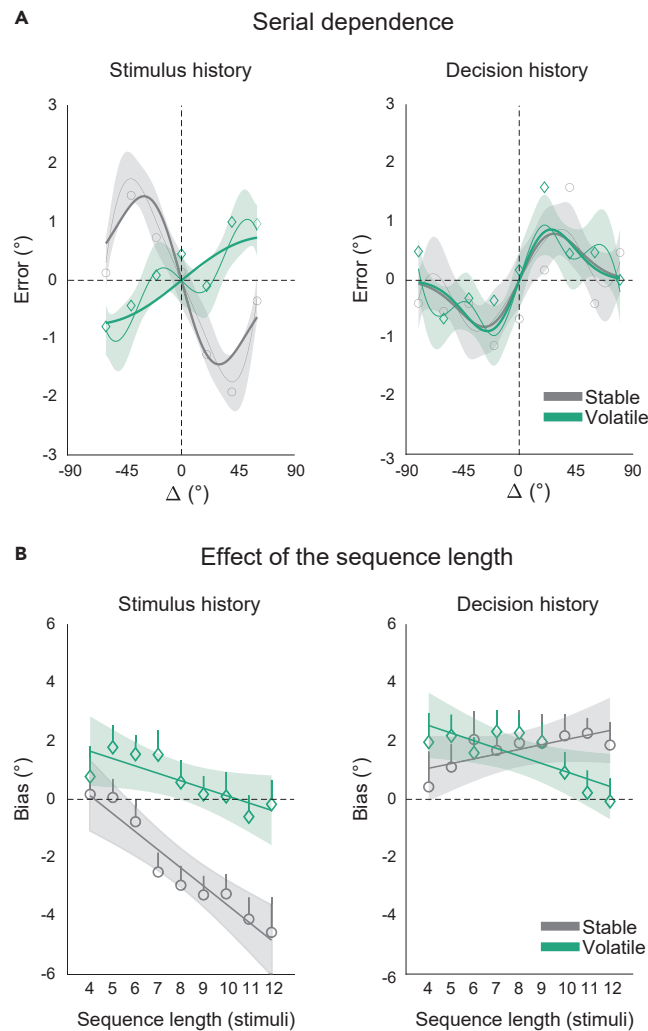


Figure 2. Results of Experiment 1

(A) Error as a function of Δ . Left panel: the effect of stimulus history in the stable (gray lines, dots, and shaded areas) and volatile condition (green lines, diamonds, and shaded areas). Right panel: the effect of decision history in the stable and volatile conditions. Lines represent the $\delta\sigma G$ fit; shaded areas are interpolated running averages of the errors on each Δ bin (showed shown by the dots and diamonds) with 1 standard deviation.

(B) Sequence length analysis and regression fits with 95% prediction intervals for stimulus history effects (left panel) and decision history effects (right panel).

negative effect of the sequence length in the stable, compared to the volatile condition. This suggests that, when the stimulus history is stable, each additional stimulus leads to a more marked increase in repulsive serial dependence.

To analyze decision history, we ran a similar linear model with the same predictors, but the dependent variable was the bias due to the stimulus reported on the previous trial. This analysis also revealed a significant regression model ($F(4; 356) = 2.76, p = 0.042, R^2 = 0.01$), with a significant interaction between the effect of sequence length and decision history ($\beta = 0.48, p = 0.006$). The attractive bias toward the stimulus reported on the preceding trial increased as a function of the number of stimuli in the stable condition, but decreased in the volatile condition, indicating that, even though decision history effects were always attractive, they were slightly modulated by local stimulus history (Figure 2B).

Experiment 2

In Experiment 1, we found repulsive serial dependence when stimulus history was stable. In contrast, decision history led to an overall attractive serial dependence. Notably, decision history effects persisted even though several stimuli intervened between consecutive decisions. This might suggest that (1) stable stimulus history can generate repulsive biases similar to adaptation, which accumulate over short time scales, and (2) decision history may manifest as a distinct form of serial dependence, operating on a separate timescale and unaffected by local stimulus history.

In Experiment 2, we investigated whether temporal statistics would affect decision-related serial dependence. To this aim, we manipulated the orientation transition probability function at the level of decision history while keeping the local stimulus history random. We presented participants with separate blocks, one with a stable condition, in which the orientation they had to reproduce varied according to a narrow transition probability distribution, and another with a random condition, in which the orientation varied according to a uniform transition probability distribution similar to classic serial dependence studies (see [STAR Methods](#)). For consistency with Experiment 1, we refer to the random condition as volatile. For this experiment, we choose to employ a uniform distribution rather than a distribution resembling the shape utilized in the volatile condition of Experiment 1 to avoid a potential imbalance in data points for small Δ values in comparison to the stable condition.

We hypothesized that if participants internalized the temporal correlation in their decisions, serial dependence would be stronger in the stable condition because previous decisions were highly similar to current ones.

The manipulation of temporal statistics at the level of decision history led to a significant difference in performance, with a lower standard deviation of adjustment errors in the stable ($8.40 \pm 1.32^\circ$) than the volatile condition (8.82 ± 1.22 ; $t(16) = 2.64$, $p = 0.018$). Serial dependence from the stimulus history was absent in both the stable ($\alpha = -0.55^\circ$, $p_{\text{perm}} = 0.110$) and volatile conditions ($\alpha = 0.46^\circ$, $p_{\text{perm}} = 0.175$). The model-based analysis also revealed no significant bias (difference in α , volatile vs. stable: 1.01° , $p_{\text{perm}} = 0.157$) and the model-free analysis revealed only a trend for a significant difference between conditions (volatile vs. stable, $t(16) = 1.83$, $p = 0.086$, $d' = 0.44$).

In contrast to the effect of stimulus history, strong attractive serial dependence on the decision history was evident in both conditions ([Figure 3A](#)). Surprisingly, however, attractive serial dependence was stronger in the volatile ($\alpha = 2.19^\circ$, $p_{\text{perm}} < 0.001$) than the stable condition ($\alpha = 1.07^\circ$, $p_{\text{perm}} = 0.001$; difference in α , volatile vs. stable: 1.12° , $p_{\text{perm}} = 0.006$), even though decisions were highly temporally correlated in the stable condition. This difference between conditions was confirmed by the model-free analysis (volatile vs. stable, $t(16) = 2.14$, $p = 0.048$, $d' = 0.52$). Hence, when manipulating temporal statistics at the level of decision history, the local stimulus history was not affected and produced no bias at all, whereas the attractive serial dependence due to previous decisions was stronger for volatile than stable sequences.

As in Experiment 1, we evaluated changes in the strength of both stimulus and decision history effects as a function of the sequence length. The model for stimulus history effects was significant ($F(4; 302) = 5.64$, $p < 0.001$, $R^2 = 0.04$), with a significant negative slope for the effect of sequence length ($\beta = -0.41$, $p = 0.004$), but no main effect of the volatile vs. stable conditions ($\beta = -1.76$, $p = 0.294$), nor a significant interaction ($\beta = 0.1$, $p = 0.609$). The model for decision history effects was also significant ($F(4; 302) = 9.16$, $p < 0.001$, $R^2 = 0.07$), with a significant main effect of the volatile vs. stable history condition ($\beta = -2.9$, $p = 0.04$), but only a tendential effect of the sequence length ($\beta = 0.19$, $p = 0.108$) and no interaction ($\beta = 0.14$, $p = 0.406$). This additional analysis revealed that local stimulus history effects tended toward repulsion with increased sequence length, while the attractive bias due to decision history increased.

One potential explanation for the reduced attractive serial dependence in the stable condition is that observers integrated information from more than one trial in the past because of the temporal correlation of decisions across entire blocks of trials. The effect of the very last trial may therefore have been reduced because previous trials also had a strong influence. To check this possibility we performed a linear regression after linearizing the relationship between Δ and single-trial errors by pre-multiplying Δ with a $\delta\sigma_G$ of the width obtained in the main analysis (i.e., considering Δ with respect to one trial back).^{25,44} Two separate linear models were generated for the stable and volatile conditions, which included the linearized effect of both the most recent ($n-1$) and the preceding trials ($n-2$) as the main predictors of the aggregated single-trial errors of all observers. In the volatile condition, a significant linear model ($F(3; 1856) = 28$, $p < 0.001$, $R^2 = 0.03$) revealed an effect of $\Delta(n-1)$ ($\beta = 0.15$, $p < 0.001$) and of $\Delta(n-2)$ ($\beta = 0.04$, $p = 0.026$). Conversely, in the stable condition, a significant linear model ($F(3; 1869) = 7.61$, $p < 0.001$, $R^2 = 0.008$) revealed only an effect of $\Delta(n-1)$ ($\beta = 0.06$, $p = 0.001$) but no effect of $\Delta(n-2)$ ($\beta = 0.01$, $p = 0.298$). Not only was serial dependence for the preceding trial reduced in the stable condition, but also how far back in time the bias extended.

DISCUSSION

We investigated the role of temporal statistics in serial dependence, an aspect that prior research has often overlooked by relying solely on random sequences of stimuli. In two experiments, we manipulated the temporal statistics of consecutive stimuli to make them either more similar or more distinct from one another. We focused on examining the effects of varying temporal statistics at two levels—the stimulus level and the decision level—that have been related to independent effects of prior history in several recent studies.^{5–7,39,40} Our results reveal a double dissociation: manipulating temporal statistics had a targeted effect solely at the level where it was applied, with distinct effects of stimulus history and decision history. High temporal correlation in the stimulus history led to the build-up of adaptation-like repulsive effects ([Figure 2A](#)), whereas high temporal correlation in the decision history reduced attractive serial dependence ([Figure 3A](#)).

These results have several important implications. Firstly, they confirm evidence that there are two distinct stages at which previous stimuli influence perception and perceptual decisions, which are largely independent of each other.⁶ Recent research supports this dissociation, as several studies have demonstrated that the influence of pure sensory stimulation typically leads to a repulsive bias.^{6,40,45–47} On the other hand, the attractive bias has been linked to higher-level processing stages that involve memory and decision-making processes where sequential perceptual episodes are combined together to maintain stable representations of the relevant stimuli features.^{12,38}

Modeling work has attempted to account for these opposing biases by positing the existence of history effects at higher-level processing stages that interact with or even counteract low-level adaptation.^{6,7} These models suggest that the repulsive bias is attributable to low-level mechanisms similar to visual adaptation and negative aftereffects, which help maintain sensitivity to changes.^{5–7} This is in line with the

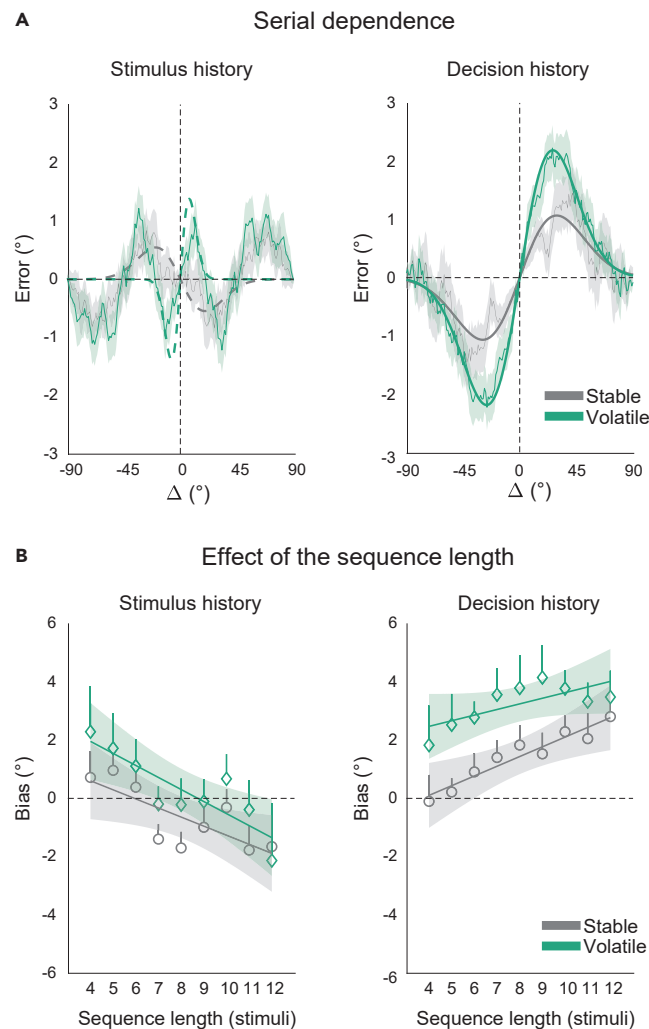


Figure 3. Results of Experiment 2

(A) Errors as a function of Δ . Left panel: the effect of stimulus history in the stable (gray lines, dots, and shaded areas) and volatile condition (green lines, diamonds, and shaded areas). Right panel: the effect of decision history in stable and volatile conditions. Note that in this experiment, the manipulation of stable and volatile temporal statistics was applied at the level of decision history. Lines represent the δ oG fit; dashed lines indicate non-significant fits; shaded areas are running averages of the group-average errors with 1 standard deviation.

(B) Sequence length analysis and regression fit with 95% prediction intervals for stimulus history effects (left panel) and decision history effects (right panel).

build-up of repulsive biases as a function of the sequence length found in our experiments, particularly when the stimulus history was stable, and suggests that the visual system gradually adapts to the prevailing flow of visual input even at short time scales. The only instance in which we observed a weak attractive effect of stimulus history was in the volatile condition where the sequence had highly diverse stimuli (Figure 2A). If we assume that these biases reflect how the brain tunes itself to external statistics, then a volatile environment should not produce any adaptation-like bias since few regularities can be discerned from such an environment, and weak attractive serial dependence from pure stimulus history might prevail. Alternatively, in extremely uncertain environments, the most recent information might serve as the dominant reference point for predicting the next state of the environment.^{48,49}

The putative computational goal of serial biases has been extensively discussed, and existing models typically propose that both repulsion and attraction stem from how the visual system tunes itself to the expected temporal statistics of the visual world. Repulsion, which has been often observed on longer time scales of seconds or even minutes, has been linked to mechanisms that reallocate processing resources based on the prevalent flow of sensory events according to efficient coding schemes⁵ and intrinsic expectations about slow changes in visual input.³⁵ Conversely, attraction has been associated with stability priors where visual events tend to be similar at shorter time scales.^{1,2,4,5} The pattern of results observed in our study appears to be the opposite, with repulsion at shorter time scales and attraction at longer ones. This may reflect the design of our sequential no-report paradigm, where rapid sequences of non-reported stimuli are interleaved with task-relevant events. As a result, attention and processing effort may be primarily allocated toward the end of event sequences, because the relevant stimulus is

expected to occur later. According to the view that attractive serial dependence requires attention to previous stimuli,¹ as well as task engagement and post-perceptual processing,^{6,12,39} reduced attention to the stimuli preceding the last one in the sequence may explain the prevalence of repulsive biases.^{6,43}

Prior studies have utilized methods such as backward masking and longer intervals between stimuli to avoid the confounding effects of repulsive aftereffects and adaptation on attractive serial dependence.^{1,50} Although these methods may enhance attractive effects over repulsive ones, they do not reflect the natural conditions under which we typically perceive stimuli and hamper the understanding of how the two effects interact. Moreover, the need for such methods underscores the presence of multiple processing stages, where the overall impact of a stimulus must be regulated to observe a particular effect. In this study, we also attempted to minimize the residual effects of the stimulus by presenting low-contrast Gabors embedded in visual noise. This approach utilized weaker sensory signals compared to previous studies using the sequential no-report paradigm.^{6,43} As a result, we observed no overall repulsive effects of stimulus history in three out of four conditions (i.e., the volatile condition of Experiment 1 and both conditions of Experiment 2), providing further support for the idea that the strength (e.g., contrast, signal-to-noise ratio) of the stimulus plays a significant role in producing repulsive effects. Nonetheless, in Experiment 1, where stimulus history was stable, we found a repulsive effect that increased with the sequence length, suggesting the accumulation of adaptation-like processes in response to short-term correlations in the stimulus (Figure 2B).

Another relevant finding is how sequence length modulates these effects. As sequence length increased, there was greater repulsion in all conditions that was even stronger within the stable sequence (Figure 2B). At the same time, there was a general increase in attraction toward the previous trial (Figure 3B). This pattern was consistent across both experiments, except for the volatile condition of Experiment 1, where it was reversed (Figure 2B). The increased attractive effect due to longer sequences is in line with a recent study demonstrating that the attractive effect of a previously reported stimulus increases as a function of the number of non-reported intervening stimuli.⁵¹ One potential explanation for this result is that all stimuli may in principle cause attractive and repulsive effects—i.e., the two opposite biases coexist. While task-relevant processing enhances the attractive component, stimuli that receive less attention and post-perceptual processing exert a stronger repulsive effect.^{1,6} The length of the sequence in the present paradigm also covaried with the interval between two decisions and, therefore, attractive effects could have also been amplified by the persistence of previously reported stimuli in working memory,^{39,52} even if the previous stimuli were no longer relevant. As mentioned, the only result that deviated from this pattern was the reverse effect of sequence length in the volatile condition of Experiment 1, where additional stimuli in the sequence decreased the attractive effect of the orientation reported on the preceding trial. The nature of this effect remains unclear. We can speculate that longer volatile sequences contained orientations that were similar to the one reported on the previous trial, interfering with and reducing the attractive effect. Alternatively, volatile sequences of stimuli may exert an impact at both the stimulus and decision history levels, leading to a reduced reliance on prior stimuli when reporting current ones.

One might question whether the repulsive effects observed in this study and previous research can be interpreted as a form of negative serial dependence that goes beyond, and is not merely a consequence of, short-term adaptation.^{1,5,6,39,43,51} Several alternative mechanisms can be proposed, including the active removal of information that is no longer relevant from working memory and the influence of reference-repulsion effects.⁵¹ Although the specific mechanisms are still debated, previous studies have demonstrated that these repulsive effects, including those observed in the sequential no-report paradigm used here, are largely specific to location and exhibit a stronger spatial tuning compared to attractive serial dependence.^{5,39,43} This may suggest an earlier origin of the effect, consistent with typical findings on visual aftereffects and adaptation.^{6,7,36} Importantly, while adaptation effects are typically observed with prolonged exposure to high-contrast stimuli, these findings demonstrate that the temporal characteristics of even weak and brief stimuli can produce repulsive effects of similar magnitude.

Lastly, a key finding is the observed decrease in serial dependence when stability was introduced at the decision history level (Figure 3B). This result may seem counterintuitive since one would anticipate greater influences of past events in the presence of true temporal correlation, a principle upheld by existing models.^{2,3,5} That is, when the similarity between consecutive stimuli is high, the prior assumption about stability could become even stronger, leading to more pronounced biases toward the past. However, our findings provide clear evidence of the opposite. An important factor that may account for this result is the lower variability in adjustment errors observed in the stable condition of Experiment 2, which indicates that participants made more accurate decisions under highly similar temporal sequences. These findings suggest that observers efficiently use temporal statistics by recalibrating their discriminative abilities based on the overall distribution and size of stimulus differences within a block of trials. When the sequence of decision-relevant stimuli is highly temporally correlated, discrimination performance around the prevailing stimulus value increases, leading to increased precision and an enhanced ability to differentiate between two slightly different stimuli. This ultimately reduces the bias toward the past.

Our findings suggest that the ability to discriminate a small change in the stimulus depends on the overall rate and size of changes in the temporal statistics. This explanation is reminiscent of Gestalt-inspired configurational theories of perception,⁵³ which suggest that perception results not only from present and past stimuli but also from “background stimuli” that reflect the broader spatial and temporal context in which stimuli are experienced. In this view, perceptual judgments are based on differences between stimuli rather than the stimuli themselves. This idea is also consistent with classic models of perceptual judgments, such as the relative judgment model.^{54,55} Crucially, the perceived difference between stimuli depends on contextual factors that extend beyond the relation between the current and immediately preceding stimulus. Our results suggest that the overall temporal statistics are a key determinant in this process, eventually revealing that under stable temporal contexts, the brain becomes better at discriminating small differences rather than relying more on the combination of previous and current stimuli, an aspect that theories and models of serial dependence should take into account.

In sum, in our daily lives, we often encounter stimuli that have stable features and require us to interact with them for extended periods. During typical perception-action cycles, we monitor these features for some time and intermittently sample the current state of the stimulus to inform our decisions and actions. Our study shows that this process may be facilitated by two mechanisms that utilize temporal correlations in stimulus statistics. These mechanisms enhance sensitivity to short-term changes and promote stable but more precise representations depending on the broader temporal context.

Limitations of the study

The sequential no-report paradigm used here, designed to disentangle stimulus and decision-related effects, differs from standard paradigms of serial dependence, in which a stimulus is always followed by a response. Thus, the generalizability of the findings to more classic paradigms will require further research. Moreover, as mentioned, we did not present a mask following each stimulus as in classic serial dependence studies. This could have favored visual adaptation and repulsive aftereffects in the stimulus history, which might have hindered attractive serial dependence. The temporal statistics investigated here were also restricted to a few conditions with a limited set of basic distributions tested (e.g., stable, volatile, and random). The effect of other, more complex distributions should therefore be tested in the future. Finally, in our work we only used visual orientations with Gabor stimuli as the main feature of interest, and therefore, further testing is needed to generalize the results to other features or more complex stimuli.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

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AUTHOR CONTRIBUTIONS

D. P. conceived the original idea and designed the experiment. P. B. and D. P. conducted the analyses and interpreted the results. P. B. and D. P. wrote the manuscript with support from A. K.

DECLARATION OF INTERESTS

The authors have no conflict of interest to declare.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Experimental data	Zenodo	https://zenodo.org/record/8109972
Experimental models: Organisms/strains		
37 participants in total. - 20 in experiment 1, 7 females, $M_{age} = 21.30$ years, $SD_{age} = 1.98$. - 18 in experiment 2, 7 females, $M_{age} = 23.50$ years, $SD_{age} = 1.98$.	N/A	N/A
Software and algorithms		
MATLAB, R2023a	Mathworks	https://matlab.mathworks.com/

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be addressed to the lead contact, Philippe Blondé (phblonde@hi.is).

Materials availability

No materials are available for this study.

Data and code availability

- The raw data for Experiments 1 and 2 is publicly accessible and can be found at Zenodo Data: <https://zenodo.org/record/8109972> and Mendeley Data: <https://data.mendeley.com/datasets/tmwd9zkmcx/1>.
- Sample code for both experiment is also available at Zenodo Data: <https://zenodo.org/record/8109972> and Mendeley Data: <https://data.mendeley.com/datasets/tmwd9zkmcx/1>.
- Any additional information required to reanalyze the data reported in this paper is available from the [lead contact](#) upon request.

EXPERIMENTAL MODEL AND STUDY PARTICIPANT DETAILS

In total 37 healthy participants from the EPFL and the University of Lausanne, 20 in Experiment 1 (7 females, 18 - 27 years, $M_{age} = 21.30$, $SD_{age} = 1.98$) and 18 in Experiment 2 (7 females, 19 - 35 years, $M_{age} = 23.50$, $SD_{age} = 4.49$), took part in the study for a monetary reward (20 CHF/hour). Ancestry, race, or ethnicity were not assessed. The sample size was based on previous work using similar stimuli and paradigms.^{6,43} Participants had normal or corrected-to-normal vision and were naïve as to the purpose of the experiments. Visual acuity was tested with the Freiburg Acuity test.⁵⁶ Written informed consent was collected from all participants beforehand.

The study was approved by the local ethics committee under the Declaration of Helsinki (except for preregistration) (World Medical Organization, 2013).

METHOD DETAILS

Apparatus and stimuli

Stimuli were presented on a gamma-corrected VG248QE monitor (resolution: 1920 x 1080 pixels, refresh rate: 120 Hz) and were generated with custom-made scripts written in Matlab (R2013a) and the Psychophysics Toolbox,⁵⁷ on a Windows-based machine. Participants sat approximately 57 cm from the computer screen, with the head held stable in a chin rest. The experiments were performed in a dim room.

Figure 1 illustrates the main aspects of the paradigm. The design of the experiments used was a variant of the 'sequential no-report' paradigm used in previous work.^{6,43} Each trial contained a sequence of 4 to 12 stimuli created by combining 50% of the image of an oriented Gabor patch (spatial frequency of 1.2 cycles per degree, peak contrast of 10% Michelson, Gaussian envelope of 1° in diameter, random phase) and 50% of white noise filtered at the same spatial frequency as the Gabor. A central fixation spot was shown for 1000 ms at the beginning of each trial and was followed by the Gabor sequence. Each Gabor was presented for 200 ms and followed by a blank interval of 400 ms. The number of stimuli in the sequence was randomly determined on each trial and 400 ms after the sequence ended, participants were shown a response tool, made of a circular frame with two small triangles. The two triangles were the extremities of an imaginary line that participants had to adjust to reproduce the perceived orientation of the last Gabor. The response was confirmed by clicking on the left mouse button.

After the response was submitted, a new trial started with a random inter-trial interval of 750-1500 ms. In total, 280 trials were presented in each experiment.

In Experiment 1, the orientation of the last Gabor in the sequence, and the orientation of the immediately preceding stimulus, were selected from the full 0:179° orientation range in steps of 20° (with the only constraint that the maximum absolute difference between orientations could not exceed 60°). The orientation of the first Gabor in the sequence was chosen at random. Within the trials, the stimuli before the last two could vary according to two conditions run in four separate blocks. Stable and volatile blocks were alternated, with the first block being randomly chosen for each participant. In the *stable* condition, orientation changes were regulated by a Von Mises circular transition probability function centred on 0° (e.g., highest probability at stimulus repetition) with concentration parameter k of 4.2073 (i.e., corresponding approximately to a normal standard deviation of 30°). In the *volatile* condition, the transition probability function was inverted (i.e., the same function as in the stable condition, but the probability of repetition was the lowest, see Figure 1B). To maximize the number of data points around small orientation differences, where serial dependence is typically more pronounced, the orientation difference between the last and the immediately preceding stimulus in the sequence was randomly determined within the $\pm 60^\circ$ range (in steps of 20°). While the constraint of $\pm 60^\circ$ across the entire sequence limited the range of orientation differences, it still allowed for an effective control over the temporal statistics of orientation changes within this range. The orientation of the last stimulus that participants had to report was independent of the last stimulus of the previous trial.

In Experiment 2, orientations were selected from the whole 0:179° range in steps of 1°, in order to have even more detailed resolution. All orientation changes within the trial sequence were randomly determined. The key manipulations in this experiment occurred at the orientation level that participants had to reproduce on each trial. In the *stable* condition, changes in the reproduced orientation across trials were regulated by a similar Von Mises transition probability distribution as for the within-trial manipulation of Experiment 1, with a small offset added to ensure orientation changes also at large orientation distances. In the *random* condition, orientation changes were randomly determined also at the level of the orientation reproduced on each trial.

For simplicity, in both experiments, we will refer to the effect of the last non-reported stimulus within the sequence as *stimulus history*, and to the effect of the stimulus reported on the preceding trial as *decision history*. At the end of each experiment, participants were asked if they had noticed any difference in either stimulus or decision history. Some participants reported that stimuli were sometimes more correlated, but none reported being fully aware of any difference in transition probabilities between the blocks.

QUANTIFICATION AND STATISTICAL ANALYSIS

All statistical analyses were conducted using Matlab (R2013a). The main analysis was based on the adjustment error metric. Adjustment errors were computed as the acute-angle difference between the reported and the true stimulus orientation, in degrees. Before analysis, errors were cleaned from outliers, considered as absolute errors larger than 45° or outside the 1.5 interquartile range. Trials with adjustment times slower than 10 s were also considered outliers. These criteria led to the exclusion of 6.33% trials in total, across the two experiments. After outlier exclusion, errors were further pre-processed by mean-centering and removing the orientation bias confound.⁶ Subjects were excluded if the percentage of outlier trials exceeded 20% or if the standard deviation of the errors (before outlier cleaning) exceeded 45°. This led to the exclusion of only one subject in Experiment 2.

Errors were analysed both using a model-based and a model-free approach.³⁸ The model-based analysis consisted of fitting a 1st derivative of a Gaussian function¹ to the adjustment errors as a function of the variable Δ , obtained as previous minus current orientation. The δoG has the following form:

$$\text{error} = \Delta \alpha w c e^{-(w\Delta)^2}$$

where c is a constant $c = \frac{\sqrt{2}}{e^{-0.5}}$ and w is the inverse of the curve width. The amplitude parameter α quantifies the deviation of the errors, in degrees, from the actual orientation, as a function of the Δ variable: positive values of α indicate a systematic deviation of errors towards the orientation of the preceding stimulus, and negative values indicate a deviation away —i.e., repulsion. The parameters of the δoG function were estimated on the aggregate data of all participants, by solving a constrained non-linear minimization problem with the sum of squared residuals as the cost function.

Model fitting was performed separately on each condition of interest. For example, in the analysis of stimulus history effects in Experiment 1, we separately estimated the model parameters for the stable and volatile condition, considering the Δ between the last non-reported stimulus in the trial sequence and the one to be reported at the end as the variable of interest. When analysing decision history effects, we considered the Δ between the orientation of the stimulus reported one trial before and the one reported now. Statistical significance of the amplitude parameter was assessed via bootstrap resampling and surrogate null statistics, by randomly shuffling the sign of adjustment errors and comparing the observed α with the distribution of surrogate α ($N = 10000$). Serial dependence between conditions was compared by randomly shuffling the condition labels 10000 times and comparing the distribution of the resulting differences against the observed one.

In the model-free approach, we subtracted the average error for Δ within the 1-50° range from the average error in the corresponding negative Δ .^{38,58} The resulting index, quantifying the amount of systematic deviation of the errors from zero (either in the positive or negative direction) was used for subsequent analysis. An estimate of the model-free bias was also used in the analysis of sequence effects, where we evaluated changes in the effect of stimulus and decision history as a function of the length of the sequence of stimuli on the current trial. For

this analysis, model-free biases were estimated for each possible sequence length (4-12 stimuli, with a sliding average of 3 stimuli) and submitted to a linear regression with sequence length, condition, and their interaction as the main predictors. For each regression, the volatile condition was coded as 0 and the stable one as 1. Hence, the effect of the condition corresponds to the difference from volatile to stable and the reported parameters of sequence length correspond to its effect for the volatile condition. In accordance with the standard significance criterion in experimental psychology, we used a threshold of $\alpha < .05$ to indicate a significant result and $\alpha < .1$ for a significant trend for all statistical tests.