No Subliminal Memory for Spaced Repeated Images in Rapid-Serial-Visual-Presentation Streams

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No subliminal memory for *spaced* repeated images in rapid-serial-visual-presentation streams

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Introduction

Recently in Psychological Science, Thunell and Thorpe (T&T) (2019) demonstrated a repetition effect in RSVP (Rapid Serial Visual Presentation) streams of images presented at 15hz. They included *One-distractor* and *Two-distractor* conditions, determined by the number of intervening distractors between repetitions. They observed a striking increase in detection of repetitions as the number of presentations increased; see Figure 1[B] – dashed red and solid purple curves, original figure in inset.

This finding seems to suggest a *durability* of memory representations for these fleeting items, which need to span presentations for a stimulus to be detected as repeating. They also apparently suggest that memory traces accumulate, with the strength of the representation of the repeating stimulus increasing across repetitions, making it progressively easier to detect; see figure 1[A] for alternative accumulation regimes.

T&T highlight the importance of the brain's detection of repetitions for its ability to learn from the statistical regularities in the environment. That is, if a stimulus repeats then the brain learns to efficiently detect it. The repetition effect T&T observed could underlie this learning.

The fact that these repetition effects were observed when stimuli were presented rapidly, and indeed in some conditions exceptionally rapidly (e.g. at 120 Hz), seems to suggest that the processes that underlie detection of repetitions, and by extension also statistical learning, operate unconsciously. This is the question we consider, with "access awareness" our focus, since reportability is taken as indicating conscious perception.

One would assume that there is at least some degree of durability of representations for *consciously experienced* stimuli presented in RSVP, as, for example, suggested by recall performance in RSVP whole-report experiments (Nieuwenstein & Potter, 2006). However, do T&T's findings definitely imply that there is also durability for presentations that do not reach awareness, which would correspond to case 2 in figure 1[A]? For example, the following, *no-subliminal-accumulation*, scenario could explain T&T's repetition effect.

1) *Repetition-independent (first) break-through*: a *pre-specified* stimulus can be effectively searched for in RSVP (Potter, 1976; Bowman et al, 2013). However, no such task-set is imposed in a pure repetition task, where *any* stimulus could be the repeating item. Additionally, it could be that below-threshold registration of a stimulus that is neither pre-specified nor familiar, dissipates rapidly, preventing unconscious detection of repetitions. Indeed, a stimulus may be propelled *for the first time* into awareness *merely* because it is poorly masked by other stimuli, and not because it has been frequently repeated.
2) *Subliminal-search, with supraliminal task-set*: however, once a stimulus has broken into awareness, it then creates a conscious memory trace, providing a template to search for in the remainder of the RSVP stream.

If there were indeed no subliminal detection of repetition, one could still observe a repetition effect in RSVP. This is because the probability that a stimulus had previously broken through (for the first time) into awareness, would increase with the number of repetitions, and the repeating item would continue to be seen with high probability in the ensuing search, with supraliminal task-set.

However, the no-subliminal-accumulation scenario makes a key prediction: the probability, on a particular presentation, of consciously perceiving a stimulus *for the first time* should not change with the number of presentations. That is, if we focus on the trials for which the repeating target was not observed on any of the previous $i - 1$ repetitions, the probability of consciously seeing the target on presentation i (relative to this set of not previously seen trials), should be the same, whatever the i.

We cannot directly observe this probability of first seeing, however, we can calculate the probability of first seeing *as a repetition* from T&T (2020)'s data, which they have kindly made openly accessible.

Methods

Thunell & Thorpe Experiment: T&T presented long sequences of images at RSVP rates (key condition: 15 hz), which included sub-sequences containing repetitions of images. Two conditions were obtained dependent upon the number of intervening distractors presented between repetitions, giving the *one-distractor* and *two-distractor* conditions. Each repetition sub-sequence contained a number of presentations of the repeating item, which varied from two to ten. Participants pressed a button when they saw a repetition. However, importantly, each repetition sub-sequence ran to completion whether a button was pressed or not. Thus, if a sub-sequence of N repetitions was presented, even if the repetition was seen earlier than the Nth repetition, that detection would count to the N presentations condition. This naturally leads to a cumulative interpretation of the experiment, whereby the N repetitions condition, can be considered the same as the N-1 condition up to the N-1st presentation. This cumulative interpretation will be key to our re-analysis of T&T's data.

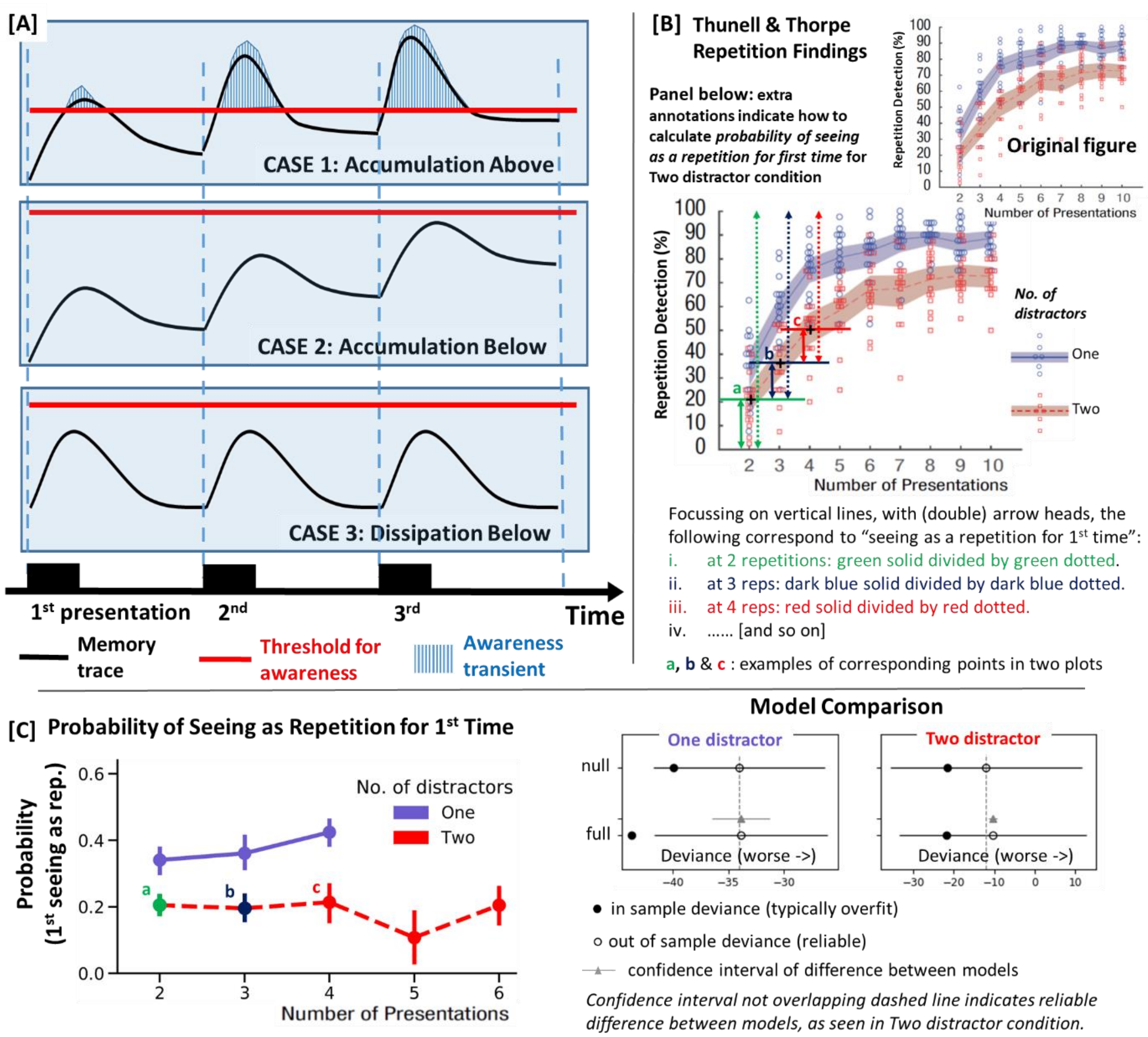

Figure 1. ***Theory and reanalysis of T&T data**: [A] three theories of how the brain responds to repeated presentations. The stimulus sequence is shown in black as three presentations of the same stimulus. The awareness transient reflects the conscious experience of the presented stimulus. Three accumulation regimes are shown. CASE 1: evidence accumulates across presentations, each of which yields an, if only brief, conscious percept. CASE 2: evidence accumulates without conscious percepts. CASE 3: evidence dissipates between presentations, none of which generate a conscious percept. [B] plot from T&T: original in inset, One-distractor (solid purple curve), Two-distractor (dashed red curve), with error regions. Main plot: probability of first seeing as repetition analysis illustrated with added annotations: vertical lines (solid and dotted) with (double) arrow heads, and three solid horizontal lines. [C] Results of probability of first seeing as a repetition analysis of data in [B], with colours and labelling indicating corresponding points. Right-side of [C]: results of model comparison on probability of seeing as repetition for first time. Models are performing better if their corresponding circles are further to the left. Generalizable (out-of-sample) comparisons are between*

open circles, which are statistically reliable if confidence interval of second-best model does not intersect vertical line.

Figure 1[B] shows their main finding (original in inset), in which the probability of detecting the repetition increases with the number of presentations in the sub-sequence. This seems to suggests that brain representations accumulate from presentation to presentation, which, in turn, suggests that memory traces must last from one presentation to the next.

Key Concepts: We first define key concepts underlying our analyses. We give informal and formal definitions alongside each other. Further details can be found in Avilés, Bowman & Wyble (2020), particularly the appendices.

1. Assume a sequence of N presentations of a repeating stimulus. We call this repeating stimulus the *target*, even though participants do not know its identity. Each presentation is labelled with a number, from 1 to N.
2. Define $See\_Repeating(j)$ to be true if the target is seen as repeating on the jth presentation.
3. Define *probability first seen as repetition* on presentation i, denoted p_i, as:
   - the conditional probability that the target is seen on presentation i, given that it has not been seen as repeating on any previous presentation, which can be formalised as,
   $$p_i = p(\ See\_Repeating(i)\ \mid\ \forall j \in \mathbb{N}\ (1 \leq j < i)\ \cdot\ \neg\ See\_Repeating(j)\ )$$
4. The key property we are interested in is *invariance to number of repetitions*, which holds if,
   - the probability that the target is first seen as a repetition is the same for all presentations, from the second onwards, which can be formalised as,
   $$\forall i, j \in \mathbb{N}\ (2 \leq i, j \leq N)\ \cdot\ p_i = p_j.$$
5. If the probability of first seeing as a repetition (p_i) is indeed invariant across presentations then there is no evidence accumulation across repetitions before the target is consciously perceived; see case 3 in figure 1[A]. Alternatively, if this probability increases then there is unconscious accumulation and memory traces can last across repetitions; see case 2 in figure 1[A].
6. This intuition was confirmed in stochastic simulations in Avilés, Bowman & Wyble (2020). Specifically, if the probability of first seeing the target was constant across repetitions and once seen its probability of continuing to be seen was 1 then a flat probability of first seeing *as a repetition* curve was generated. In contrast, if the probability of first seeing the target increased across repetitions, as it would if evidence accumulated, then an increasing probability of first seeing *as a repetition* curve was generated; see figure B1 in the appendix of Avilés, Bowman & Wyble (2020).

Reanalysis: The key step to assessing the probability of first seeing as a repetition in T&T's data, is to determine for any number of presentations, i, the number of times that the repetition would have *already* been seen within $i - 1$ presentations. As already discussed, a natural way to do this is to consider the cumulative probability; indeed Bowman & Avilés (2022) mathematically verified that this cumulative approach is consistent with the probability of first seeing as a repetition intuition. The cumulative approach proceeds as follows:

1. We are interested in the cumulative probability that the target has been consciously perceived at least once as a repetition by presentation i. We denote this as, $cp(i)$. For example, in figure 1[B main panel], $cp(3)$ is data point **b**, which also corresponds to the sum of two vertical solid double arrowed lines: **green** and **blue**.
2. The second concept is the proportion of trials for which the target has *not* been consciously perceived as a repetition by presentation i. This is denoted $np(i)$ and defined as,
$$np(i) = 1 - cp(i)$$
For example, in figure 1[B], $np(2)$ is the vertical **blue** *dotted* double arrow line.
3. "Repetitions detected by ith presentation" minus "repetitions detected by $(i - 1)$th presentation" gives the repetitions that one would expect to have been detected *for the first time* on the ith presentation. This corresponds to $cp(i) - cp(i - 1)$. For example, in figure 1[B] $cp3 - cp(2)$ is given by the **blue** vertical solid double arrowed line.
4. Using these concepts, we can now give a definition of the probability of first seeing as a repetition, denoted p_i above, as follows,
$$p_{(i+1)} = \frac{cp(i + 1) - cp(i)}{np(i)}$$
For example, in figure 1[B], $p_3 = (cp(3) - cp(2))/np(2)$ corresponds to a fraction formed from vertical double arrowed lines, i.e. dark **blue** solid divided by dark **blue** dotted.
5. Again, the key property that underlies our claims is *invariance to number of repetitions*, i.e. $\forall i, j \in \mathbb{N}\ (2 \le i, j \le N)\ \cdot\ p_i = p_j$.

This then enables us to calculate what we are interested in from T&T's data, giving us the results shown on the left in Figure 1[C]. We only present data points associated with the rising arm of the curve from T&T, since the data saturates at a lower ceiling than 100%.

Model comparison: In Figure 1[C], there are two plausible models: 1) subliminal accumulation (the alternative hypothesis; see figure 1[A], case 2): curve increases with the number of presentations, i.e. slope is positive, and 2) subliminal dissipation (the null hypothesis; see figure 1[A], case 3): curve is horizontal, i.e. slope is zero. We operationalised the alternative hypothesis as a full Bayesian regression model, which incorporates positive or zero slopes, and the null hypothesis as a Bayesian regression model with just a constant term. For the model comparisons, the posterior distributions were sampled using the No U-Turn Monte Carlo Markov Chain Sampler (Hoffman & Gelman, 2014), implemented in the Python package PyMC3 (Salvatier et al., 2016).

We used leave-one-out-cross-validation (Vehtari et al., 2017) to determine the best fitting model, see right-side of Figure 1[C], and Bayes Factors were obtained using Savage-Dickey (Wetzels et al., 2009).

Results

For the model comparison, our results focus on the out-of-sample deviances, which are presented as open circles in Figure 1[C, right side]. For the One-distractor condition, the Full model (Intercept+Number of presentations, i.e. zero or positive slopes) performed better than the Null model (Intercept, i.e. zero slope), although the difference in deviance (0.29, SE=2.37) was inconclusive, as was the Bayes Factor (BF_{10}=1.83). For the Two-distractor condition, results were conclusive, with the Null model having the lowest deviance (best fit) (difference in deviance=1.96, SE=1.13) and the Null model's deviance did not fall in the confidence interval of the Full model's deviance. Consistent with this, the Bayes Factor for the Two-distractor condition indicated moderate evidence for the Null (BF_{01}=4.01).

With respect to this Null finding, a possibility that we cannot completely exclude is that there is unconscious evidence accumulation, but its occurrence in the data is counteracted by another effect that reduces across presentations. A candidate for this reducing effect would be variability in the ease with which different images can be perceived in RSVP, with easy repeating images perceived with high probabilities of detection, on earlier presentations and hard with lower probabilities, on later presentations. However, in order to generate a completely horizontal probability of first seeing as a repetition curve, these two effects would have to perfectly counteract each other, which may be considered unlikely. Investigation of this alternative explanation awaits further research.

Additionally, T&T observed above chance recognition (in a final memory recognition test) for repeating images that were not detected as repeating. However, it could be that this residual memory is exclusively due to images that are repeated but only consciously perceived once. As a result, these images would not be seen as repeating, but would be recognizable. Additionally, the increase in memory through repetitions could be due to recency effects and/or an increasing probability of perceiving a stimulus (although not seeing it as repeating) with the number of presentations.

Discussion

Thus, our findings suggest that, at least in the Two-distractor condition, first break-through into awareness may be totally uninfluenced by the number of previous presentations. This suggests that the registration of a stimulus in RSVP dissipates rapidly, if that registration does not itself generate a break-through into awareness. Given the suggested link between performance on the repetition task and statistical learning, such dissipation indicates that stimuli presented amongst competitors (as is the case in RSVP) that are not consciously perceived need to be repeated very rapidly for learning to occur. Once there is an SOA more than perhaps 220ms between repetitions, representations do not accumulate consciously and thus, do not seed learning. Additionally, an SOA of 220ms is small; indeed, one might argue that such brief intervals between presentations are extremely rare in the real world.

The essence of the repetition task is that a stimulus only becomes salient when it is repeated, e.g. it is not salient on its first presentation, but a trace of that first presentation needs to endure in order that it can be observed as salient on future presentations. Thus, a precondition for the brain being able to perform the repetition task is that it exhibits what could be called *incidental durability*, i.e. builds resilient memories for stimuli that are currently *not* salient. The finding of a flat curve for the probability of first seeing as a repetition for the Two-distractor condition suggests that incidental durability may be highly limited for subliminal representations. This in turn may suggest that the representation of episodic information, which is fundamentally incidental in nature, is only available consciously. This idea resonates with theories of conscious experience proposed by us, *the tokenized percept hypothesis* (Avilés, Bowman & Wyble, 2020) and Kanwisher (2001).

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