

## Research Report

# Visual Memory Decay Is Deterministic

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**ABSTRACT**—*After observers see an object or pattern, their visual memory of what they have seen decays slowly over time. Nearly all current theories of vision assume that decay of short-term memory occurs because visual representations are progressively and randomly corrupted as time passes. We tested this assumption using psychophysical noise-masking methods, and we found that visual memory decays in a completely deterministic fashion. This surprising finding challenges current ideas about visual memory and sets a goal for future memory research: to characterize the deterministic “forgetting function” that describes how memories decay over time.*

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The ability to form memories is crucial to human perception and cognition. Given the important role memory plays in perceptual processing, it is not surprising that the decay of short-term perceptual memories over time has long been a source of great interest (Kennedy, 1898; Laming & Scheiwiller, 1935; Lee & Harris, 1996; Magnussen & Greenlee, 1999; Sperling, 1960; Stigler, 1978). Most models of perceptual memory assume that short-term memories decay in a random fashion (Cornelissen & Greenlee, 2000; Durlach & Braida, 1969; Inui, 1988; Kinchla & Smyzer, 1967; Sakai & Inui, 2002). For instance, the influential diffusion model (Kinchla & Smyzer, 1967) proposes that when one first views a pattern, it is encoded in some representational scheme, and that over time one forgets the encoded pattern as the representation takes a random walk through the representational scheme, drifting further and further from the initial, correct representation as time passes. This theory and other stochastic theories imply that when one sees and forgets the same visual pattern several times, one forgets the pattern in a different way each time. In the language of signal detection

theory (Green & Swets, 1966), such theories assert that visual memory decay occurs because of the gradual accumulation of noise in visual representations over time.

An alternative possibility that has been largely overlooked is that memories may decay deterministically. For example, one of the few theories that takes this approach suggests that decay of short-term visual memory involves a progressive loss of fine details, as if the memory were being blurred by coarser and coarser optics with the passage of time (Harvey, 1986). If such a deterministic decay process takes place in short-term memory, this would imply that a repeatedly viewed pattern decays in the same way each time it is encoded and forgotten. That is, rather than decaying because noise accumulates over time, memories may instead decay in a nonrandom way.

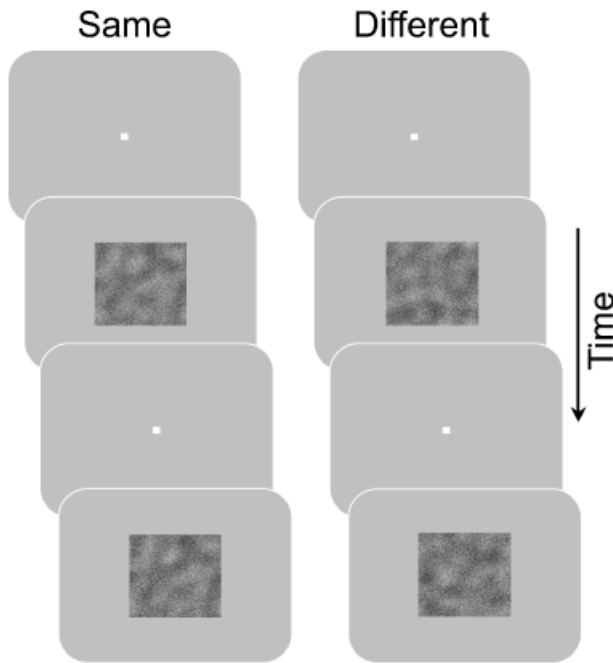
To distinguish between these two broad classes of theories, we used two psychophysical measurement techniques: external noise masking (Gold, Bennett, & Sekuler, 1999; Gold, Sekuler, & Bennett, 2004; Legge, Kersten, & Burgess, 1987; Lu & Doshier, 1999; Pelli, 1990; Pelli & Farell, 1999; Tjan, Braje, Legge, & Kersten, 1995) and double-pass response consistency (Burgess & Colborne, 1988; Gold et al., 1999, 2004). Contrary to the predictions of nearly all models of visual memory, both techniques showed that internal noise plays no role in the decay of short-term visual memory.

## EXTERNAL NOISE MASKING

In our first experiment, 5 naive observers performed a same/different discrimination task. On each trial, observers viewed a texture pattern (128 × 128 pixels, 2.6° × 2.6°) on a computer monitor, then a blank screen for an interstimulus interval (ISI) of 100, 500, or 2,000 ms, and finally a second texture pattern (see Fig. 1). A positive-contrast central fixation point (2 × 2 pixels, 0.04°) preceded the stimulus display for 500 ms and also appeared for the duration of the ISI. The task was to judge whether the two texture patterns were the same or different. The textures

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**Fig. 1.** Illustration of the sequence of events on *same* (left) and *different* (right) trials. On each trial, two texture patterns corrupted by Gaussian white noise were presented in successive intervals, separated in time by a variable interstimulus interval (100, 500, or 2,000 ms). The textures were identical in each interval on *same* trials and were different on *different* trials. However, the noise added to each interval was unique for both kinds of trials. Observers were asked to indicate whether the underlying textures were the same or different.

were random samples of band-pass Gaussian noise (uniform average power spectral density over 2–4 cycles per image; 0.77–1.54 cycles/deg), which had bloblike spatial features that varied in location, shape, and size. We used these textures to make it unlikely that observers would use verbal coding strategies to perform the task. On half of the trials (*same* trials), the same texture sample was shown in the first and second stimulus intervals, and on the other half (*different* trials), different texture samples were shown. After each trial, accuracy feedback was given in the form of a high or low beep.

The texture patterns in both intervals were shown in white Gaussian masking noise: A random luminance increment or decrement was added to each stimulus pixel. On each trial, the standard deviation of the Gaussian masking noise was randomly set to one of five values (power spectral density =  $0.02 \times 10^{-6}$ ,  $0.04 \times 10^{-6}$ ,  $1.30 \times 10^{-6}$ ,  $7.32 \times 10^{-6}$ , or  $41.17 \times 10^{-6}$  deg<sup>2</sup>). Independent samples of masking noise were shown in the first and second intervals, and consequently even on *same* trials, the stimuli in the first and second intervals were slightly different (i.e., the texture patterns were the same, but the masking noise samples were different). We varied the contrast energy (i.e., integrated squared contrast) of the texture patterns across trials according to an adaptive staircase procedure, in order to measure the texture contrast required for 71% correct performance at each of the five levels of masking noise. There was

not enough time in a single 1-hr session to measure thresholds for all ISIs, so we ran each ISI separately, in either one (100- and 500-ms ISIs) or two (2,000-ms ISI) 1-hr experimental sessions. The order of ISI conditions across sessions was randomly assigned for each observer.

Human performance in psychophysical discrimination tasks has often been modeled successfully as a two-stage system (Burgess, Wagner, Jennings, & Barlow, 1981; Gold et al., 1999; Legge et al., 1987; Pelli, 1990) that involves the addition of an internal noise of fixed variance (*contrast-invariant* internal noise) to the external stimulus, followed by a contrast-invariant calculation (e.g., a template match) that results in the observer's identification response. According to this model, human thresholds in various levels of externally added Gaussian noise will follow the form

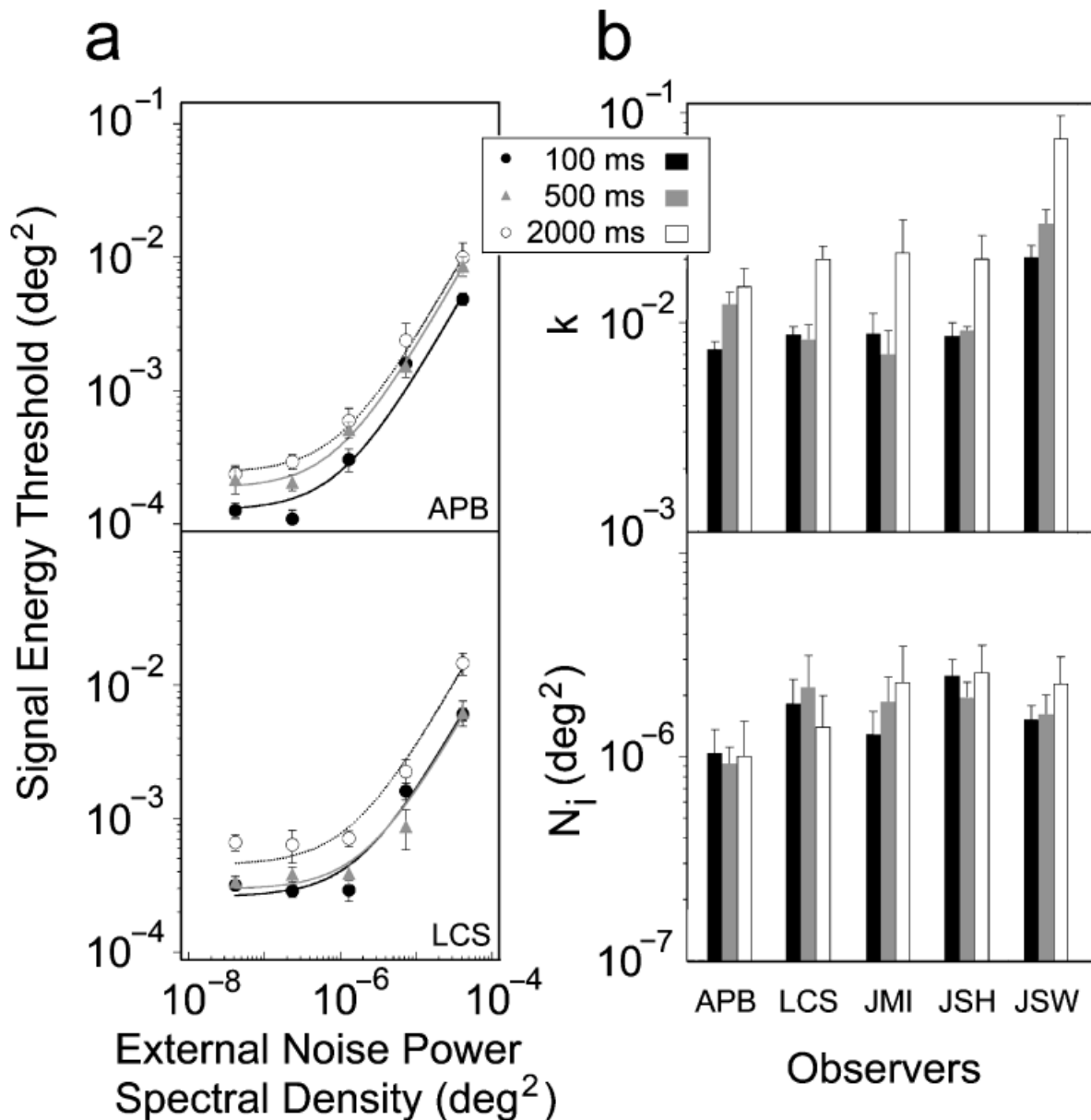
$$E = k(N_e + N_i) \quad (1)$$

where  $E$  is the observer's contrast energy threshold,  $N_e$  is the power spectral density of the externally added noise,  $N_i$  is the power spectral density of the contrast-invariant internal noise, and  $k$  is inversely proportional to the goodness, or *efficiency*, of the observer's calculation.

With each ISI, observers were forced to remember the texture patterns for a different amount of time. We determined what effect varying the delay between intervals had on contrast-invariant internal noise ( $N_i$ ) and the efficiency of internal calculations ( $k$ ) underlying performance in our pattern-matching task.

Figure 2 summarizes the results of this experiment. Figure 2a plots signal energy thresholds as a function of external-noise power spectral density for 2 representative observers at each of the three ISIs. The lines are the weighted least-squares fits of Equation 1 to the observers' thresholds at each ISI. In these log-log plots, an increase in  $N_i$  would raise thresholds only at low levels of external noise, whereas an increase in  $k$  would raise thresholds uniformly across all levels of external noise (Gold et al., 2004; Pelli, 1990). The graphs clearly show that increasing the ISI increased  $k$  but had little or no effect on  $N_i$ , indicating that memory decay in our task was the result of a decrease in calculation efficiency and not an increase in contrast-invariant internal noise. The effect of ISI on increases in  $k$  from the 100- to the 2,000-ms conditions was large according to Cohen's  $d$  ( $d > 2.7$ ,  $r > .8$ ); the effect of ISI on changes in  $N_i$  from the 100- to the 2,000-ms conditions was small (absolute  $d < 1.0$ ,  $r < .4$ ) and varied in direction across observers. Figure 2b highlights the effect of varying ISI by plotting  $k$  and  $N_i$  for all 5 observers in each ISI condition.

Although the model described by Equation 1 incorporates a contrast-invariant internal noise source whose variance is independent of stimulus contrast, there is both physiological (Tolhurst, Movshon, & Thompson, 1981) and psychophysical (Burgess & Colborne, 1988) evidence for a second source of internal noise whose variance grows in proportion to stimulus contrast (*contrast-dependent* internal noise). Like a decrease in calculation efficiency, an increase in contrast-dependent



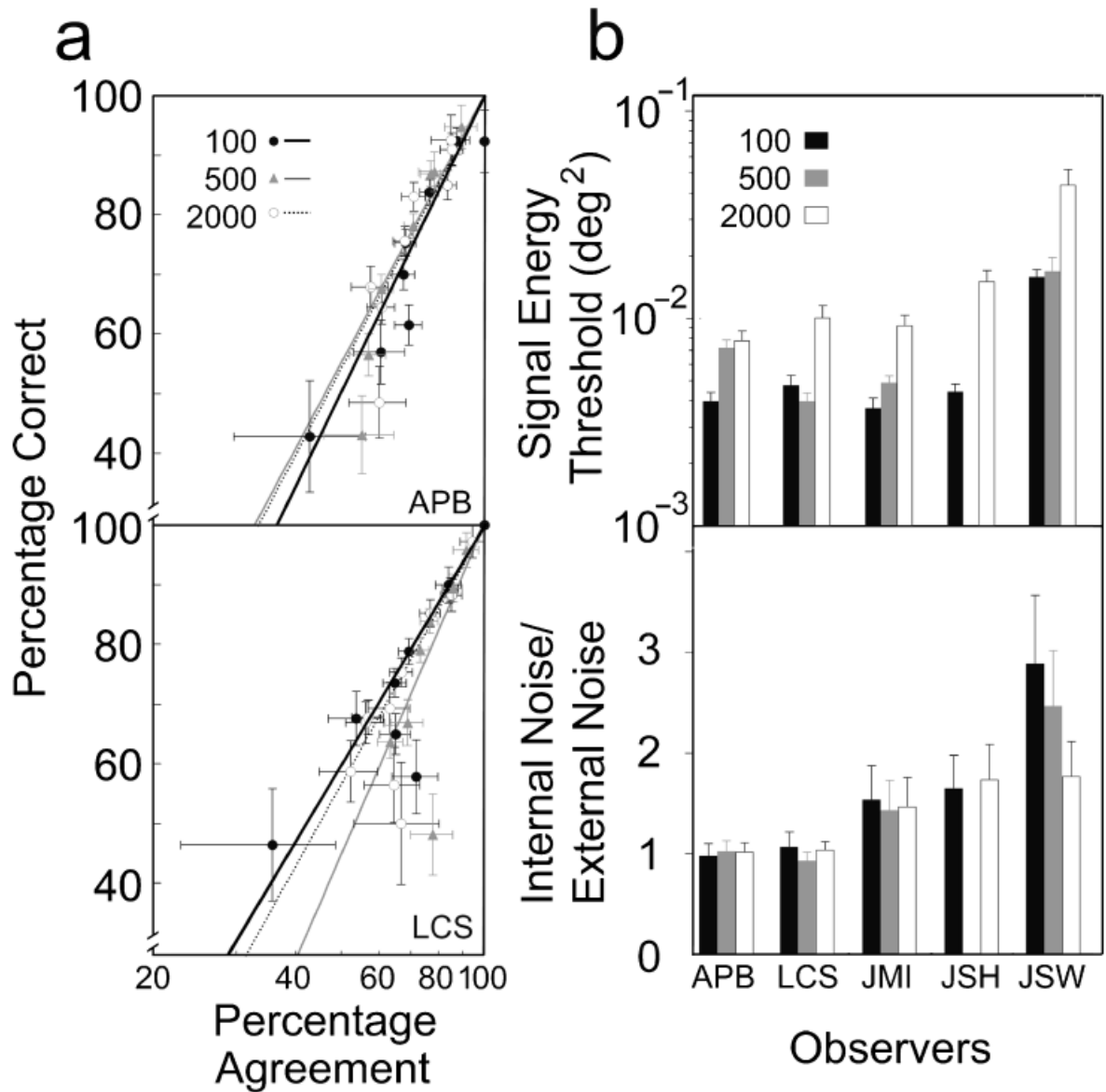
**Fig. 2.** Results from the first experiment. In (a), same/different discrimination thresholds are plotted as a function of external-noise spectral density for 2 representative observers at each interstimulus interval (100 ms, 500 ms, and 2,000 ms). The line passing through each set of symbols corresponds to the weighted least-squares fit of the data to Equation 1 (see the text). Error bars correspond to  $\pm 1$  standard deviation (determined by bootstrap simulations; Efron & Tibshirani, 1993). The histograms (b) present indexes of calculation efficiency ( $k$ ; upper panel) and estimates of contrast-invariant internal noise ( $N_i$ ; lower panel) for all 5 observers at each interstimulus interval; error bars correspond to  $\pm 1$  standard deviation.

internal noise will increase the value of parameter  $k$  in Equation 1 (Gold et al., 1999, 2004); consequently, the effects of deterministic changes in calculation efficiency and contrast-dependent internal noise are indistinguishable using the noise masking procedure of our first experiment.

#### DOUBLE-PASS RESPONSE CONSISTENCY

To determine the contribution of contrast-dependent internal noise to the changes in  $k$  observed in our first experiment, we

conducted a second experiment using a double-pass response-consistency procedure (Burgess & Colborne, 1988; Gold et al., 1999, 2004; Green, 1964; Spiegel & Green, 1981). Each observer performed the same task as in the previous experiment, but with only the highest level of external noise. In addition, each subject made a second pass through an exact duplicate of each trial sequence within each experimental session (i.e., the identical stimuli, including both the textures and the external noise, were shown on corresponding trials in the two passes). An observer with no internal noise would make the same response



**Fig. 3.** Results from the second experiment, which used a double-pass response-consistency procedure. In (a), percentage of correct responses is plotted as a function of percentage of agreement on corresponding trials for 2 representative observers at each interstimulus interval. Each symbol corresponds to performance at a given stimulus level, and error bars correspond to  $\pm 1$  standard deviation. The line passing through each set of symbols corresponds to the weighted least-squares fit of the data to the equation  $p_c = m \log_{10}(p_a/100) + 100$  (see the text). The histograms (b) present same/different discrimination thresholds (top panel) and ratios of internal to external noise (bottom panel) for all 5 observers at each interstimulus interval; error bars correspond to  $\pm 1$  standard deviation. One observer (J.S.H.) was not able to finish the experiment and perform the task with the 500-ms interstimulus interval.

when a stimulus is presented in the second pass as when it was presented in the first pass. However, an observer with internal noise would exhibit some inconsistency between the two passes, with greater amounts of internal noise resulting in lower consistency. The degree of response inconsistency can be used to estimate the ratio of internal to external noise (Burgess & Colborne, 1988; Gold et al., 2004). The use of high-contrast external noise ensures that any inconsistency between the two passes will be almost exclusively due to the effects of contrast-dependent internal noise (Gold et al., 2004).

The results of this experiment are shown in Figure 3. Figure 3a plots the percentage of correct responses at each level of signal contrast, as a function of the percentage of agreement of responses between corresponding trials in the two passes, separately for each ISI (same 2 representative observers as shown in Fig. 2a). As in the first experiment, the signal contrast was varied across trials according to a coarsely sampled adaptive staircase procedure. Each line passing through the symbols in Figure 3a corresponds to the least-squares fit of the equation  $p_c = m \log_{10}(p_a/100) + 100$  to the data at a particular ISI (where  $p_c$  is

percentage correct,  $p_a$  is percentage agreement, and  $m$  is a fitted parameter that determines the slope of the line; Gold et al., 1999, 2004). An increase in contrast-dependent internal noise with increasing ISI would decrease the percentage of agreement between the two passes for a given level of percentage correct, resulting in shallower slopes for longer ISIs in these plots. Contrary to this prediction, the slopes show no significant change for either observer, despite a significant effect of ISI on threshold (top panel of Fig. 3b).

We also used the relationship between percentage correct and percentage agreement to derive estimates of the ratio of internal to external noise (i.e., the ratio of the standard deviations of the contrast-dependent internal noise and the externally added stimulus noise) for all 5 observers at each ISI (lower panel of Fig. 3b; Burgess & Colborne, 1988; Gold et al., 1999, 2004). For all but 1 observer, these estimates were invariant over changes in ISI, indicating that memory decay did not result from an increase in contrast-dependent internal noise. In fact, the observer for whom the estimates varied across ISI (J.S.W.) showed a small decrease in the ratio of internal to external noise as ISI increased.

Taken together, our results indicate that visual memory decay is not the result of a random corruption of visual representations over time, but is instead due to deterministic changes in the fidelity of observers' memory traces. Moreover, our results imply that the effects of short-term memory decay can be characterized and predicted in their entirety by a deterministic "forgetting function" that maps the visual representation of a stimulus to the representation  $t$  seconds later, after the initial representation has undergone memory decay. A corollary of this finding is that if one knew the forgetting function exactly, one could use it to reduce or even eliminate the effects of memory decay. For example, imagine that on the *same* trials in a same/different task like the one in our experiments, the stimulus in the second interval were the same stimulus shown in the first interval modified by the forgetting function. In effect, the second stimulus would resemble the memory trace of the first stimulus after it had undergone memory decay during the ISI, making it easier for observers to recognize that the two stimuli were the same. By modifying visual patterns this way, using the forgetting function, it may be possible to improve performance on a wide range of important tasks that rely on short-term visual memory.

One candidate for the forgetting function is a process similar to the one we described earlier: Fine details may be systematically removed from the representation over time according to a time-dependent blurring function (Harvey, 1986). Another possible model is one in which, over time, local stimulus regions are deleted in an orderly fashion from the internal stimulus representation on the basis of some aspect of the stimulus such as contrast or visual eccentricity. These two possibilities are by no means exhaustive, but they illustrate an important new direction for memory research that follows from our finding that decay of short-term visual memory is deterministic.

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