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A Theory Of Visual Information Acquisition and Visual Memory with Special Application to Intensity-Duration Tradeoffs

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We describe a theory of memory for visual material in which the visual system acts as a linear filter operating on a stimulus to produce a function, a(t), relating some *sensory response* to t, the time since stimulus onset. Stimulus information is acquired at a rate proportional to the product of (1) the magnitude by which a(t) exceeds some threshold and (2) amount of as-yet-unacquired information. Recall performance is assumed to equal proportion acquired information. The theory accounts for data from two digit-recall experiments wherein stimulus temporal waveform was manipulated. We comment about the theory's account of the relation between two perceptual events: the *phenomenological experience* of the stimulus and the memory representation that accrues from stimulus presentation. We assert that these two events, although influenced by different variables, can be viewed as resulting from two characteristics of the same sensory-response function.

We are concerned here with perception of and memory for complex visual stimuli. By "complex" we mean stimuli such as alphanumeric characters, words, or naturalistic scenes, that must be pattern recognized, interpreted, and processed by the cognitive system, rather than simple, to-be-detected light patches or sine-wave gratings. Our major goal is to incorporate a model that has been successfully used to account for a variety of low-level visual phenomena (e.g., time-intensity tradeoffs, and flicker perception) into a broader theory designed to account for higher-level cognitive tasks such as recall and picture recognition.

Our theory development is motivated in part by the substantial body of research implying intimate perceptual connections between stimulus duration on the one hand, and stimulus intensity on the other. Before describing the theory we will, accordingly, provide a brief sketch of this research, and describe an experiment designed to relate it to memory for visual material.

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Bloch's Law: Strong Intensity-Duration Tradeoffs with Simple Visual Stimuli

The most fundamental duration-intensity relation is captured in *Bloch's Law*, which asserts that for stimuli shorter than some critical duration (around 100 ms) there is an almost perfect tradeoff between intensity and duration with respect to threshold detection performance. Essentially, detection performance in the critical range depends only on the integral of intensity, irrespective of how this intensity has been distributed over time. Bloch's Law has been confirmed many times, but almost always within the context of simple stimuli and simple tasks[1].

[1] Instances of these confirmations are: Hood & Grover (1974), Kahneman (1968), Kahneman & Norman

Weaker Intensity-Duration Tradeoffs with Complex Visual Stimuli

Does Bloch's Law apply within the context of more complex stimuli and/or using memory tasks rather than threshold detection tasks? This question is important, as an affirmative answer would set the stage for modifying models originally designed to account for low-level perceptual tasks in such a way as to account for higher-level cognitive tasks as well.

The answer to this question is thus far unclear. Memory for complex visual stimuli has been found to improve with greater stimulus duration (e.g., Loftus & Kallman, 1978; Potter & Levy, 1969; Shaffer & Shiffrin 1972) and also with greater stimulus intensity (e.g., Loftus, 1885; Loftus, Kaufman, Nishimoto, & Ruthruff, 1993). However, the only exact measurement of the duration-intensity relation using complex stimuli in a memory task was reported by Turvey (1973) who found a data pattern conforming to Bloch's Law with respect to memory for digit trigrams in a backward-masking paradigm. Provocative though it was though, this finding was ancillary to Turvey's major goals (which principally involved an empirical and theoretical investigation of masking); also, Turvey's duration and intensity ranges were limited.

Loftus (1985; Loftus et al., 1993a; see also Sperling, 1986) found evidence for a weak form of intensity-duration tradeoff with complex pictures whose memory was tested in both short-term and long-term memory tasks: Specifically, lowering intensity required that duration be increased by some factor k (referred to as the "slowdown factor") to achieve some criterion memory performance. Within certain boundary conditions, the slowdown factor was independent of the particular criterion performance level that was chosen, i.e., the relation between intensity, φ, and duration, d, could be described by,

$$p(d, \varphi_1) = p\,(kd, \varphi_2) \qquad \text{Eq. 1}$$

where p(x, y) is performance for a stimulus of duration x and intensity y, $\varphi_1 > \varphi_2$ and $k > 1.0$. Such a finding is consistent with the proposition that decreasing intensity simply slows down perceptual processing by the slowdown factor, k, without otherwise affecting the system.

The multiplicative relation between intensity and duration implied by Equation 1 is necessary, but not sufficient, to infer a simple Bloch's-Law relation in a relatively complex memory task. To show that Bloch's Law held would require determining that in Equation 1, $\varphi_1 = k\varphi_2$. However, no existing experiment provides the data necessary make such a determination. In some relevant experiments, the stimuli were complex, naturalistic color photographs. Here, each stimulus included a wide range of colors and intensities, and stimulus intensity couldn't be precisely measured; thus only qualitative conclusions were possible, viz., the less intense the stimuli, the greater the slowdown factor (Loftus, 1985; Loftus, et al., 1993a). In other experiments the complete intensity/slowdown function could not be characterized because either the range of stimulus durations and/or the range of stimulus intensities was too small and/or use of a backward mask obscured conclusions made purely on the basis of duration and intensity (e.g., Turvey, 1973; see Eriksen, 1980, for a discussion of problems making conclusions based on data from experiments in which a mask is used). It was to fill this empirical void that we carried out Experiment 1.

Experiment 1: Measurement of Duration-Intensity Tradeoffs in a Digit-Recall Paradigm

Experiment 1 was designed to allow precise measurement of the function relating the slowdown factor to stimulus intensity in a memory task. To accomplish this, we used simple black-on-white digit arrays as stimuli, along with a relatively wide range of both duration and intensity. Both duration and intensity were precisely controlled.

Method

The basic procedure consisted of a series of *trials.* On each trial, a four-digit string was presented for some exposure duration on the order of 5 - 150 ms. The observer's task was to immediately report as many of the digits as

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(1964), Kaswan & Young (1963), Raab & Fehrer (1962), and Zacks (1970). Reveiws are provided by Watson (1986) and Wasserman and Kong (1979, plus associated commentaries) possible in their correct positions, guessing if necessary.

Observers

Four observers participated in the experiment: the two authors (GL and ER), an undergraduate (KG) and a graduate student (CA). All observers were familiar with the purposes of the experiment. All observers were highly practiced, having participated in a minimum of 3000 practice trials prior to beginning the experiment.

Stimuli and Apparatus

Stimuli were prepared as 35-mm slides. A stimulus consisted of a 4 (columns) x 3 (rows) array of black digits on a white background. Eighty such stimuli were prepared and used repeatedly. The 4 x 3 x 80 = 960 digits comprising all stimuli were selected randomly and without replacement from the set of ten digits. Each digit subtended a visual angle of 0.56^{o} vertically, and 0.28^{o} horizontally. Digits were separated by 0.37^{o} vertically, and 0.74^{o} horizontally. On a given experimental trial, one four-digit row of one stimulus was the to-be-reported target. Target row was blocked over trials; accordingly, an observer always knew which row was the target.

Intensity control was accomplished by attenuating stimulus luminance using a Wrattan neutral-density filter[2]. Each observer viewed stimuli at four different intensity levels. For two observers (GL and ER) intensity ranged from 1.33 to 7.84 cd/m^2. The other two observers (CA and KG) were substantially better at the task; to avoid ceiling performance, their intensity levels were lower, ranging from 0.90 to 4.10 cd/m^2. A summary of luminances, contrasts, and intensities for the four observers is provided in Table 1.

All stimuli were displayed via Kodak projectors equipped with Gerbrands tachistoscopic shutters. A random-access projector was used to display the stimuli, while standard carousel projectors were used to present a constant, uniform adapting field, and a fixation point that initiated each trial. Responses were made on a numeric keypad. All display equipment was enclosed in a soundproof box. All display and response collection was under the control of an AT-compatible computer system described by Stoddard and Loftus (1988).

Design and Procedure

For each observer, 24 conditions were defined by four intensity levels and six exposure durations within each intensity level. The exposure-duration values within each intensity level were selected with the goals of (1) producing roughly equal performance ranges within each intensity level (which meant that durations within the lower intensity levels had to be suitably longer than corresponding durations within the higher intensity levels) and (2) maintaining performance (proportion of correctly recalled digits) within a range of roughly 0.1 - 0.9.

Within each observer's intensity level, the six exposure durations were specified by two experimental parameters: *base*, the minimum duration, and *factor*, the amount by which each duration was multiplied to obtain the next higher duration. Table 2 provides these parameters for each of the 16 observer/intensity level combinations.

Each observer participated in 24 *blocks* of 80 trials per block. Recall that stimuli were prepared as three, four-digit rows. On any given block, only one row (top, middle, or bottom) was the to-be-reported target. Also, stimulus intensity remained constant over a block. Intensity was changed on a given block by adjusting the luminance of the target-slide projector via the neutral-density filters. A uniform adapting field remained at a constant level (of 21.21 cd/m^2) at all times during an experimental session.

The sequence of events for a given 80-trial block was as follows. First, the observer ascertained that the filter configuration was correct for that block's intensity level (noting in the process what the stimulus intensity would be on that block). Next, a high, medium, or low

[2]There are numerous ways of defining intensity. We defined "contrast" to be the difference between background and foreground luminance divided by the sum of background and foreground luminance. Intensity was then defined to be the product of contrast and background luminance. This definition was appropriate to the nature of our display apparatus which, unfortunately, did not allow contrast variation without concommitant variation in background intensity. Other definitions of intensity (or simply using contrast rather than intensity) did not materially change our results or our conclusions.

Table 1
Summary of Background Luminances, Foreground (Digit) Luminances, Contrasts, and Intensities for each of the Four Observers. Luminances and Intensities are in cd/m^2

Observers: CA and KG	**Intensity**			
	Level 1	**Level 2**	**Level 3**	**Level 4**
Background	23.961	25.200	27.531	31.689
Digits	22.218	22.680	22.890	24.423
Contrast	0.038	0.053	0.092	0.129
Intensity	0.904	1.326	2.534	4.103

Observers: GL and ER	**Intensity**			
	Level 1	**Level 2**	**Level 3**	**Level 4**
Background	25.200	27.531	31.689	37.926
Digits	22.680	22.890	24.423	24.927
Contrast	0.053	0.092	0.129	0.207
Intensity	1.326	2.534	4.103	7.844

tone (2000, 1000, or 500 hz) signaled the observer that the top, middle, or bottom row would be the target row for that block (i.e., for the next 80 trials). Next, eight practice trials were presented. The durations for these practice trials were selected randomly, and without replacement. Next, 72 experimental trials were presented. The six durations were randomly intermingled over the 72 trials, with the restriction that each duration occurred 12 times. Stimulus-presentation order was quasi-random[3].

[3]The 80 stimulus slides were fixed in the 80 slots of a carousel tray. We wanted to preclude observers' ability to memorize and make use of sequential, slide-to-slide information (e.g., we did not want middle row "7184" to always follow middle row "0072.") We accomplished this goal as follows. On each block, the 72 experimental stimuli were randomly divided into two 36-stimulus groups (Group A and Group B). The carousel circled twice within each block: on pass 1, all Group A stimuli were shown, and on pass 2, all Group B stimuli were shown. This scheme insured that stimulus ordering differed unpredictably from one block to the next.

The to-be-reported row was changed systematically over blocks (in a top-middle-bottom-top... sequence); thus, each row served as target in eight of the 24 blocks. Assignment of durations to trials within a block was also changed over blocks. As noted, intensity also changed over blocks. Each intensity level occurred once within each four-block sequence. Although observers were not forced to participate in all 24 blocks at once, they were constrained to participate in four-block modules, each of which incorporated all four intensity conditions. The 24 total blocks for each observer included two instances of each of the 12 intensity-level/to-be-reported-row combinations.

As noted, a block consisted of 80 trials. The sequence of events within each trial was as follows. First, a 500-ms tone warned the observer to look at a small fixation point which simultaneously appeared, superimposed over the adapting field, positioned such that it would be in the middle of the upcoming stimulus (i.e., between the second and third digits of the middle row). Warning-tone frequency was 2000, 1000, or 500 hz and reminded the observer which row (top, middle, or bottom) was the target during the current block. Following

ing tone was the stimulus, superimposed on the adapting field, presented for its appropriate duration. The observer typed in four responses after stimulus presentation, guessing on a digit if uncertain. Following responding, there was feedback in the form of four 150-ms beeps. Each beep was 2000 hz if the corresponding digit had been correctly reported, and 500 hz if the corresponding digit had not been correctly reported. Following feedback was a 300-ms interval prior to the start of the next trial.

Results

Our basic performance measure, p, is the proportion of digits recalled in the correct position (corrected for the 0.10 chance rate).

Performance Curves

We present our data in the form of *performance curves* which are functions relating performance to exposure duration with different curves for different intensity levels. Past work using this paradigm (e.g., Busey & Loftus, 1993; Loftus, Duncan & Gehrig, 1992; Loftus, Busey, & Senders, 1993; Shibuya & Bundesen, 1988; Townsend, 1981) indicates that performance curves can be described almost perfectly by the equation,

$$p = \begin{cases} 0 & \text{for } d \le L \\ A(1.0 - e^{-(d-L)/c}) & \text{for } d > L \end{cases} \qquad \text{Eq. 2}$$

where A, L, and c are free parameters. The interpretations of the parameter values are as follows. First, L (mnemonic for "liftoff") is the performance curve's d-intercept, i.e., the minimum stimulus duration necessary for above-chance performance. Second, c is the post-liftoff duration (i.e., the duration exceeding L) required for performance to reach a criterion level of p = A(1.0 - 1/e) Finally, A is asymptotic performance. In the present paradigm, observers had the capability of reporting all four digits perfectly following sufficiently long exposure durations; thus any less-than-1.0 A values resulted from keypress errors, lack of vigilance, etc[4]. Accordingly, the value of A is

Table 2

Parameters for Generating Exposure Durations for each Observer and Intensity Level. beginning with the Lowest Duration ("Base" in ms) Each Successive Duration was Computed by Multiplying its Predecessor by "Factor"

		Observer			
Intensity		**CA**	**KG**	**GL**	**ER**
Level 1	base	26	16	18	33
	factor	1.22	1.21	1.32	1.32
Level 2	base	18	13	10	14
	factor	1.23	1.18	1.40	1.32
Level 3	base	8	6	6	11
	factor	1.24	1.17	1.41	1.37
Level 4	base	6	5	3	6
	factor	1.23	1.17	1.38	1.32

the warning tone was the stimulus, superim-

uninteresting from the present perspective. We estimated A for each observer, but do not discuss it further[5].

For simplicity of analysis and discourse, we define a new dependent variable, P, to be: $P = -\ln(1.0 - p/A)$, which, given Equation 2, implies,

$$P = \begin{cases} 0 & \text{for } d \le L \\ (1/c)d - L/c & \text{for } d > L \end{cases} \qquad \text{Eq. 3}$$

That is, if Equation 2 holds, then the performance measure P is related linearly to duration

[4] To ascertain that the lower-than-1.0 asymptotic values are not perceptual effects, we carried out a control experiment in which stimuli were displayed as long as the observer wanted. After the observer signalled "enough," the stimuli were removed, and the observer responded. Performance was essentially 100%,

[5] The estimated asymptotes were: 0.90 (CA), 1.00 (KG), 0.97 (GL), and 0.89 (ER).

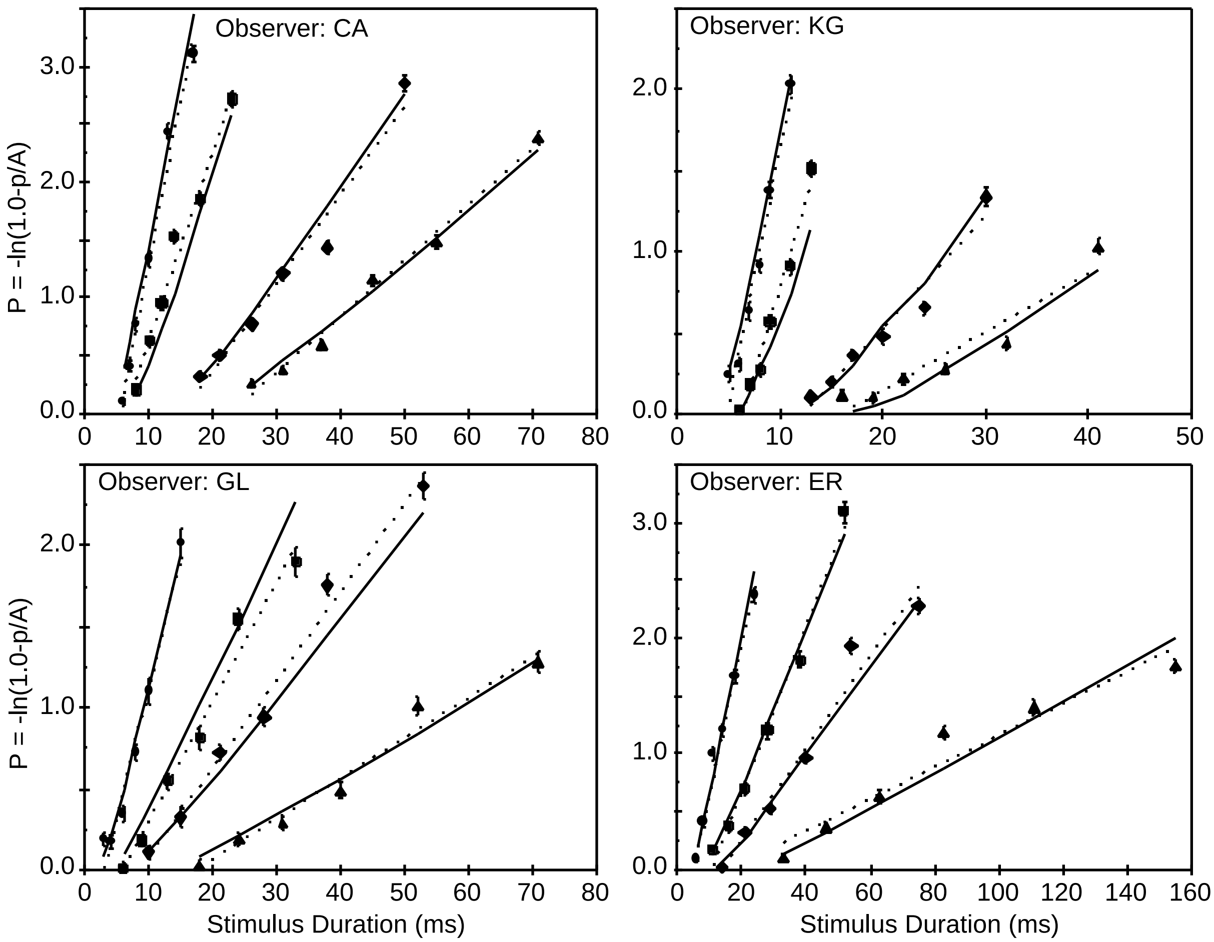

Figure 1. Experiment 1: Performance curves (recall performance measured in P = -ln (1.0 - p) as functions of stimulus duration). Each panel shows data from one observer. The four curves within each panel are for the four intensity levels. The curve symbols represent data points (lowest intensity: triangles; next intensity: diamonds; next intensity: squares; highest intensity: circles). Dashed lines are best linear fits, and solid lines are best fits from the theory described in the text.

with a slope of 1/c and a P-intercept of L/c. We assert that a performance curve's slope can be interpreted as the rate at which information is acquired from the stimulus: the greater the slope, the higher the information-acquisition rate. For the moment, we leave status of this assertion as "intuitively reasonable." Later, we will see that it is an implication of our theory.

Figure 1 shows the performance curves. Each panel shows one of the four observers; within each panel, the four curves represent the four intensity levels, with increasing intensities corresponding to leftward curves. The dashed lines through the data points are the best-fitting regression lines obtained via Equation 3. The solid lines are predictions from the theory that we describe below. The increasing performance-curve slopes with higher intensities indicate that with higher intensities, stimulus information is acquired at a higher rate. Table 3 provides the regression data—c, L, and Pearson r^2 values—for each observer and each intensity. Table 3 (bottom row) also provides root-mean-square errors between the data points and predicted regression values.

Two aspects of these data are notable. First, the performance curves are well fit by linear functions. Of the 16 curves, one produces a Pearson r^2 of 0.90, and the others all produce r^2's of 0.94 or higher. Nine of the 16 r^2's are 0.98 or higher. This replicates past data using this paradigm (Busey & Loftus, 1993; Loftus, et al. 1992; Loftus et al., 1993b; Shibuya & Bundesen, 1988). Second, the parameters c and

Table 3

Regression Fits for each Observer and each Intensity Level. Upper Rows Show Parameter Values and Pearson r^2 Values. Bottom Row Shows the Overall Root-Mean Square Errors

		Observer			
Intensity		**CA**	**KG**	**GL**	**ER**
Level 1	**c**	20.69	27.70	40.19	72.46
	L	22.59	15.94	17.27	16.02
	r^2	0.99	0.90	0.97	0.94
Level 2	**c**	13.11	14.45	18.39	25.22
	L	15.16	12.29	8.42	13.48
	r^2	0.96	0.95	0.99	0.97
Level 3	**c**	6.12	4.74	13.51	13.98
	L	6.13	6.26	5.91	10.55
	r^2	0.98	0.98	0.98	0.99
Level 4	**c**	3.53	3.18	6.27	8.09
	L	5.38	4.75	2.91	4.39
	r^2	0.98	0.98	0.97	0.99
RMSE (regressions)		0.155	0.110	0.113	0.153

Although there are deviations from linearity

L both decrease with increasing intensity. This means that with increasing intensity, (1) a smaller stimulus duration is required for performance to exceed chance (implied by decreasing L) and (2) once performance has exceeded chance, less additional stimulus duration is required to achieve any given criterion performance level (implied by decreasing c).

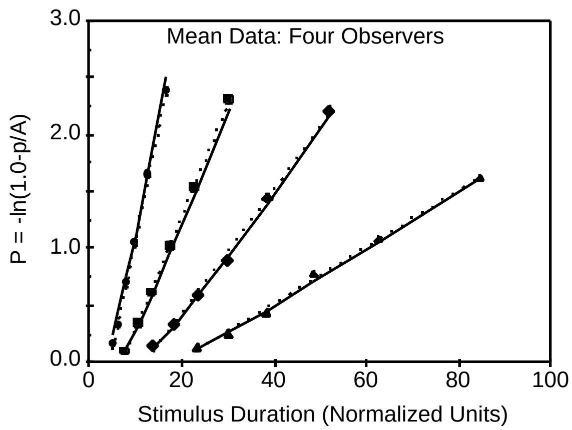

Figure 2. Experiment 1: Mean performance curves (recall performance as functions of duration, averaged across observers, normalized for different exposure durations). The four curves are for the four intensity levels. The curve symbols represent data points (lowest intensity: triangles; next intensity: diamonds; next intensity: squares; highest intensity: circles). Dashed lines are best linear fits, and solid lines are best mean fits from the theory described in the text.

Are the Performance Curves Fundamentally Linear?

there are deviations from linearity in the individual subject curves, they do not seem to be systematic. Figure 2 shows the mean performance curves (across observers), normalized for the different observers' different exposure durations. Again, dashed lines represent the best linear fits, and solid lines are to-be-described theoretical predictions. It is clear that the mean curves are highly linear; all r^2 values exceed 0.99. Accordingly, we conclude that individual deviations from linearity are nonsystematic, and that something very close to linearity (Equation 3) accurately describes performance curves in this paradigm.

Intensity-Duration Tradeoffs

So far we have merely shown that with higher intensity, performance increases faster with stimulus duration. We now consider the intensity/duration relations in more detail and in particular inquire whether they conform to Bloch's Law.

Our general logic is as follows. Consider some *criterion performance level*, P_C. Bloch's Law asserts that the product of duration, d, and

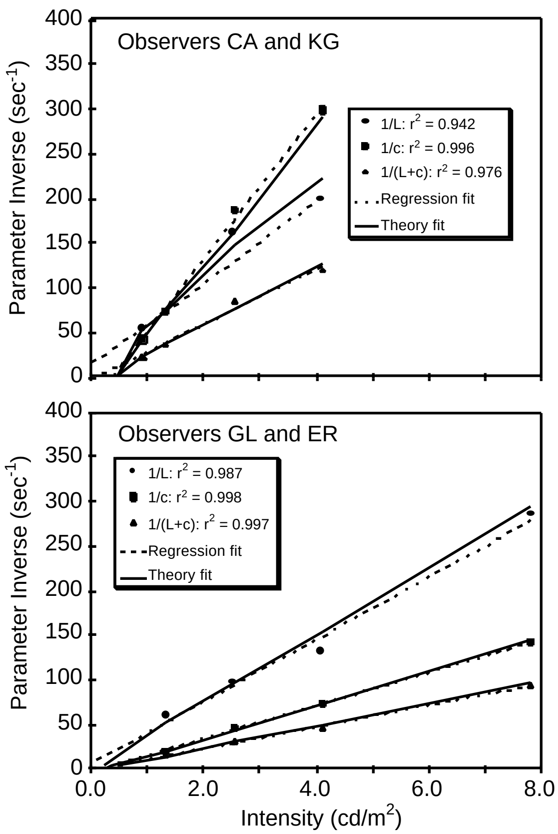

Figure 3. Experiment 1: Each panel shows 1/L, 1/c, and 1/(L+c) as functions of stimulus intensity averaged over two observers. Dashed lines are best linear fits, and solid lines are best fits from the theory described in the text.

the intensity, φ, required to achieve P_C is constant, i.e., that:

$$\varphi \times d = k_1$$

where k_1 is a constant, or

$$\frac{1}{d} = k_2 \times \varphi \qquad \text{Eq. 4}$$

where $k_2 = 1/k_1$ is also a constant. Thus, the prediction is that, across intensity levels, the reciprocal of d be linearly related to stimulus intensity with an intercept of zero.

What should we use as P_C, the criterion performance level? As indicated by the shape of our performance curves, increasing stimulus duration leads to two successive achievements. First, at duration L, performance rises above chance. Second, with additional duration beyond L, performance rises linearly. The Bloch's-Law prediction, Equation 4, can be tested for both these effects. Using as the first performance criterion the rise from chance that occurs at duration L ms, the prediction becomes,

$$\frac{1}{L} = k_L \times \varphi \qquad \text{Eq. 5}$$

where k_L is a constant.

Using as the second performance criterion the achievement of P = 1.0, which occurs at duration c following liftoff, the prediction becomes,

$$\frac{1}{c} = k_c \times \varphi \qquad \text{Eq. 6}$$

where k_c is a constant.

One important note is in order here. The criterion performance level of P = 1.0 used as a basis for determining the duration c is, of course, arbitrary. However, because the performance curves are linear beginning at duration L, using a different criterion performance level (call it P') would simply entail a rescaling of the original c values by a factor of P' across intensity levels. Equation 6 would still hold, although the constant of proportionality (k_c in Equation 6) would be different.

Equations 5 and 6 thus make analogous predictions for each of the performance-curve parameters, L and c: the parameter's reciprocal should be proportional to intensity, φ. For the record, we can also test an analogous "standard" Bloch's Law prediction which is that the *total* duration (L+c) required to achieve any criterion performance level trades off with intensity. This prediction is that,

$$\frac{1}{L+c} = k_{L+c} \times \varphi \qquad \text{Eq. 7}$$

where k_{L+c} is a constant. We must, however, regard the prediction of Equation 7 with some wariness, because unless the ratio, L/c, is constant across intensity levels, Equation 7's validity will depend on the particular performance level that is chosen. There is no apriori reason to expect any particular relation between L and c.

Recall that observers CA and KG had one intensity range, while observers GL and ER had a different intensity range. Figure 3 shows 1/L, 1/c, and 1/(L+c) as functions of intensity averaged over CA and KG (top panel) and over

GL and ER (bottom panel). As in Figures 1 and 2, the dashed lines represent the best linear fit, and the solid lines represent theoretical predictions to be discussed later. It is clear that the predictions embodied in Equations 5-7 hold quite well: as indicated in the figure legends, the curves are quite linear, and the intercepts are quite close to zero

Discussion

The purpose of Experiment 1 was to determine the relations between stimulus duration and stimulus intensity in a digit-recall task. Several findings emerged. First, in accord with other studies using this paradigm (e.g., Loftus, et al., 1992) performance as a function of stimulus duration was described well by a linear function (or by an exponential approach to an asymptote if proportion correct is the dependent variable). This finding, demonstrated in Figures 1 and 2, is interesting in and of itself, and is discussed in detail by Loftus, et al. (1993b). For present purposes, however, we regard this performance-curve simplicity as a convenient tool for carrying out other analyses.

In particular, the nature of the performance curves facilitated a detailed investigation of the relation between duration and intensity. As indicated in Figure 3, we discovered that Bloch's Law held quite well in terms of two fundamental durations and associated performance criteria. First, intensity traded off with L, the *initial* duration required for performance to exceed chance. Second, intensity traded off with the *additional* duration required to rise from chance to any criterion above-chance performance level. At the risk of redundancy, we reemphasize that this latter duration is equal to the regression parameter c if a criterion performance level of P = 1.0 is used. However, the linearity of the performance curves implies that the tradeoff between intensity and post-liftoff duration will hold independent of the particular above-chance criterion performance level that is chosen.

In addition to the tradeoffs between intensity on the one hand, and the durations L and c on the other hand, we discovered that intensity also trades off quite well with the *total* duration required to achieve above-chance performance. This observation indicates that the relation between the durations L and c is not arbitrary; rather, it is such that the ratio c/L is independent of intensity level.

In short, we have discovered strong regularities in the duration-intensity relation underlying performance in a digit-recall task. These regularities suggest that performance in this task can be described by a relatively simple theory of perception, memory, and immediate recall. We now describe such a theory.

A Linear-Filter/Information-Acquisition Theory

The theory we describe in this section is a concatenation of two components—models—that have been used in the past to describe two different domains: low level visual processes, and higher-level cognitive processes.

Overview

We refer to the first component as the *sensory-response model.* We assume, in particular, that the initial stages of the visual system act as a linear low-pass temporal filter that operates on a physical stimulus, to produce what we term a *sensory-response function*, designated a(t). This function relates the magnitude of some form of neural activity associated with stimulus presence to time, t, since stimulus onset[6]. This kind of temporal-filter model has been used to account for a variety of low-level visual phenomena such as flicker detection, and time-intensity relations in simple detection tasks (see Watson, 1986 for an overview); however linear-filter models have been used only sporadically to account for higher-level cognitive phenomena (e.g., Dixon & Di Lollo, 1993; Groner, Bischof, & Di Lollo, 1988).

The second component of the theory, termed the *acquisition-rate model* has been described by Loftus and his colleagues to account for relatively high level picture-processing tasks[7],

[6]The designation of the sensory response function as a(t) is historical. In previous formulations of the model, the a(t) function has been termed "proportion of available information" and was constrained to vary between 0.0 and 1.0. In the present formulation, the conceptual definition has been broadened and the range constraint has been dropped.

[7]See, for example, Loftus and Hogden (1988) and Loftus, Hanna, and Lester (1988) for general descriptions. The model is applied to temporal-integration tasks by Loftus and Hanna (1989) and

and builds on several earlier models[8]. The acquisition-rate model begins with the assumption that there is some sensory-response function, a(t), that rises following stimulus onset, and decays following stimulus offset[9]. The model further assumes the following. First, information is acquired from a stimulus and placed into a more permanent memory where it can be used as the basis for either an immediate response or further cognitive processing. Second, such information acquisition occurs at a rate, r(t) that is, among other things, proportional to a(t). Third, any measure of subsequent memory performance is monotonically related to amount of acquired information.

We will show that this model makes an important prediction: that memory performance is monotonically related to total area under the a(t) function, which we designate A(∞). Thus, any two stimuli that engender the same area (e.g., a short, high-intensity stimulus and a longer, lower-intensity stimulus) must lead to identical performance. As we shall see, it is this property of the model that allows it to account for the duration/intensity relation that we observed in Experiment 1.

In the what follows, we will describe the acquisition-rate model and the sensory-response model in detail. We describe the acquisition-rate model first as this component presupposes *some* sensory-response function. We then describe the sensory-response model.

The Acquisition-Rate Model

The logic of the acquisition-rate model is as follows. First the physical stimulus presentation engenders a sensory response. The sensory response forms the basis for acquisition of stimulus information, which in turn leads to the memory representation, upon which subsequent memory performance depends. More precisely,

1. A physical stimulus is characterized as a *temporal-input function,* f(t), relating stimulus intensity to the time, t, since stimulus onset. The left panels of Figure 4 illustrates six f(t) functions: these are square-wave functions of the sort used in most perceptual experiments, including the present Experiment 1. Because they are square-wave functions, the term "intensity" can be informally used to describe the function's *maximum intensity*. Intensity is 1.0 in the first three panels, and 2.0 in the last three panels.

2. The stimulus input function engenders the sensory-response function, a(t). The a(t) functions resulting from the Figure-4 stimuli are shown in the right panels of Figure 4. The vertical lines represent stimulus offset[10]. Generally speaking, a(t) lags behind, and is temporally blurred relative to f(t). Below we describe both the mathematical origin of these functions, and the meaning of the horizontal lines just above the abscissas.

3. The subject's task is construed as *acquiring information* from the stimulus, and transferring it to more permanent storage. At time t following stimulus onset, some *proportion*, I(t) of all stimulus information has been acquired. Information is acquired at an instantaneous rate, r(t) which is the derivative over time of acquired information, d[I(t)]/dt. The value of r(t) is the product of two entities: first, a(t) and second, some function h[I(t)], of already-acquired information. The only constraints on h[I(t)] are that it is positive, finite, monotonically decreasing, and is zero when I(t) ≤ 1.0. Thus, new information is acquired at a rate that is proportional to the sensory response, and inversely related to amount of already-acquired information[11]. Note that, given the constraints on r(t), I(t) cannot exceed 1.0.

Loftus and Irwin (1993). It is applied to the sort of digit-recall task used in the present Experiment 1 by Busey and Loftus (1993) and Loftus, et al. (1993b). It is applied to partial report by Loftus and Busey (1992) and Loftus and Irwin (1993). Di Lollo & Dixon (1992) present an opposing viewpoint.

[8]Notably, Bundesen (1990), Kowler and Sperling (1980), Loftus and Kallman (1979), Massaro (1970), Rumelhart (1969), and Townsend (1981).

[9]In previous formulations of the model, this a(t) function was defined somewhat arbitrarily—that is, on the basis of intuition—rather than generated on the basis fundamental principles.

[10]The portion of a(t) that follows stimulus offset can be identified with the iconic image.

[11]These assumptions imply that r(t) generally declines following stimulus onset as a result of the decreasing h[I(t)] component. Following stimulus offset, r(t) begins to decline more precipitiously as a result of the additional decrease in the a(t) component. Clark and Hogben (1991) offer a visual-processing model in which system output is defined by fiat to have this form.

4. Performance, p, is a monotonic function, m[I(∞)], of the total acquired information, I(∞).

Appendix A shows that, given the logic thus far, a powerful prediction ensues: *Performance, P, is a monotonic function of the total area under the a(t) function.* We term this total area A(∞). Others (e.g., Nisly & Wasserman, 1989; see their Figure 2) have informally proposed that the area under some sensory-response function might be suitable as a theoretical basis of stimulus identification. The reasoning that we have just provided establishes a formal basis for this proposition.

The Sensory-Response Model

Where does the presumed sensory-response function, a(t), come from? Loftus et al. (1992) assumed a semi-arbitrary a(t) function, but pointed out that it was deficient in that it did not derive from basic principles. Loftus et al. did, however, sketch a means by which the function *could* be derived from more basic principles based on the proposition, alluded to above, that a linear low-pass temporal filter operates on the

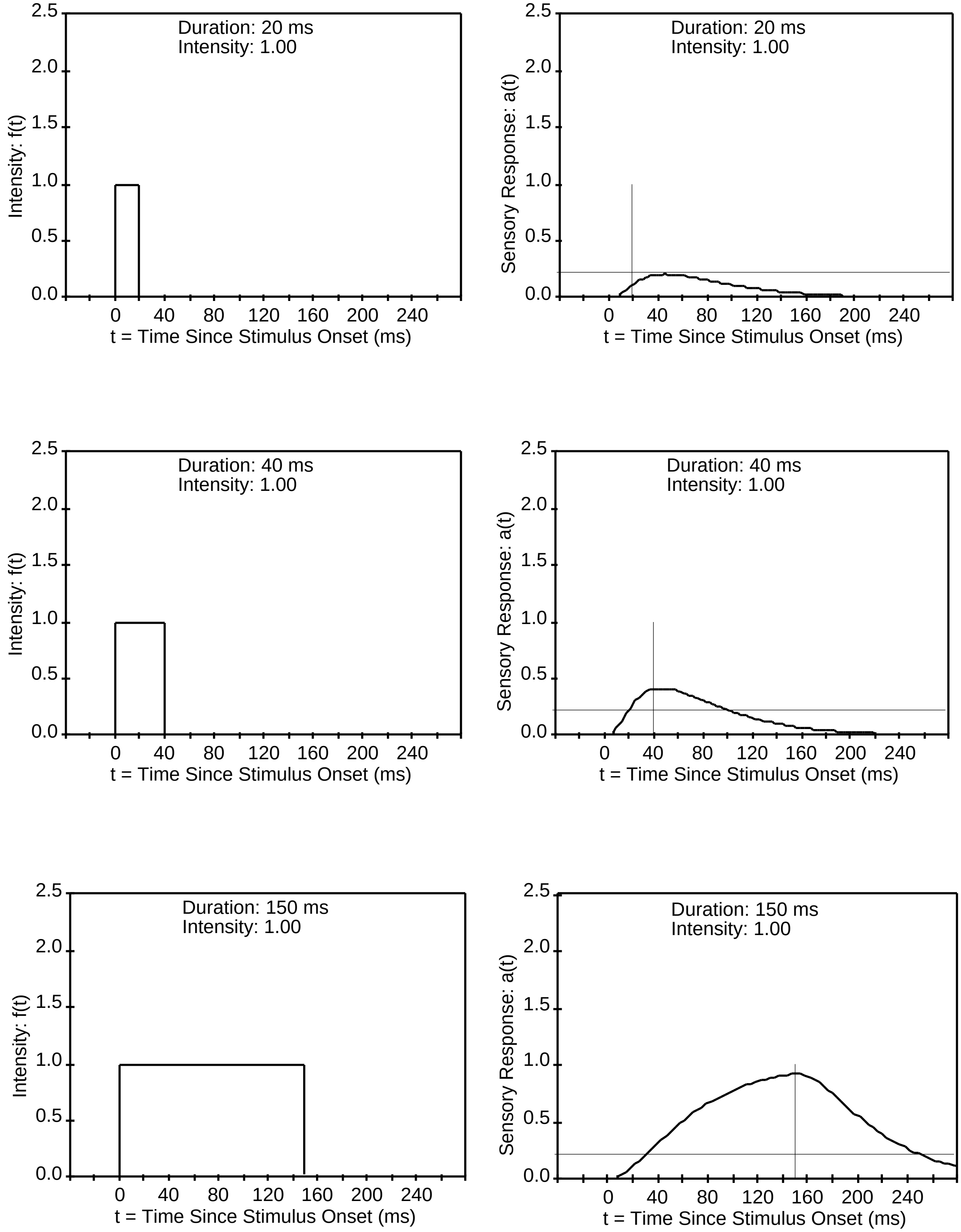

Figure 4. Stimulus input functions (f(t), left panels) and the resulting sensory-response functions (a(t), right panels). In the a(t) functions, the vertical line represents the time of stimulus offset, and the horizontal lines represent sensory-threshold values. Panels above are for intensities of $\varphi = 1$; Figure continues next page for intensities of $\varphi = 2$.

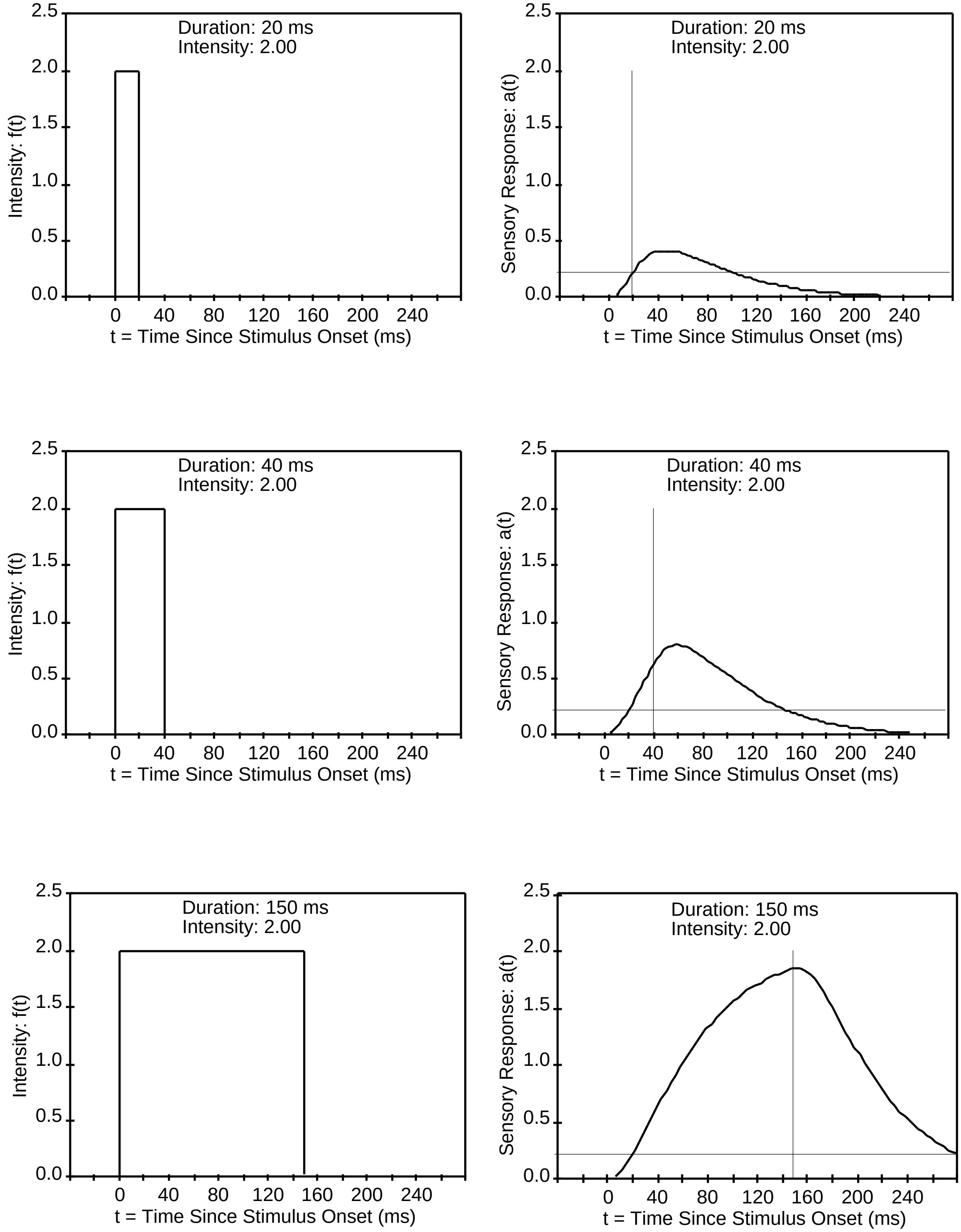

Figure 4 (continued). Stimulus input functions (f(t), left panels) and the resulting sensory-response functions (a(t), right panels). In the a(t) functions, the vertical line represents the time of stimulus offset, and the horizontal lines represent sensory-threshold values.

stimulus input function to generate the sensory-response function.

The Impulse and the Impulse-Response Function

The linear-filter-based model begins with the assumption that an input consisting of an instantaneous[12] *impulse* engenders what is termed the *impulse-response function.* The impulse-response function is often assumed to be a gamma function, of the form,

$$g(t) = \textbf{Error!} \qquad \text{Eq. 7}$$

where n and τ are free parameters: n is a positive integer, and τ is a positive real number (cf. Watson, 1986). The impulse-response function of Equation 7 is illustrated in Figure 5. As noted in Figure 5 the total area under the impulse-response function is 1.0. The gamma function is rooted in physical reality, in that it describes the response of a system of n independent stages where the input to Stage 1 is the impulse, the input to each subsequent stage is the response of the previous stage, and the response of each stage decays exponentially with decay constant τ.

Linear Responses to an Arbitrary Input Function

The model next assumes that any input function may be viewed as a series of impulses, *scaled by intensity*, and that the resulting sensory-response (a(t)) function is the sum of the resulting linearly scaled impulse response functions. More precisely, given input function f(t) and impulse-response function, g(t), the resulting sensory-response function, a(t) is the *convolution* of f(t) and g(t).

Sensory Response to a Square-Wave Input

In Experiment 1, we used square-wave displays as shown in the left panels of Figure 4: to display a stimulus, the projector shutter opened, essentially instantaneously[13], remained open for some duration, d, and then closed, again essentially instantaneously. This makes computation of the f(t) and g(t) convolution

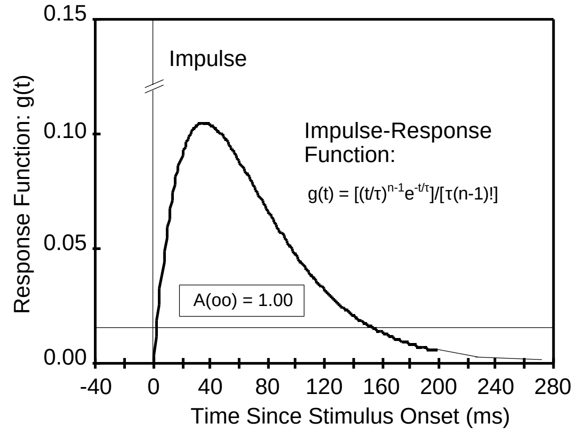

Figure 5. An impulse and the resulting impulse-response function.

quite simple. For a d-ms square-wave function whose maximum intensity is φ, the resulting a(t) function is,

$$a(t) = \begin{cases} \varphi G(t) & \text{for } t \leq d \\ \varphi[G(t) - G(t-d)] & \text{for } t > d \end{cases} \qquad \text{Eq. 8}$$

where G(x) is the integral from zero to x of g(x) dx. The a(t) functions shown in the right panels of Figure 4 were generated from Equations 7 and 8.

Accounting for Bloch's Law

The theory that we have so far described is quite simple. To summarize, an a(t) function is generated by a linear filter that operates on the stimulus input function. Information is acquired at a rate r(t) = a(t)h[I(t)], and performance, P, is a monotonic function, m, of $I(\infty)$, the total information acquired from the stimulus. As we have noted, this theory implies performance, P, to be a monotonic function of $A(\infty)$, the total area under the sensory-response function, a(t). Because a(t) is generated by a linear process operating on f(t), the total area under a(t), $A(\infty)$, must be proportional to the total area under f(t), $F(\infty)$ (with the constant of proportionality being φ, the intensity.)

It is easy to see that the theory as described so far implies something close to our Bloch's-Law finding. The f(t) function is a rectangle whose width is duration and whose height is intensity. Because performance is monotonically related to $A(\infty)$, it is also monotonically related to $F(\infty)$, which is the rectangle's area. This implies a perfect duration/intensity trade-

[12] More precisely, an impulse is defined to be a stimulus of infinitesimal duration, infinite intensity, and unit area.

[13] In fact, it took approximately 2 ms both for the shutters to completely open and for them to completely close.

off: if duration is multiplied by some factor, intensity must be divided by the same factor to maintain equal area.

Accounting for the Experiment-1 Data

So far, however, the theory does not account for either the linear performance curves or for the non-zero liftoff values that we observed in Experiment 1. To remedy these deficits, the theory requires two modifications. First, the linear performance curves result if the presumed monotonic functions, h[I(t)] and m[I(∞)] are strengthened in suitable ways. Second, the non-zero liftoff values result with one additional assumption about the nature of the information-acquisition rate, r(t).

Linear Performance Curves: Strengthening the h([I(t)] and m[I(∞)] Functions

In Experiment 1 we observed linear performance curves. The theory predicts such linearity if the functions h[I(t)] and m[I(∞)] presently assumed to be only monotonic are strengthened such that

$$h(I) = \frac{1.0 - I(\infty)}{c} \qquad \text{Eq. 9}$$

where c is a free parameter, and

$$m[I(\infty)] = I(\infty) \qquad \text{Eq. 10}$$

These strengthened assumptions are both reasonable. Equation 9 asserts that information acquisition rate is proportional to the remaining to-be-acquired information at any given time. This relation, implied as it is by an ecologically common Poisson process, describes many physical processes, such as radioactive decay. Equation 10 simply asserts that proportion correct is equal to the proportion of acquired information. Appendix B shows that with these strengthened assumptions, performance curves are described by the equation,

$$P = \frac{d}{c} \qquad \text{Eq. 11}$$

where the parameter c is proportional to 1/φ, the inverse of stimulus intensity.

Equation 11 almost, but not quite, describes the observed performance curves. According to Equation 11, all performance curves pass through the origin. However, the observed performance curves do not pass through the origin. Instead, as we have seen (Figures 1 and 2), the observed performance curves intersect the duration axis at some positive value L that increases with decreasing intensity. The theory is, accordingly, still deficient.

Nonzero Liftoffs: The Threshold Assumption

This deficiency can be remedied by inclusion of one additional assumption: that information acquisition does not begin until the sensory-response function exceeds some threshold. This threshold is represented by the horizontal lines just above the abscissas in the right-hand panels of Figure 4. We refer to this sensory threshold value as a_t.

The simplest way of incorporating such a threshold within the theory is to assume that the information-acquisition rate, r(t) is proportional not to a(t), but to the magnitude by which a(t) exceeds a_t. It is easy to show that the theory then predicts performance to depend on the total area under the a(t) function above threshold (see Appendix C). We refer to this value as $A_t(\infty)$. The performance-curve equation then becomes,

$$P = \frac{A_t(\infty)}{c}$$

where c is approximately proportional to 1/φ. Note that $A_t(\infty)$ is zero for durations less than some *threshold duration*. For any given intensity level, the threshold duration is the longest duration such that a(t) never exceeds the threshold, a_t. These assertions are illustrated by the a(t) functions in Figure 4, right panels. Here, the horizontal lines represent threshold values. Note first that when intensity is 1.0, the d = 20 ms a(t) function never achieves threshold; accordingly, $A_t(\infty)$—and performance—would be zero for all values of 20 ms or less. When intensity is 2.0, however, the d = 20 ms curve does exceed threshold; accordingly, $A_t(\infty)$—and performance—would exceed zero. This threshold assumption thereby accounts qualitatively for two observed aspects of the data: first that the critical "liftoff" stimulus duration generally exceeds zero, and second that this liftoff value decreases with increasing intensity levels (see Figure 3, top panel).

This revised theory no longer predicts exactly linear performance curves. As we shall see, however, it predicts performance curves that are *almost* linear.

Theoretical Fit

To summarize, the theory has five free parameters: the asymptote, A, the two impulse-response function parameters, n and τ; the sensory-response threshold, a_t; and a scaling parameter, c. As noted earlier, the asymptote for each observer was already estimated in the process of producing the best linear performance curves, and will not be considered further here. In what follows, we consider only the parameters n, τ, c, and a_t.

We found the best-fitting values of these four parameters for each of the four observers using a grid search procedure. The goodness of fit was remarkably impervious to the value of n. This is demonstrated in Table 4 which shows the best-fitting values of τ, c, and a_t, along with the root-mean-square errors letting n = 2 (top of Table 4) and n = 10 (bottom of Table 4). The RMSE depends only very slightly on the value of n. The value of c depends not at all on n, the value of a_t depends slightly on n, and the value of τ depends quite a bit on n.

The threshold (a_t) values are in intensity units (cd/m^2). The rationale underlying this assertion is as follows. As the stimulus remains on indefinitely, a(t) will asymptote at a value equal to the stimulus intensity level. Accordingly, the threshold can be interpreted as the maximum stimulus intensity level at which no information would be acquired even if the stimulus were of infinite duration.

Predicted Performance Curves

The predicted performance are shown as the solid lines in Figure 1 (individual data) and Figure 2 (mean data across the four observers). The predicted best-fit P values are essentially identical for any value of n from 2-10; for the record, the predictions shown are based on n = 10 (an n value that often emerges when the linear-filter model is used to account for low-level sensory data; see Watson, 1986). The predicted mean performance curves (Figure 2) were generated by simply averaging the individual predicted curves, normalizing for different observers' different exposure durations (as was done to produce the mean data). It is obvious that the mean predicted curves correspond closely to the data and are virtually indistinguishable from their linear counterparts.

Table 4

Model Fits for each Observer. Top: Data for n = 2. Bottom: Data for n = 0. Within each n Value, Upper Three Rows Show Best-Fitting Values for the other 3 Parameters and Bottom Row Shows Root-Mean Square Error

n = 2	**Observer**			
	CA	**KG**	**GL**	**ER**
τ (ms)	3.3	2.7	4.4	3.6
c (ms)	12	10	44	52
a_t (cd/m^2)	0.32	0.37	0.23	0.48
RMSE (Model)	0.210	0.145	0.154	0.171

n = 10	**Observer**			
	CA	**KG**	**GL**	**ER**
τ (ms)	5.7	3.9	8.1	6.7
c (ms)	12	10	45	52
a_t (cd/m^2)	0.35	0.48	0.25	0.52
RMSE (Model)	0.214	0.148	0.151	0.165

Predicted 1/L, 1/c, and 1/(L+c) Curves

The predicted 1/L , 1/c, and 1/(L+c) curves are shown as the solid lines in Figure 3. Predicted values were obtained by finding the best linear fits (L and c values) to the *predicted* performance curves for each observer and then averaging the resulting 1/c and 1/L values separately for CA and KG and for GL and ER (as was done to produce the data). The predicted intensity-axis intercepts were the estimated threshold values: if intensity is at (or below) the threshold value, no information is ever acquired; hence both L and c would be infinite and their reciprocals would be zero.

Recall the Bloch's-Law predictions embodied in Equations 4 and 5: that 1/L and 1/c are proportional to intensity. The theory makes something very close to this prediction; however, at small intensities, the predicted curves bow downward, and intercept the intensity axis at small positive values. As discussed earlier, these departures result from the theory's nonlinearity embodied in the sensory threshold.

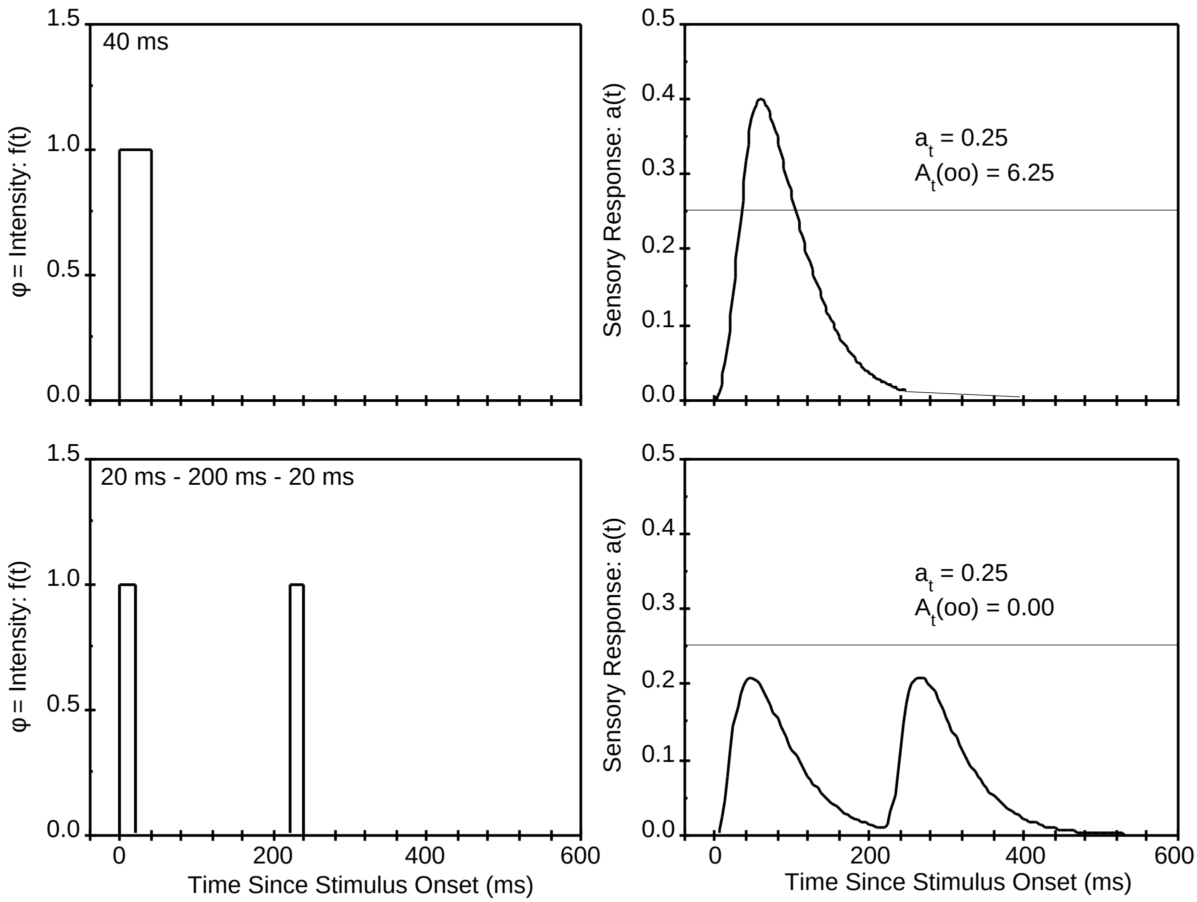

Figure 6. Experiment 2: Stimulus input functions (f(t), left panels) and the resulting sensory-response functions (a(t), right panels) for the no-gap and gap conditions..

We have argued that the most fundamental Bloch's-Law predictions are those involving the tradeoffs between intensity and the durations L and c. Other research designed to investigate Bloch's Law has typically examined the tradeoff between intensity and *total* duration. In Experiment 1, there turned out to be an almost-perfect tradeoff between intensity and total duration, (L+c); as is evident in Figure 3c, this tradeoff is predicted by our theory.

Experiment 2: An Additional Test of the theory

Experiment 2 is designed to test a straightforward implication of the theory's threshold assumption. To understand this prediction, consider for a moment the theory *without* the threshold assumption. Without a threshold, the theory would imply memory performance to depend on $A(\infty)$, the total area under the sensory-response function. $A(\infty)$ is, in turn, equal to $F(\infty)$, the total area under the stimulus input function.

Suppose now that we generate a stimulus of intensity, φ, whose total duration is d ms. We create two conditions. In the first condition, the stimulus is simply presented as a square-wave function for the d ms. In the second condition, the d ms is divided into two separate square-wave presentations of durations d_1 ms, and $d_2 = (d - d_1)$ ms which are displayed successively, separated by some temporal gap. We refer to these conditions as the *no-gap* and the *gap* conditions, respectively. For instance, a no-gap condition might consist of a single 40-ms stimulus, while the corresponding gap condition might consist of a 20-ms stimulus, followed by a 250-ms blank period, followed by the stimulus for another 20 ms.

Figure 6 shows the f(t) and a(t) functions resulting from these two conditions. The two a(t) functions are quite different from one another.

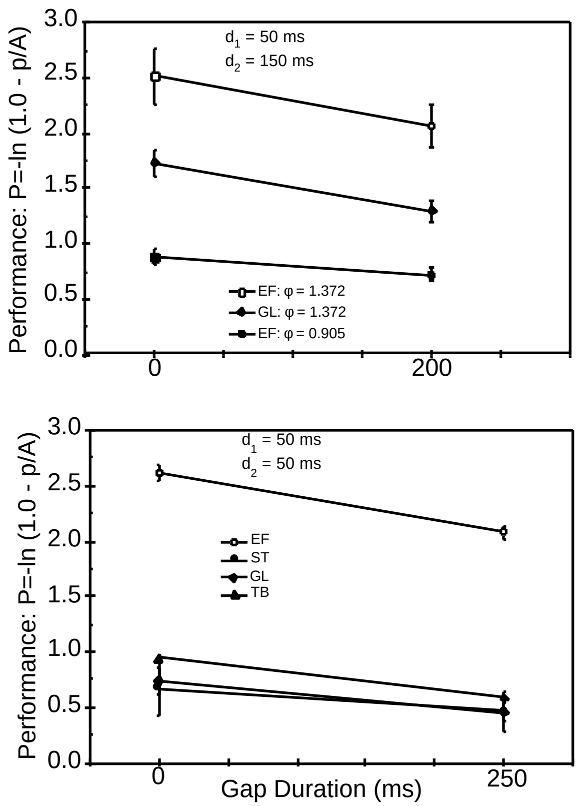

Figure 7. Experiment 2: Performance as a function gap size. The different panels represent two different first-half/gap/second-half configurations. Curves within each panel represent different observers and/or intensity levels.

However, because the system is linear, the total areas, $A(\infty)$ must be the same; in the example, they both equal 40. In the absence of a threshold, therefore, the two conditions are predicted by the theory to yield equal performance.

However, if a threshold is introduced, the no-gap condition is predicted to yield a higher $A_t(\infty)$, and hence higher performance than the gap condition. This mathematical truth may or may not be intuitively obvious, but the criterion has been selected in the Figure-6 example to illustrate it as forcefully as possible. In the gap condition, a(t) never exceeds the threshold; hence $A_t(\infty)$ and performance are both zero. In the no-gap condition, however, a(t) does exceed threshold; hence $A_t(\infty)$ and performance are both above zero. More generally, the prediction is that, assuming a threshold, performance will be worse in the gap condition than in the no-gap condition.

Method

Experiment 2 was actually a collection of mini-experiments using the same stimuli and display procedures as Experiment 1. In all mini-experiments, there was a gap and a no-gap condition. We used various combinations of d_1, d_2, and gap duration. With one exception, only a single intensity was used: $\varphi = 1.372$ cd/m^2. Observers included one of the authors (GL) along with other graduate and undergraduate students working in the laboratory.

Results and Discussion

The results were clear-cut: performance in the gap condition was invariably inferior to performance in the no-gap condition. This was true for all miniexperiments. Figure 7 illustrates these results from two of the mini-experiments. The theory's prediction is thus confirmed.

General Discussion

We first summarize what we have shown thus far. We then discuss two additional issues: first, the relations among Bloch's Law, the Experiment-1 results and our theory; and second, the relation between initial phenomenological appearance of some visual stimulus and information acquired from that stimulus.

Summary

In Experiment 1, we demonstrated several strong regularities in the relations between stimulus intensity and stimulus duration in a digit-recall task: the product of stimulus intensity and each of two observed durations—the duration, L, required for above-chance performance and the additional duration required for performance to rise from chance to any criterion performance level—was approximately constant. In addition, the product of intensity and *total* time required to reach a criterion level was approximately constant. This regularity approximately confirms Bloch's Law as it is applied to memory performance for relatively complex visual stimulus. It also replicates and extends Turvey's (1973) finding that the product of intensity and duration determines the probability with which an alphanumeric stimulus will escape being masked.

The theory we used to account for these findings incorporated a front-end linear filter that operates on the stimulus intensity function to produce what we term a sensory-response function. The theory then assumes an information-acquisition process that, at any given time, is proportional to the product of (1) the magnitude by which the sensory response exceeds some threshold sensory response and (2) the proportion of yet-to-be-acquired stimulus information. This four-parameter theory accounts quite well for the Experiment-1 data, predicting in the process the form of our duration-intensity tradeoffs that we found.

In Experiment 2, we tested and confirmed a particular prediction of this linear-response-with-threshold theory: that with brief, low-intensity displays, a stimulus presented once is recalled better than a stimulus presented for the same total time, but broken into two temporally distinct halves.

Bloch's Law, Perceptual Metamers, and "Memory Metamers"

We now discuss the interrelations between our Experiment-1 results, Bloch's Law, and our theory. We begin by considering three stimulus pairs, each pair configured such that the duration x intensity product is the same for each member of the pair. We refer to such stimuli as *equal-product* stimuli. Denoting a stimulus in terms of its intensity value x duration value, the first pair is 2 cd/m^2 x 10 ms and 1 cd/m^2 x 20 ms; the second pair is 2 cd/m^2 x 40 ms and 1 cd/m^2 x 80 ms; and the third pair is 2 cd/m^2 x 100 ms and 1 cd/m^2 x 200 ms. The a(t) functions emerging from these six stimuli are shown in Figure 8. In each panel, the solid line corresponds to the shorter, more intense stimulus, and the dashed line corresponds to the longer, less intense stimulus.

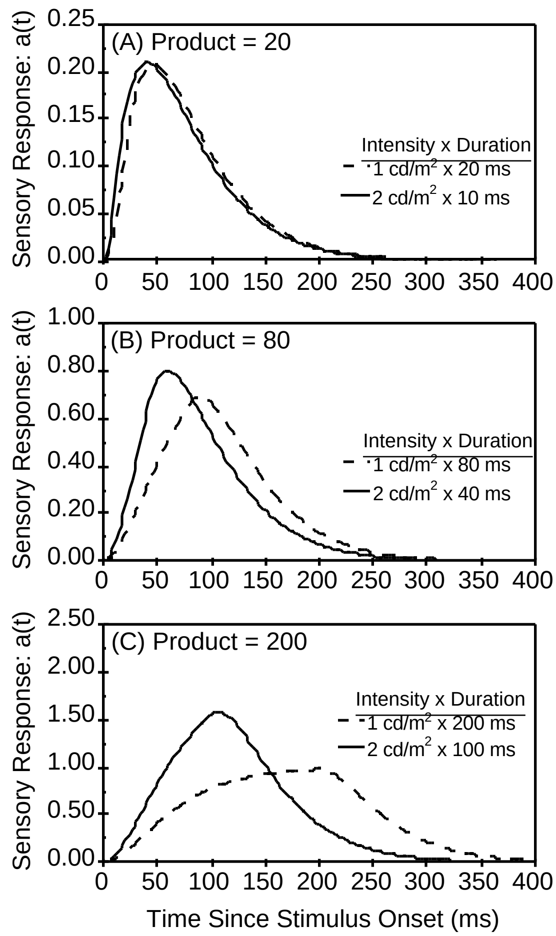

Figure 8. Three examples of sensory-response functions associated with equal-product stimulus pairs. In each panel, the solid line represents the shorter, more intense pair member, while the dashed line represents the longer, less intense pair member..

When Different Stimuli Lead to Similar Sensory-response Functions

As noted by Watson (1986) the stimulus representations in Figure 8 suggest a parsimonious explanation for Bloch's Law: two equal-product stimuli will be detected with similar probability to the degree that they produce similar sensory-response functions. This explanation follows no matter what specific detection mechanism is hypothesized as long as detection occurs "downstream" from the sensory-response function (i.e., somewhere in the system where the only available information about the stimulus is based on the sensory-response function). This is because, by definition, any downstream part of the system cannot have more information about a stimulus than is contained in the stimulus's sensory-response function. Thus, in the extreme, if two equal-product stimuli produced identical sensory-response functions (as is essentially the case with the Figure 8A stimuli), they would be indistinguishable by any possible test (including in particular any detection test) that is based on a downstream representation.

Metamers

In color vision, the term *metameric* is used to describe two stimuli composed of physically different wavelength mixtures that are perceived to be identical. In the present context, two stimuli producing the identical sensory-response function could similarly be termed metameric if, in general, metamers are defined to be physically different stimuli that produce identical responses at some peripheral stage of the perceptual-cognitive system.

So, for instance, the two Figure 8A stimuli must lead to equal detection performance (or any other kind of performance), because they produce essentially identical responses at some presumably early stage. However, as equal-product stimuli get longer, the corresponding sensory-response functions become less similar: As indicated in Figures 8B and 8C, the longer member of the pair produces a longer, flatter function than does the shorter member. Thus, the longer a pair of equal-product stimuli, the more distinguishable become their sensory-response functions, and the easier it is for the system to devise a test that will distinguish them. In one class of detection models, for instance, detection occurs if the sensory-response function exceeds some threshold; thus as illustrated in Figure 8, the longer are the stimuli, the more probable it is that the shorter brighter one will be detected relative to the longer dimmer one (and indeed, this is exactly what happens). This is a reasonable explanation of why Bloch's Law "breaks down" at long durations.

Memory Metamers

However, although it is *possible* for the perceptual-cognitive system to distinguish a shorter-duration from a longer-duration, equal-product stimulus, it does not follow that any representations generated by system to such pairs can be distinguished. In particular, any stimulus representation that depends only on the area under the sensory-response function cannot serve as a basis for distinguishing *any* of the Figure-8 stimulus pairs, as the area under the two curves is identical in all three cases. The theory that we have presented supposes such representations; accordingly, the "Bloch's Law-like" effects observed in the data would, unlike real Bloch's-Law effects, continue to hold with indefinitely long stimuli (see Kahneman & Norman, 1964; Wasserman & Kong, 1989 for additional discussion about why Bloch's Law applies in somewhat different ways to different tasks involving the same physical stimuli). Generalizing the notion of a metamer yet further, such stimulus pairs might be termed "memory metamers": the two pair members would yield different perceptual experiences, but identical memory representations. *Perceptual metamers* could, in contrast, be defined as stimuli, such as classical color metamers, that are indistinguishable by any stage of the perceptual-cognitive system.

Information Extraction and Phenomenology

These remarks bring us to our last topic: the link between the phenomenological appearance of some stimulus on the one hand, and the ultimate memory representation that issues from the stimulus on the other hand.

Essentially, we have argued that, while these two facets of perception and cognition are separable, and influenced by different variables, they are, within the context of our theory, determined by two facets of the same function: the sensory-response function. Roughly speaking, phenomenology is determined by the *shape* of the sensory-response function, while the memory representation is determined by the *area under* the sensory-response function.

This argument is aptly illustrated by results from another project in our laboratory (Loftus, Futhey, & Russon, 1993) within which we carried out several modifications of the present Experiment 2. As in Experiment 2, we displayed stimuli of constant total physical duration in either a no-gap or a gap-condition. However, instead of being simple digits tested by immediate recall, the stimuli were complex, naturalistic scenes, tested by delayed recognition. Of some importance is that these pictures were presented at much higher intensities than were the present digit stimuli[14]. We reasoned that, with high-intensity stimuli, the presumed sensory threshold would be low relative to overall intensity and accordingly, any threshold-driven effect—such as the gap effect—would be substantially diminished. We discovered, indeed, that there was *no* significant gap effect. Power analyses indicated that any *actual* gap effect couldn't have been greater than about 2% as gap size was increased from 0 to 250 ms.

Thus, in accord with the predictions of the simplest—i.e., threshold-less—linear-filter

[14] Because the pictures involved different areas of different intensity and color, "intensity" could not be precisely measured. But roughly speaking, a the contrast of a typical object in a typical picture, against a typical background, was an order of magnitude greater than the contrasts used in the present experiments.

model, the gap and no-gap conditions produced memory representations that we have just characterized as memory metamers, To determine whether the two conditions were perceptually distinguishable, we also asked observers to distinguish between gap and the no-gap stimuli *at the time of original viewing*. Observers were able to make this distinction perfectly, which meant that the gap and no-gap conditions did *not* produce perceptual metamers. The ability to perceptually distinguish gap and no-gap stimuli destined to be indistinguishable in a later recognition test is quite understandable within the context of our theory. It is, in particular, a consequence of the gap and no-gap stimuli having two entirely differently shaped sensory-response functions (see Figure 6 above) which led to different (nonmetameric) sensory experiences—but with the same areas under the sensory-response functions, which led to identical (metameric) memory representations. In short, these two salient aspects of perception—phenomenological appearance and information acquisition—are united as two aspects of the same sensory-response function.

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Appendix A

Proof that performance is monotonically related to area under the a(t) function.

Information extraction rate, r(t) is the derivative of acquired information, I(t) with respect to time. Also, r(t) is assumed to be the product a(t) and h[I(t)]. Thus,

$$r(t) = \frac{d[I(t)]}{dt} = a(t)h[I(t)]$$

or,

$$\frac{d[I(t)]}{h[I(t)]} = a(t)dt \qquad \text{Eq. A1}$$

Integrating both sides of Equation A1,

$$H[I(t)] = A(t) + k$$

where A(t) is the integral of a(t), H[I(t)] is the integral of {1/h[I(t)]}, and k is the constant of integration. When t = 0, A(t) = 0 and I (t) = 0; hence k = H(0). Therefore,

$$H[I(t)] = A(t) + H(0) \qquad \text{Eq. A2}$$

Because H is an integral, it is monotonically increasing and has an inverse, H^{-1}, which is also monotonic. From Equation A2,

$$I(t) = H^{-1}[A(t) + H(0)]$$

or, when t = ∞,

$$I(\infty) = H^{-1}[A(\infty) + H(0)]$$

Therefore I(∞) is a monotonic function of A(∞). Because p is assumed to be a monotonic function of I(∞), and P is assumed to be a monotonic function of p, P is a monotonic function of A(∞). This completes the proof.

Appendix B

Linear performance curves result from the assumptions that h[I(t)] is linear and that m is the identity function.

Let $h[I(t)] = [1.0 - I(t)]/c'$, where c' is a constant. Substituting into Equation A1 (Appendix A, above),

$$\frac{d[I(t)]}{[1.0 - I(t)]} = \frac{a(t)dt}{c'} \qquad \text{Eq. B1}$$

Integrating both sides of Equation B1,

$$-\ln[1 - I(t)] = \frac{A(t)}{c}\,' + k$$

where k is the constant of integration. When $t = 0$, $A(t) = 0$ and $I(t) = 0$; thus $k = 0$, and

$$-\ln[1 - I(t)] = \frac{A(t)}{c'}$$

Because $p = I(\infty)$,

$$-\ln[1 - p] = \frac{A(\infty)}{c'}$$

Substituting $P = -\ln(1 - p)$ and $A(\infty) = F(\infty) = \varphi d$,

$$P = \frac{\varphi d}{c'}$$

Letting c be proportional to $1/\varphi$, or $c = (1/\varphi)c'$,

$$P = \frac{d}{c}$$

This completes the proof.

Appendix C

Proof that when r(t) is proportional to the magnitude by which a(t) exceeds threshold, a_t, P is monotonically related to area under a(t) above threshold.

We have already shown (Appendix A) that when $r(t) = a(t)H[I(t)]$, performance, P is a monotonic function of $A(\infty)$. We define a new function,

$$a_t(t) = a(t) - a_t$$

and let $r(t) = a_t(t)H[I(t)]$, as assumed in the text. Then by the arguments in Appendix A, P must be a monotonic function of $A_t(\infty)$, the total area under $a_t(t)$. This is equal to the area under a(t) that is above the threshold, a_t.