RESEARCH PLAN

I include ten appendices. While they shouldn't be necessary for understanding this proposal, they do provide auxiliary details and examples. References in the proposal to grant-supported articles are of the form [n] or [n, Am] where n is the reference number listed on proposal pp. 28-29 and, when the reference is included as an Appendix, m is the Appendix number. Proposal Section B.2.e below provides background information that is particularly important for understanding much of the proposed research.

A. SPECIFIC AIMS

I propose to continue work in several ongoing areas and to launch work in several new areas. The primary research focus is on visual perception and visual memory. A secondary focus is on theoretical, methodological, statistical, and data-presentation issues, with an ultimate goal of substantially changing how research problems are conceptualized and how data sets are thought about, analyzed, and interpreted. These two foci underlie seven intertwined specific aims. The first five aims involve specific content areas, while the other two are more general and pervade much of the proposed research. The aims are these.

1. Stimulus contrast effects. Measurement of stimulus contrast has long been a staple of basic vision research. I propose to continue investigating contrast effects on higher-level cognition. Three sub-aims are (a) demonstrating how a form of Bloch's Law (that low-level detection performance depends strictly on the product of duration and contrast) can be applied to short-term and long-term memory for complex visual material, (b) testing the proposition that stimulus contrast scales visual processing rate (however defined) in a manner that is independent of the stimulus, observer, or task, and (c) assessing contrast effects on eye-fixation durations (see Aim 5).

2. Spatial-frequency decomposition. I propose to continue investigating how visual information corresponding to different spatial frequencies is combined and used in visual memory tasks. Of particular interest are (a) representation of global and local information by low and high spatial frequencies (see [10, A5]) and (b) the role of spatial frequencies in face processing (see [15, A10] and Aim 3).

3. Face processing. During the present granting period, I have begun to focus on several aspects of face processing. This research has developed partly in response to current scientific and practical interests in face processing (see e.g., [7, A4]; Wenger & Townsend 2001; Rakover, 2001) and partly because faces provide a limitless collection of homogeneous stimuli that are methodologically useful for various kinds of visual-memory investigations. Particular planned foci of investigation are (a) effects of viewer-person distance on face perception (see [15, A10]), (b) the face-inversion effect (see [14, A9]), and (c) processing differences between faces of familiar and unfamiliar people (see [12, A8]; [14, A9]).

4. Confidence and accuracy. I propose to continue investigating the relation between confidence and accuracy in visual memory. Our work on this problem so far has concerned how well people can estimate the effects of certain variables on eventual visual memory. We have discovered for instance that people overestimate the degree to which visual rehearsal affects memory ([3, A2]), but estimate almost perfectly the degree to which stimulus contrast affects memory ([12, A8]). Why is this? We propose that effects of low-level, sensory variables such as contrast are assessed using the same invariant responses of the perceptual system that underlie actual memory performance, whereas effects of higher-level cognitive variables such as rehearsal are assessed partly on such responses, but partly also on biased metacognitive beliefs.

5. Acquisition of information within eye fixations. David Irwin and I plan to investigate how visual information is acquired within each of a series of eye fixations on scenes. We will base our initial work on a proposition by Loftus (1972) that a single eye fixation is designed to acquire one "quantum" of information from a picture—and that while various manipulations (e.g., stimulus contrast variation) can affect the time to acquire such quanta, a particular quantum, once acquired, is always worth the same in terms of its contribution to memory.

6. Testing specific quantitative theories. During this funding period, we have developed quantitative theories of various phenomena, including (a) the relation between global and local processing ([10, A5]), (b) representation of observer-image distance in terms of image spatial-frequency composition ([15, A10]), and (c) configural versus featural information in face processing ([14, A9]). Also, over the past 10 years, we have been developing, evaluating, and extending a theory called the Sensory Response/Information-Acquisition (SRIA) theory (see [1, A1]). I plan numerous studies to test these theories, to develop new ones, and to measure specific assumed parameters of the human perceptual-cognitive system.

7. General theoretical/methodological issues. The final aim which, like Aim 6, permeates the present and planned work, is to critique widespread theoretical, methodological, and statistical practices within psychology (and other fields) and to develop alternatives. Grandiose though this aim may sound, it is one on which progress has been made over the past decade. My own contribution to this progress has been a series of articles describing (a) problems with null hypothesis significance testing as a basis for statistical inference (e.g., Loftus, 1991; 1996; [6, A3]), (b) problems with using the omnipresent linear theory as a basis for thinking about problems, designing experiments, and drawing conclusions from particular data patterns (e.g., Loftus, 1978; 1985c; Loftus & Bamber, 1990; [6, A3]; [14, A9]), and (c) development of solutions to these problems (e.g., Loftus & Masson, 1994; [8]; [6, A3]; [12, A7]; [14, A9]).

B. SIGNIFICANCE AND PROGRESS REPORT

Because the significance of the proposed work is closely intertwined with the work done during the current funding period, I commingle the Significance and Progress Report sections. There is no Section C.

During this funding period, we have done research in diverse areas that are summarized in the article list on pp. 28-29 below. Regarding dissemination, I have published mostly lengthy, integrative, theory-laden articles, including four *Psychonomic Bulletin & Review* theory/review articles, one *Psychological Review* article, and one *Stevens Handbook* chapter.

B.1. Overview

Much of the current and proposed research is concerned with the numerous perceptual and cognitive activities that come into play when a person observes a visual stimulus with the intent of being able to later remember something about it. Some of these activities—those at the sensory end of the system—occur always, and occur independently of the nature of the stimulus and of the to-be-performed task. Other activities—attention, short-term memory encoding strategies, and recognition decision processes—do not always occur in the same fashion, are under the observer's control, and do depend on the nature of the stimulus and the task.

These various processes occur repetitively during normal visual behavior, wherein the eye presents the brain with successive discrete chunks of information in the form of eye fixations. Questions about how the processes operate and mesh together therefore divide themselves naturally into two categories: those concerned with how information is acquired within an eye fixation e.g. Sperling, 1960) and those concerned with how information is integrated across eye fixations (e.g., Irwin, 1991). This dichotomy has played a central role in much of my work for the past 30 years (e.g., Loftus, 1972; Christianson, Loftus, Loftus, & Hoffman, 1991).

B.2. Topic Areas

We have investigated a variety of sensory, perceptual, and cognitive activities, and the research proposed here continues this work in the following areas.

B.2.a. Stimulus Degradation

Any driver who has tried to decipher the environment through a mist-covered windshield on a damp October morning has experienced having to cope with degraded visual stimuli. Indeed many real-life situations entail visual degradation in one form or another: For a colloquium audience, low-contrast slides are difficult to read if the room lights have been left on; for a commuter arriving home at night, the house key is difficult to find if the porch lights have been left off; and for skiers, terrain texture disappears in the flat light of a foggy day.

Although effects of these and other forms of degradation have been extensively investigated by vision scientists (see e.g., Hood & Finkelstein, 1986; Olzak & Thomas, 1986 for overviews), such investigations have typically involved simple stimuli such as monochromatic light patches or sine-wave gratings, and have mostly addressed factors that determine visual threshold, rather than those that affect processing in everyday suprathreshold situations. Fewer still such investigations have been carried out using complex and/or natural, stimuli. Two kinds of degradation are relevant to my past and proposed research.

B.2.a.i. Stimulus-Contrast Reduction: Bloch's-Law-Like Effects. While stimulus contrast has been a central variable in vision research, there is surprisingly little work on contrast effects in higher-level cognition. We have found that *Bloch's Law* provides a convenient starting point for understanding such higher-level effects. In its classic form, Bloch's Law states that for durations less than about 100 ms, low-level performance, e.g., detection, depends only on the product of stimulus luminance and stimulus duration. This is consistent with the proposition that, below this threshold, the visual system simply integrates incoming photons over time, and that the system's response depends only on total photons. Bloch's Law has been extended to similarly describe the relation between *contrast* and duration, although the duration threshold is lower (Gorea & Tyler, 1986; Musselwhite & Jeffreys, 1982; Spekreijse, Van der Twell, & Zuidema 1973).

We have reported numerous experiments investigating the relation between contrast and duration as it affects higher-level processes such as long-term picture recognition. To conceptualize this relation, it is useful to think of Bloch's Law as stating that variation in stimulus contrast causes an associated variation in the *rate at which processing occurs*. The lowest-level such "processing," to which Bloch's Law was originally applied, is just photon accumulation. But for higher-level processing, e.g., edge detection, object recognition, etc., we can also entertain and stringently test the hypothesis that contrast variation causes associated variation in processing rate, no matter how "processing" is defined. These notions are formalized in [12, A7, pp. 198-200]. For illustrative purposes, I consider here two nested theories. First, by a weaker, *multiplicative theory*, processing rate is proportional to some monotonic function, f, of stimulus contrast; thus if contrast is changed by some factor x, processing rate is changed by a factor, f(x). Second, by what is referred to in [12, A7] as a stronger *Bloch's-Law theory*, f is the identity function; i.e., f(x) = x. As reported in [12, A7] we evaluated these two theories by comparing memory performance for stimuli shown at two contrast levels, C_2 and C_1 , whose ratio can be expressed as $C_2/C_1 = r_C$ (e.g., in [12, A7, Experiment 2], C_2=0.077 and C_1=0.047; thus r_C=1.638). We then measured (using techniques described in [12, A7, pp. 203-204] and in Section B.2.e.ii.(e), p. 26 below) the ratio of visual processing rates given the two contrasts, which may be expressed as r_P. The Bloch's-Law theory prediction is that these two ratios be the same, i.e., that $r_P/r_C = 1.0$. In fact, r_P/r_C ranged from about 1.3 to 1.7, thereby allowing us to reject the Bloch's-Law theory. In [12, A7] we also found, however, that r_P remained constant over a wide range of circumstances, thereby confirming the multiplicative theory and implying, at the very least, that $f(r_C) > r_C$.

Despite rejecting Bloch's Law, we did not consider it prudent to abandon Bloch's Law altogether. Because Bloch's Law holds in some low-level tasks, it provides a starting point—a kind of plausible null hypothesis—for predicting the precise effect of contrast on perception and memory tasks. The nature of *departures* from Bloch's Law—e.g., that r_P/r_C systematically exceeds 1.0—provide instructive clues as to how the system *is* working.

In particular, it is useful to consider the possibility that Bloch's Law indeed governs the effect of contrast on information acquisition, but in a disguised fashion. As an analogy, consider Newton's law of gravitation which states that a falling object accelerates at a constant rate. In fact, an object falling in an atmosphere will be observed to accelerate at a decreasing rate (eventually ceasing to accelerate when it reaches terminal velocity). However, no one would conclude from this observation that Newton's laws are disconfirmed; rather one would note that an additional factor, air friction, is preventing the Newton's-law prediction from being met.

Perhaps in similar fashion Bloch's Law truly describes the way in which contrast and duration combine to produce the information that underlies visual recognition, but its workings are obscured by some other factor. One such possibility, consistent with the finding that $r_P/r_C > 1.0$, is that there is a contrast *threshold* involved in perception of our stimuli such that the effect of contrast "begins at" some greater-than-zero contrast level. To gain a rough intuition about what is meant by this, suppose that from the visual system's point of view, a stimulus contrast of 0.03 corresponded to zero—i.e., that the system did not respond to contrasts less than 0.03. Now consider two contrasts, 0.12, and 0.06. From the experimenter's point of view, the ratio of these two contrasts is $r_C = 2:1$, while from the visual system's point of view, the ratio is (0.12 - 0.03):(0.06 - 0.03) = 3:1. Therefore, the visual system could be responding linearly to *its* representation of contrast, but not to *the experimenter's* representation of contrast—and by this logic, r_P, the ratio of the two processing rates (3.0 in this example) would exceed r_C, the ratio of the two contrast levels (2.0 in this example).

Over the past decade, my colleagues and I have developed a theory, the SRIA Theory, that makes exactly this kind of assumption. This theory, sketched below in Section B.2.f has accounted for copious duration x contrast visual-memory data essentially perfectly (e.g., Busey & Loftus, 1994; Olds and Engel, 1998). We have concluded that the visual system treats the relation between duration and contrast in a Bloch-Law fashion, but that the contrast threshold systematically obscures the Bloch's-Law behavior in the actual data. We can, however, use the SRIA Theory as a tool to "correct" for the threshold and recover, if they exist, any Bloch's-Law properties that underlie the data.

B.2.a.ii. Spatial Filtering. It is well known that any visual image can be represented equivalently in *image space* (the standard representation) or *frequency space*, i.e., contrast energy and phase as functions of spatial frequency and orientation. It is similarly known that the visual system is in some fundamental respects, frequency-space oriented, in that it separates information into different spatial frequencies at an early stage and then re-integrates them at a later stage (Blakemore & Campbell, 1969; Campbell & Robeson, 1968; Graham, 1989; Olzak & Thomas, 1986; De Valois & De Valois, 1980; 1988). The broader implications of these processes for memory and cognition have been studied in a variety of domains (see e.g., for reading, Legge, Pelli, Rubin, & Schleske, 1985; Parish & Sperling, 1991; Solomon & Pelli, 1994; for picture perception, Olds & Engel, 1998; Schyns & Oliva, 1994). Our recent and proposed work involves two aspects of such spatial-frequency decomposition.

B.2.a.ii.(a). Global and Local Processing. Since the time of Neisser's (1967) classic *Cognitive Psychology*, visual scenes have been conceptualized as being decomposable into *global* and *local* information: Global information corresponds to overall scene structure, while local information corresponds to fine details. "Global" and "local" can be operationalized in many ways. One of them is in terms of spatial frequencies (e.g., Hughes, Nozawa, & Kitterle, 1996; Schyns & Oliva, 1994, but see Morrison & Schyns, 2001) where low spatial frequencies (LSF's) correspond to global information, and high spatial frequencies (HSF's) correspond to local information.

In [10, A5] (see also Section D.3.a below), we organized, formalized, quantified, and specified the logical relations among three broad theories of the relation between global and local processing. By *independence theories* (e.g., Olds and Engel, 1998), global and local information are acquired independently and combined additively. By *global-precedence* theories (e.g., Loftus, Nelson, & Kallman, 1983; Navon, 1977; Parker & Costen, 1999; Schyns & Oliva, 1994; Watt, 1987), acquisition of global information *precedes* acquisition of local information, but the two are still combined additively. By *interactive theories* (e.g., Navon, 1977; Sanocki, 1991; 1993; 2001), not only does global information precede local information, but acquisition rate of local information *depends on* the amount of already acquired global information. That is, acquired global information provides a spatial framework, within which local information can be interpreted and integrated—and the more complete the global information, the more efficient is such local processing. Thus, by interactive theories, LSF and HSF signals do not combine additively—LSF and HSF information presented together are more effective than the sum of their individual contributions. In [10, A5] we showed that in relatively simple digit-recall tasks (as used in [10, A5]) and object-identification tasks (as used by Olds and Engel, 1998), the relations among low spatial-frequency only, high spatial-frequency only and complete (low plus high spatial-frequency) versions of the stimuli can be accounted for by a global-precedence theory, and we developed a quantitative version of such a theory.

B.2.a.ii.(b). Face Perception: Observer Distance Simulated by Resizing or Filtering an Image. The role of spatial frequency in face perception has increasingly been a topic of investigation, with different researchers demonstrating that face recognition can be carried out either with low or with high spatial-frequency information (e.g., Costen, Parker, & Craw, 1994; 1996; Fiorentini, Maffei, & Sardini, 1983) but suggesting various spatial-frequency ranges, on the order of 8-12 cycles/face (c/face), that are optimal for face processing (see Morrison & Schyns, 2001, pp. 462-464, for a summary).

A project in our laboratory involving spatial frequencies and face processing was triggered by a legal case in which an eyewitness to a crime claimed to have identified the perpetrators from a distance of 450 ft. The resulting research, described in [15, A10], was designed to account for and quantify the effect of viewer distance on face recognition in particular and on visual processing in general. The logic relied on a well known property of the human visual system: that like any image-processing system, it progressively removes higher spatial frequencies in a manner that is governed by some *modulation-transfer function* (MTF). The MTF is a spatial filter: It assigns an *amplitude scale factor* that modulates the contrast of each spatial frequency by a factor ranging from 1.0 for spatial frequencies that are completely passed by the filter to 0.0 for spatial frequencies that are completely blocked by it. Although the suprathreshold human MTF is not precisely known, it is reasonable to expect, based on various kinds of data (e.g., Georgson & Sullivan, 1975; Hayes, Morrone, and Burr, 1986; Parish & Sperling, 1991) that spatial frequencies lower than about 10 cycles/degree (c/deg) are completely passed by the filter, spatial frequencies as high as 60 c/deg are completely blocked, and that the MTF declines in some systematic fashion in between.

These observations suggest a quantitative incarnation of a general proposition about the relation between distance and face processing. The general proposition is that at progressively greater distances, progressively coarser facial features become unavailable to the visual system. To understand the quantitative instantiation of it, consider a particular facial feature, such as a mouth. The representation of such a feature, viewed from a particular distance, is carried by a spatial-frequency range that depends both on the feature's distance and its size. For instance, from a distance of 40 ft, a mouth would subtend (vertically) approximately.04 deg of visual angle, which means that information about it would be carried in the reasonably perceptible spatial-frequency range of 1/.04 = 25 c/deg. Now suppose that the face is moved further away by a factor of 4, to 160 ft. The mouth would then subtend a visual angle of .04/4 = .01 deg, and would be carried by spatial frequencies in the range of 1/.01 = 100 c/deg, which are filtered out; thus the mouth wouldn't be perceptible at that distance.

We developed these ideas in [15, A10] as follows. Suppose the relevant MTF is some function, M(F) where F is *absolute frequency*, that is, frequency in c/deg. Now consider the MTF in terms of *image frequency*, i.e., in c/face, which we termed M(f). If a face is viewed from a distance of 43 ft (actually, technically 43 ft/(face/deg)), it subtends a visual angle of 1 deg, which means that M(f) = M(F). In general, for distance D, f = F x (43/D). For instance, if a face is viewed from a distance of D = 86 ft, it would subtend a visual angle of 43/86 = 0.5 deg/face and an absolute frequency of, say, F = 60 c/deg would correspond to an image frequency of, f = 60 c/deg x 0.5 deg/face = 30 c/face. In other words, the visual system can be construed as spatially filtering a face seen from distance D by M(f) = M[F x (43/D)].

We can thus represent a face viewed from distance D in two ways. The most straightforward way—dictated simply by geometry—is to resize the face's image so that it subtends to the viewer a visual angle of 43/D deg. The second way, whose validity depends on the logic I have just sketched, is to filter the image by a MTF whose form is M(f) = M[F x (43/D)]. Because M, for reasons described in [15, A10]), is assumed to be *low-pass*, i.e., to decline over spatial frequency, such filtering results in a blurred image whose degree of blur increases with D. By this reasoning, a general *equivalence prediction* emerges: In any sort of visual-processing task, performance on a face seen from distance D ft should equal performance on the same face close up, but filtered by M[F x (43/D)].

Making use of this logic assumes that we know the form

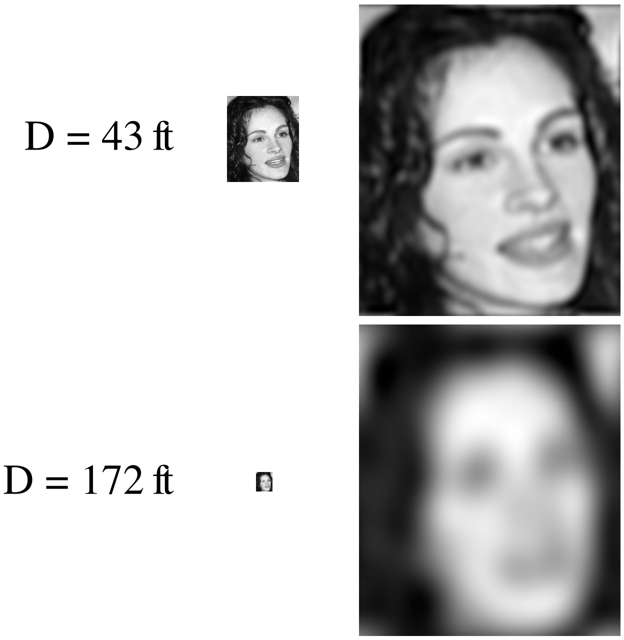

Figure 1. Two theoretically equivalent representations of a face viewed from 43 and 172 ft: resizing (left) and filtering (right). With caveats indicated in Footnote 1, left panels are valid if viewed from 11" away.

of M(F) to begin with. As I noted, we don't, at least not very well, but we can begin with some rough guesses and then bootstrap our way to a better estimate by determining the rules governing the distances and degrees of filtering that lead to the same performance. If these rules are found to be robust, then we have some scientific certainty that the resulting MTF estimate is reasonably accurate. The first goal of the experiments reported in [15, A10] was to quantitatively test the equivalence prediction just described. Two very different experimental paradigms provided converging evidence in this quest. I will describe these paradigms and their results in Section D.4.a; suffice it to say here that the prediction was confirmed essentially perfectly, thereby allowing the form of M to be estimated. Figure 1 shows an example: Julia Roberts' face both sized and filtered to produce equivalent representations of the effect of two distances[1].

B.2.b. Face Processing

Because of forensic relevance, the need for artificial face-recognition systems, as well as intrinsic scientific interest, face processing has lately become a major topic of scientific scrutiny (the list of relevant references could go on for pages, but see, e.g., Gauthier, Curran, Curby, & Collins, 2003; Kanwisher, McDermott, & Chun, 1997; reviews in Wenger & Townsend, 2001; Rakover, 2001). Past and proposed work in my laboratory has increasingly focused on face-perception and face-memory problems.

I have just sketched one face-processing project: a spatial frequency representation of distance. Three additional interrelated face-processing topics are also relevant. The

[1] This argument ignores potential image degradation by pixel loss when image size is reduced on a computer screen. Our solution is to present the size-varying pictures on a 10-ft distant, high-resolution monitor (see [15, A10], p. 11, "Apparatus" section).

first is the *face-inversion effect* (FIE) which refers to a finding first reported by Yin (1969) and subsequently by many others (see, e.g., Bradshaw, Taylor, Patterson, & Nettleton, 1980; Diamond & Carey, 1986; Ellis & Shepherd, 1975; Leehey, Carey, Diamond, & Cahn, 1978; Phelps & Roberts, 1994; Phillips & Rawles, 1979; Valentine & Bruce, 1986) that the processing disadvantage of inverting a visual stimulus is worse for faces than for other kinds of visual stimuli, e.g., houses. The FIE is one of the primary bases for the claim that face processing is special, i.e., is qualitatively different from processing other visual stimuli: As noted in a classic review article, for example, "…the evidence from the effect of inversion…provides the most direct indication that face recognition may involve a unique process" (Valentine, 1988, p. 472). The FIE is also observed when defined as relative activity to upright and inverted faces and non-faces in the face fusiform area (Kanwisher, Tong, & Nakamaya, 1998; Rossion & Gauthier, 2002). We have carried out a number of FIE experiments ([14, A9]), two of which are described below in Section B.2.e.ii.(c).

The second topic is an oft-noted distinction between two types of visual processing that are presumed to be particularly relevant for face perception: Depending on the specific theory, upright face processing is assumed to be, more than other kinds of visual stimuli, based on "second-order features" or on "configural information" (e.g., Carey & Diamond, 1977; Collinshaw & Hole, 2000; Rhodes, 1988), or on "second-order relational information" (e.g., Diamond & Carey, 1986), or on "holistic" or "gestalt" information (Farah, Tanaka, & Drain, 1995; Farah, Wilson, Drain, & Tanaka, 1998; Sargent, 1984), or "carried out in parallel" (e.g., Bradshaw & Wallace, 1971). This processing mode is contrasted to "featural" or "serial" processing that is assumed to be relatively more important in processing non-face and/or inverted stimuli. Despite the pervasiveness of this kind of distinction, precise quantitative instantiations of it are rare, and we have attempted to fill this gap. As I describe in Section D.4.c, we have developed a theory that quantifies the contributions of configural and featural information to face processing, and demonstrates how the relative contributions determine when a FIE does or does not occur.

The third topic involves processing of familiar versus unfamiliar faces, particularly in anticipation of a subsequent recognition test. It would seem obvious that these two kinds of processing must differ in that while a verbal label ("Oh, it's Julia Roberts") might suffice to eventually recognize a familiar face, storage of visually based information is required to eventually recognize an unfamiliar face. Some work, much of it with a practical-applications slant has been done on this topic (e.g., Bruce, Henderson, Newman, & Burton, 2001; Collinshaw & Hole, 2000; Hancock, Bruce, & Burton, 2000). In our own lab, we have determined that, although familiar and unfamiliar faces are different with respect to the FIE ([14, A9]), they are affected in the same way by stimulus contrast ([12, A7]). The distinction between familiar and unfamiliar faces forms a theme that weaves through much of the proposed face-processing work.

B.2.c. Confidence and Accuracy in Visual Memory

Recently, we have carried out experiments concerning relations between confidence and accuracy that have integrated our methodologies and content questions with work in forensic psychology and in metacognition. This research was motivated partly by an intrinsic interest in the relations between confidence and accuracy and partly by real-life consequences in legal cases. Often, a critical issue in a court of law is the accuracy of some witness's memory (of, for example, a criminal, an accident, or the exact details of some event). Unlike a scientist in a laboratory, a trier of fact, i.e., a judge or jury, does not have the luxury of knowing what the correct answers are in this "memory test." Accordingly the major means by which the trier of fact judges accuracy is to assess the confidence expressed by the witness in his or her memory, under the dubious assumption that such confidence directly reflects the reported memory's underlying accuracy.

Whereas there has been much work done concerning inter- or intra-observer correlations between confidence and accuracy (e.g., Deffenbacher, 1980), our own research has focused on observers' ability to assess the effects of certain independent variables on eventual accuracy. Many such variables affect confidence; for instance, Wells, Ferguson, and Lindsay (1981) reported that being interviewed about a previously viewed crime increases witnesses' confidence that they had correctly identified the culprit. The tack we have taken is to manipulate some variable in the study phase of a recognition test, collect prospective confidence ratings at the time of study, and then determine the degree to which such prospective confidence correctly predicts the variable's effect on eventual recognition performance. We have determined that observers overestimate the benefit of visual rehearsal ([3, A2]) but correctly assess the effects of contrast ([12, A7]). Part of the proposed research is to investigate, and to develop a theory of, the general proposition that effects of low-level variables such as contrast are correctly predicted, while effects of higher-level variables such as visual rehearsal, are subject to all manner of metacognitive strategies that distort prediction.

B.2.d. Eye Fixations

In most visual memory experiments, stimulus durations fall naturally into those that are shorter than an eye fixation duration (i.e., less than around 300 ms) and those that are longer. When eye movements are not recorded, results from experiments in which longer durations are used become difficult to model because of loss of control over, and knowledge about how many eye fixations have been made and where on the stimulus they have fallen.

These limitations can be addressed by recording eye fixations and/or by guiding them (e.g., Henderson & Hollingworth, 1998; Hollingworth, in press). David Irwin and I have planned a series of picture-processing experiments in which eye movements will be recorded, and the scope of some of our theories will thereby be extended to presentations involving multiple eye fixations. Irwin has the equipment and the expertise to run such experiments. Logistically, Irwin and I will design the experiments, I will create the stimuli, Irwin will collect the data at the University of Illinois, I will analyze them, and we will jointly use the results to arrive at conclusions and evaluate theories. Irwin and I have successfully completed such a collaboration in the past (Loftus & Irwin, 1998).

We have recently launched this project: I have written software and created stimuli (heterogeneous complex scenes) for a simple picture-recognition pilot experiment. Irwin is in the process of implementing the software in his eye-movement laboratory. This pilot study, in which only stimulus duration is manipulated at study, will allow us to fine-tune our logistics and to ensure that we get the same basic results in experiments done in Irwin's lab in Illinois as in my lab in Seattle. After any kinks are ironed out of our methodology, we will proceed to eye-movement studies, an example of which is described below in Section D.2.b.

B.2.e. Linear Theory, Dimensional Theory, and Unidimensional Theory

Specific Aim 7, which pervades most of the present and proposed research, revolves around theory and methodology in psychology. In this section I describe more specifically what this aim is all about. I first summarize the almost-universally used *linear theory*. I then sketch a less used alternative, *dimensional* theory, emphasizing its simplest form, *unidimensional theory*. These issues are discussed at length in Bamber (1979) and Dunn and James (2003). An upcoming *Psychological Review* article ([14, A9]) is devoted largely to the relation between these theories. Most of the proposed work will be interpreted within the context of dimensional theory.

B.2.e.i. Linear Theory. The vast majority of experiments in many disciplines, including psychology, are designed, analyzed, and interpreted within the context of linear theory. Linear theory, described at least implicitly in any statistics text, and explicitly in any mathematically-based statistics text (e.g., Hays, 1973), holds that the dependent variable in an experiment is computed as the sum of terms corresponding to main effects of, and interactions among independent variables, plus any error terms applicable given the experimental design. Conclusions are based on the inferred presence or absence of such effects. For example, in face-processing experiments, a FIE would be inferred from a statistically significant stimulus type x orientation interaction.

While linear theory has been a standard tool in understanding myriad data sets, it has some serious disadvantages. Briefly, they are these. First, linear theory is entirely *linear*, hence its name. While linearity may bear an approximation to some actual psychological relations, many other such relations are decidedly nonlinear, which means that interpreting them within the context of linear theory can produce profoundly misleading conclusions. A classic example of this problem involves interpretations of interactions (see, e.g., Bogartz, 1976; Loftus 1978; 1985; Loftus & Bamber, 1990): As interpreted within the context of linear theory, nonordinal interactions observed with one dependent variable (e.g., recognition performance) can disappear or reverse with another dependent variable (e.g., d') or a theoretical construct (e.g., "memory strength") that is monotonically, but nonlinearly related to the dependent variable.

A second disadvantage of linear theory is more subtle but also more insidious: Because linear theory is both seductively plausible and almost universally welcomed, it blinds investigators to alternative theories that might better elucidate underlying psychological processes.

B.2.e.ii. Dimensional Theory We have argued that dimensional theory is one such theory. The general idea of dimensional theory is that independent variables combine at various stages into internal psychological *dimensions* that directly underlie performance. By determining (1) how many such dimensions are necessary to account for performance in a given situation, along with (2) the nature of the mathematical functions that describe how the independent variables combine to produce the dimensional values, the underlying nature of the relevant psychological structures can be unveiled.

Dimensional theory is related to conjoint measurement (e.g., Krantz, Luce, Suppes & Tversky, 1971; Krantz & Tversky, 1971; Tversky & Russo, 1969), functional measurement (e.g., Anderson 1974; 1979), multidimensional scaling (e.g., Kruskal, 1964; Shepard, 1962), the concept of integral and separable dimensions (Garner, 1964), and the concept of "mental modules" (Pinker, 1997). The incarnation of it on which we have focused was independently described by Bamber (1979) and Dunn and Kirsner (1988). Dimensional theory has proven useful in illuminating various psychological phenomena, including visual displacement discrimination (Palmer, 1986a, b), the relation between iconic memory and visible persistence (Loftus & Irwin, 1998), the relation between confidence and accuracy in face recognition ([3, A2]), the relation between degree of original learning and forgetting rate (Loftus, 1985b; Loftus & Bamber, 1990), the relations among stimulus duration, stimulus contrast, confidence, and accuracy in visual recognition ([12, A7]), the genesis of the FIE ([14, A9]), and the logical, theoretical, and empirical underpinnings of the dissociation technique (Dunn & Kirsner, 1988). Dunn and James (2003) have recently developed a technique founded on dimensional theory called "signed difference analysis" and have illustrated its use in addressing classic problems within cognition, such as: Does the "remember-know" distinction in recognition memory reflect qualitatively different cognitive states, or different regions on some unidimensional scale?

Dimensional theory is central within vision science: Two examples of its use there are color metamers (that an indefinitely large number of independent variables, in the form of different monochromatic hues, reduce, in the form of cone quantum-catch values, to three retinal-output dimensions whose values determine color perception) and Bloch's Law (that, as described earlier, the two independent variables of stimulus duration and stimulus intensity combine multiplicatively into a single dimension of "total intensity" whose value determines brightness perception).

B.2.e.ii.(a). D-Dimensional Theory. By dimensional theory, a particular combination of M independent variables in some experiment yields D values, one on each of D internal psychological dimensions. The value, V_d on the d^{th} dimension is,

$$V_d = f_d(IV_1, IV_2, ..., IV_M) \quad (1)$$

where the IV_m's are the independent variables and f_d is an unconstrained function. The D values are then mapped to N dependent variables, the n^{th} of which is computed as,

$$DV_n = g_n(V_1, V_2, ..., V_D) \quad (2)$$

When D=1, i.e., when there is only a single dimension, g_n is monotonic. When D > 1, the situation is somewhat more complicated, but the g_n's are still constrained in a manner described by Dunn and James (2003). Equations 1-2 thereby define a D-dimensional structure. If the inferred number of internal dimensions, D, is less than the number of independent variables, M, one concludes that at least two of the independent variables have lost their unique representations somewhere in the structure, when they merge into fewer dimensions.

An illustration of a dimensional structure is found in color metamers mentioned above. Suppose that a mixture of M monochromatic hues of differing intensities is presented to the visual system. Each hue acts as an independent variable; thus the different experimental conditions correspond to the different combinations of hue intensity. It has long been known that the sensory result of any combination of such hue intensities can be described completely by the three numbers corresponding to the three cone quantum catches engendered by that combination. Therefore, any dependent variable used to measure color perception in this kind of experiment depends only on D=3 dimensions corresponding to the output of the three cone classes. This finding, embodied in the classic color-matching experiment, was pivotal in color science: It formed the basis for the trichromacy theory of color vision, and laid the groundwork for the eventual discovery of cone photoreceptors.

B.2.e.ii.(b). Unidimensional Theory. The simplest dimensional theory is a *unidimensional* theory in which D=1, i.e., only a single dimension is required to account for a data set. An illustration of unidimensional theory is Bloch's Law. As described earlier, Bloch's Law states that when duration is below around 100 ms, perception, measured e.g., by detection, depends only on the *product* of duration and intensity; in other words, the two independent variables, duration and intensity, combine (multiplicatively) to produce a value on the D=1 dimension of "summed intensity." This is consistent with the simple proposition that neither the physical value of duration nor the physical value of intensity is represented within the sensory system; rather, only their product is represented. Bloch's Law is useful in understanding how the sensory system processes intensity, *viz*., for about 100 ms, the system simply integrates arriving photons over time and maintains a representation of the photon sum.

B.2.e.ii.(c). Example Experiments. Developing and testing unidimensional theories will be, as it is now, an ever-present activity in the proposed research. In this, and the next three subsections I describe how this is done.

To provide context for these descriptions, consider two old-new recognition experiments investigating the FIE, reported as Experiments 1 and 2 in [14, A9]. In each experiment, three variables were manipulated: the duration at which a stimulus was presented at study, stimulus orientation at study (upright or inverted), and stimulus type (faces or houses). In Experiment 1, unfamiliar faces were used as stimuli, while in Experiment 2, familiar (celebrity) faces were used. The main results are shown in Figures 2AB (Experiment 1) and 2DE (Experiment 2). Each panel shows recognition performance as a function of study exposure duration for faces (Panels A and D) and houses (Panels B and E). In each experiment, we found a classical orientation x stimulus type interaction; the difference between the upright and inverted curves was greater for faces than for houses. However, we argued (strenuously) that conclusions based on such interactions are ephemeral at best (see also Loftus, 1978), and that a more productive course of action would be to interpret the results within the context of dimensional theory.

Accordingly, we constructed a to-be-tested unidimensional theory in which there was no FIE. By this theory, the two "perceptual" variables, duration and orientation, combine into some unidimensional value (call it "Strength"). Recognition performance for the two stimulus types, faces and houses is then determined by monotonic functions, m_F and m_H of Strength. Note that such a theory implies no FIE, in that the orientation value (as well as the duration value) is lost when duration and orientation are combined into Strength; thus there is no

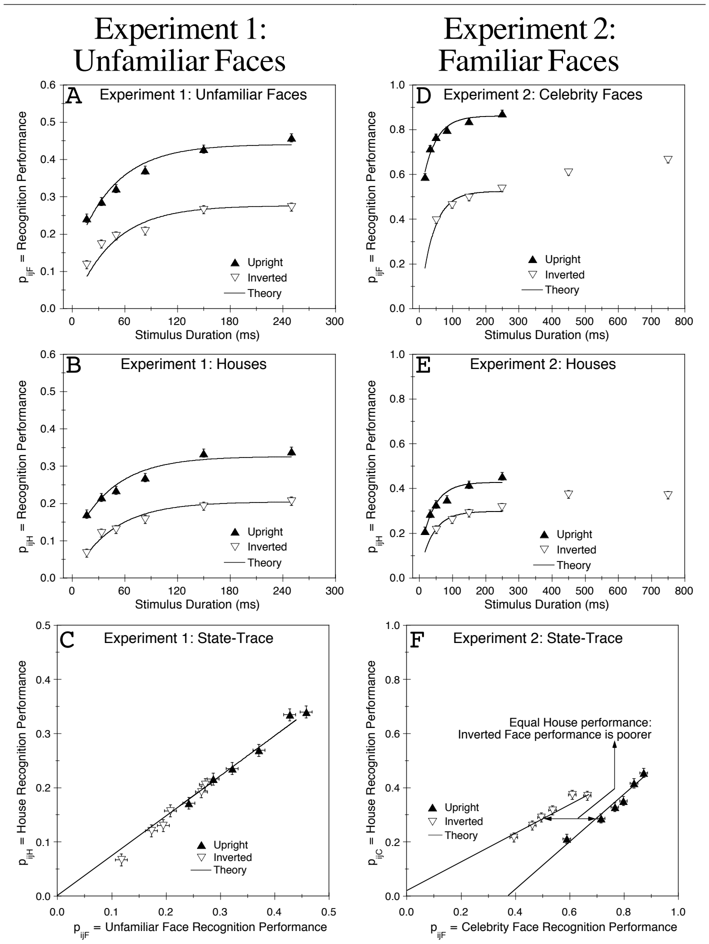

Figure 2. Results of [14, A9], Experiments 1 and 2. Solid and open curve symbol correspond to upright and inverted pictures. Solid lines are theory predictions described in proposal, Section D.4.c. Error bars are standard errors.

differential effect of orientation on face versus house performance.

B.2.e.ii.(d). State-Trace Analysis. To evaluate a unidimensional theory, one constructs a *state-trace plot* Bamber (1979), which is a plot of one dependent variable against another dependent variable over experimental conditions (reminiscent of the familiar ROC or ROC plot of hit probability plotted against false-alarm probability). In this case, house performance is plotted against face performance over all 12 duration x orientation conditions. Now consider any two duration x orientation conditions, C_1 and C_2. Suppose that face performance is greater in C_2 than in C_1. Because the function relating Strength to face performance is monotonic, we can go backward from performance to infer that Strength is likewise greater in C_2 than C_1—from which we can then likewise infer that house performance is greater in C_2 than in C_1. Thus the prediction of this FIE-less unidimensional theory is that the ordering of any two conditions must be the same for faces and houses, i.e., that the state-trace plot be *monotonic* across all 12 conditions. This logic underlies interpretation of many of the experiments proposed in Section D.

Figures 2C and 2F, show the state-trace plots. Figure 2C, the unfamiliar-face state-trace plot, is monotonic, thereby confirming a unidimensional theory which would imply no FIE. Figure 2F, the familiar-face plot is nonmonotonic, disconfirming a unidimensional theory and implying a FIE. More specifically, in Figure 2F the inverted data points are to the left of the upright points. This means that, as indicated in the figure, if one considers any two orientation x duration conditions—a longer-duration inverted condition and a shorter-duration upright condition—that produce equal performance for houses, then face recognition performance is poorer in the inverted condition than in the upright condition. This means that inversion reduces celebrity face performance more than house performance. The Figure-2 pattern thereby confirms Valentine's (1988) suggestion that a FIE emerges when familiar faces are retrieved from memory, but not when unfamiliar faces are encoded for subsequent recognition.

In [14, A9] we demonstrate that two theoretical dimensions can account for both these data sets. We selected the dimensions, which we termed "Configural Strength" and "Featural Strength" along with their assumed characteristics based on past theories of face processing (see references on p. 22 above), and constructed quantitative instantiations of them that resulted in the Figure-2 theoretical predictions. The estimated parameter values were such that the two dimensions emerged for Experiment 2, but the two dimensions collapsed into a single dimension for Experiment 1. In summary, analysis of these data within the context of dimensional theory reveals that (1) a FIE emerges when familiar, but not unfamiliar faces are encoded in anticipation of a subsequent memory test, and (2) the FIE can be harmoniously explained via two internal dimensions that are generally associated with explanations of face processing "specialness." I return to these points in Section D.4.c.

B.2.e.ii.(e). Equivalence Equations to Describe Stronger Unidimensional Theories. The just-described experiments are typical of many carried out in my lab. In them, we manipulate study duration, along with some other *focal variable* (orientation in the example), whose effect on information acquisition is under investigation. The focal variable's effect is generally assessed by comparing *performance curves*, examples of which are shown in Figure 2ABDE: performance plotted against duration, with different curves corresponding to different focal-variable levels.

If a unidimensional theory is confirmed, then stronger versions of the theory can often be constructed using what I have termed *equivalence equations*, which are rules that govern the durations which yield equal performance for different focal-variable levels. The general equation relating performance curves for two focal-variable levels is:

$$p\,[F_i, d] = p[F_j, f(d)] \tag{3}$$

where $p[F_i, d]$ and $p[F_j, f(d)]$ denote performance for levels i and j of the focal variable, d and f(d) are durations, and f is a monotonic function.

Of theoretical interest in a given situation is the nature of the function f(d) on the right side of Equation 3. Different f(d)'s are implied by different hypotheses about the focal variable's effect. I illustrate with two simple hypotheses. The first is that the focal variable's effect is *additive,* i.e., that f(d)=d+k, which means that,

$$p\,(F_i, d) = p(F_j, d+k) \tag{4}$$

Here, k is a constant in units of time. The interpretation of an additive effect is that being in level i of the focal variable is equivalent to having an additional k ms of stimulus duration compared to being in level j. Thus an additive theory, predicts performance curves to be *horizontally parallel*, separated by k ms. An example is provided in [10, A5], where high spatial-frequency (HSF) versions of target digit strings were presented at varying durations to observers who attempted to recall them. These HSF targets were either preceded or not preceded by a 40-ms *prime* consisting of a LSF version of the same digits. Figure 3A shows the results: Unsurprisingly, performance is better for longer durations and for primed compared to unprimed stimuli. Figure 3B shows the same data, but with the primed curve shifted to the right by k=49 ms. The curves align well, confirming an additive effect—which, as demonstrated in [10, A5] suffices to disconfirm an interactive theory by which early LSF information affects subsequent acquisition of HSF information. The results can be succinctly summarized as: A LSF prime is *worth* an additive 49-ms HSF "preview." This confirmation of an additive effect is analogous to conclusions reached via similar methodology and logic that an iconic image is worth a 100-ms "postview" of the physical stimulus (Loftus, Johnson, & Shimamura, 1985; Loftus, Duncan, & Gehrig, 1992).

The second hypothesis is that the focal variable's effect is *multiplicative,* i.e., that f(d)=cd, which means that,

$$p(F_i, d) = p(F_j, cd) \tag{5}$$

Here c is a dimensionless constant. The interpretation of a multiplicative effect is that being in level i of the focal variable *speeds up processing* by a factor of c, compared to being in level j. A multiplicative hypothesis can be conveniently tested by plotting performance on a log-

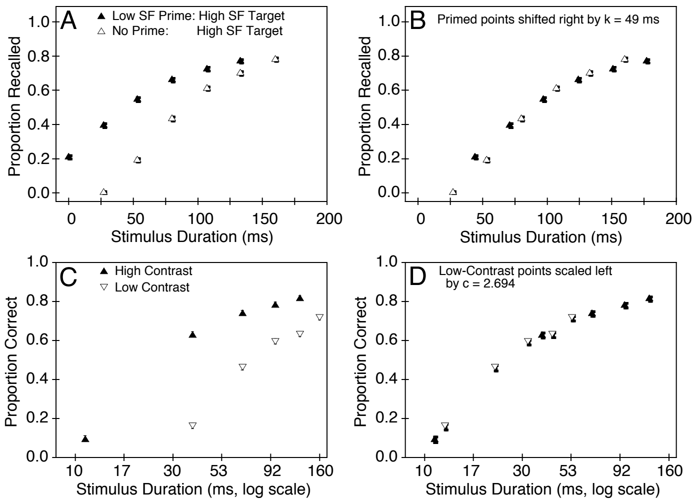

Figure 3. Examples of an additive shift (top panels) and a multiplicative scaling (bottom panels). Error bars are standard errors.

duration scale instead of a linear-duration scale. When d is on a log scale, Equation 5 becomes,

$$p[F_i, \ln(d)] = p[F_j, \ln(c)+\ln(d)] \qquad (6)$$

and performance curves are predicted to be horizontally parallel, separated by a constant of ln(c) which, after being estimated, can be exponentiated to recover c. Figures 3CD show an example from [12, A7, Experiment 2]. Here either high-contrast or low-contrast random forms were presented at varying durations, followed by a 2-alternative, forced-choice (2AFC) recognition test. Figure 3C shows, again unsurprisingly, that performance is better for longer durations and for high-contrast compared to low-contrast stimuli. Figure 3D shows the same data, but with the low-contrast curve scaled (i.e., shifted on a log axis) to the left by 0.991 log units, which corresponds to a scaling factor of $c = e^{0.991} = 2.694$. Again the curves align quite well, confirming a multiplicative effect. The results can be succinctly summarized as: High-contrast stimuli are *processed faster* by a factor of 2.694 compared to low-contrast stimuli. This example demonstrates how a processing-rate ratio, r_P = 2.694 here, can be measured—thereby fulfilling the promise made in Section B.2.a.i, p. 19, right column above.

We have used such equivalence techniques to investigate effects of numerous focal variables on information acquisition, including stimulus masking (Loftus, et al., 1985; Loftus et al., 1992), stimulus degradation (Loftus, 1985c; Loftus, Kaufman, Nishimoto, & Ruthruff, 1990), observer age (Loftus, Nelson, & Truax, 1986), and various sorts of priming (Reinitz, Wright, & Loftus, 1986; [10, A5]). We have also used equivalence techniques to study effects of original learning on forgetting (Loftus, 1985a, b; Loftus & Bamber, 1990). Finally, as described earlier, we have used them to study distance effects on face perception: Here distance took the place of duration, and the equivalence equation was, M(f) = M(F/43D) where f and F were spatial frequency in c/face and c/deg (see Equation 8, p. 37 below).

B.2.e.ii.(f). On Interpretation of Interactions. Above I have been discussing ways of identifying the fundamental nature of *interactions* among variables. The kinds of analysis and interpretation techniques that I have described allow conclusions that are more generalizable and robust than are conclusions based on traditional statistical interactions inferred within the context of standard linear theory. Loftus (1978; 1985a) and [14, A9] provide more detail, but essentially because performance curves are compared horizontally, any conclusion issuing from the comparison (e.g., that the curves are or are not horizontally parallel on a linear or on a log-duration axis) is invariant over all monotonic transforms of the performance measure: Any set of points that are equal in one scale must also be equal in any monotonically related scale. Therefore, conclusions based on such equivalence techniques apply not only to the particular dependent variable being measured (e.g., proportion correct) but also to any theoretical construct assumed to be monotonically related to the dependent variable (e.g., "memory strength") and to any dependent variable that is monotonically related to the dependent variable being measured (e.g., d').

B.2.f. SRIA Theory

Much of the work in my laboratory over the past decade has been designed to test and extend a particular quantitative theory, the SRIA theory, developed to provide an interface between low-level sensory processing and high-level phenomena such as visual memory. This theory is described in many places (e.g., Busey & Loftus, 1994; Loftus & Ruthruff, 1994; [1, A1]; [10, A5]); Olds and Engel, 1998, so I provide here only a brief sketch of it. The theory's functions and parameters are summarized in Table 1, next page.

B.2.f.i. Description. The theory begins with the temporal waveform of the visual stimulus—stimulus contrast as a function of t, time since stimulus onset, termed f(t)—which is usually, although not always, a rectangular-wave function, whose width and height are duration and contrast. A *temporal impulse-response function* describes the system's response to an instantaneous stimulus. The impulse-response function, termed g(t), is modeled as a gamma function which is the convolution of n exponential-decay functions, each with a decay parameter of □ ms (see Watson, 1986). The convolution of f(t) and g(t) is a hypothetical *sensory response function*—the magnitude of some neural response as a function of t—which is termed a(t), There is assumed to be a sensory-response *threshold*, termed □, such that information acquisition occurs only when the sensory response is above threshold (see the informal discussion of threshold in Section B.2.a.i, p. 20 above). Stimulus information is assumed to be acquired at a rate, r(t), which is proportional to the product of the magnitude by which the sensory response exceeds threshold, and the proportion of yet-to-be acquired information, with a proportionality constant of 1/c. The integral over time of r(t) is, by definition, acquired information. Finally the theory assumes some reasonable dependent variable, e.g., proportion recalled digits to equal total acquired information, thereby completing the linkage from the observable f(t) to the observable dependent variable.

Mathematically, the theory is straightforward to under-

Table 1. Parameters and Functions of the Sensory-Response/Information-Acquisition (SRIA) Theory

Functions	Definition	Comments
f(t)	Stimulus temporal waveform	Generally a rectangular-wave function, but can be any shape (e.g., see ramping functions described by Busey & Loftus, 1994, Experiment 5).
g(t)	Impulse-response function	Theoretical response of the system to an impulse: Assumed, per past literature, to be the convolution of n exponential functions, each with decay parameter τ.
a(t)	Sensory-response function	Assumed neural response triggered by physical stimulus presence: calculated as the convolution of f(t) and g(t).
$a_\theta(t)$	Magnitude by which a(t) exceeds threshold: Defined to be $(a(t)-\theta)$ for $a(t) > \theta$ and 0 otherwise	
I(t)	Acquired information	In units of percent total information relevant to task at hand
r(t)	Information-acquisition rate	In units of percent total information/ms. Assumed to be the product of $a_\theta(t)$ and [1–I(t)]. Note that r(t) is the derivative of I(t), i.e., r(t) = dI/dt.
Parameters	**Interpretation and effects**	**Comments**
τ, n	Jointly determine the (gamma) impulse-response function	The parameter n, a positive integer, represents number of sequential exponential stages and is always set to 9. The parameter τ (in ms), a positive real number, represents the average duration of each stage. Typical value of τ is 10 ms.
θ	Sensory threshold: When the sensory response function is below threshold, no information acquisition takes place	Interpreted in contrast units. Typical value is 0.03. Above-threshold area under the sensory-response function determines eventual memory performance. When θ is zero, SRIA theory is a Bloch's-Law Theory: In that special case, area under the sensory-response function, which determines performance, equals duration x contrast.
c	Governs information-acquisition rate	The "cognitive" parameter. Generally, different levels of cognitive variables (e.g., stimulus type, attention, etc) are accorded different c values. Units are percent total information/ms.
w_L	Weighting given to low spatial-frequency information	When applying the SRIA theory to experiments involving high and low spatial frequency information ([10, A5]) the low spatial-frequency sensory-response function is weighted by w_L, while the high spatial-frequency sensory-response function is weighted by $(1-w_L)$. The theory was modified by allowing w_L to vary over time by, $w_L(t)=e^{-kt}$ where k is a free parameter that replaces the original w_L.

stand when derived stage by stage (e.g., as in [1, A1, pp. 385-398]); to save space here, I provide only the bottom-line equation:

$$p = 1-\exp\left[-\left(\int\left[f(t) * \frac{(t/\tau)^{n-1} e^{-t/\tau}}{\tau(n-1)!}\right] - \theta\right)/c\right] \qquad (7)$$

where p is observed proportion correct, " * " signifies convolution, the expression to the right of the " * " within the square bracket is g(t), and the integral is over all values of t for which $a(t)>\theta$. It is a mathematical fact that (assuming a nonnegative impulse-response function) if $\theta = 0$, the value of the integral equals the area under f(t) which is usually the product of duration and contrast: Because performance, p, is determined by this product, this zero-θ special case of the SRIA theory is a generalization of Bloch's Law with no "critical duration."

B.2.f.ii. Applications. Work on the SRIA theory during the current funding period has included (1) formalizing its relation to, and accounting for Bloch's Law and the Bloch's-Law critical duration ([12, A7]), (2) extending and applying it to acquisition of different kinds of spatial-frequency information ([10, A5]; see also Olds and Engel, 1998), and (3) demonstrating its applications, as well as its limitations in describing visual memory for line drawings ([1, A1]), random forms ([12, A7, Experiments 1-2]), and natural pictures shown at both single eye-fixation and multiple eye-fixation durations ([12, A7, Experiments 3-6]). We have also measured the temporal luminance profiles of visual display devices with discrete frame rates, e.g., CRTs and LCD projectors, and have confirmed, using the SRIA theory's estimated parameters, that such displays are, from the visual system's perspective, temporally blurred such that they are indistinguishable from rectangular-wave contrast profiles [17].

B.2.g. Statistics and Data Presentation

A lengthy *Stevens' Handbook* chapter [6, A3] summarizes and expands on much of my work over the past ten years concerning statistical methodology and data presentation. A second article ([8]) builds on the Stevens' Handbook chapter and other prior work, describing computation of confidence intervals for various kinds of experimental designs.

B.2.h. Visual Hindsight Bias

There is a large literature on the topic of *hindsight bias* which is the tendency for individuals with outcome knowledge to claim more prior knowledge of some outcome than is objectively warranted (e.g., Fischhoff, 1975). Our own interest in hindsight bias was piqued by a legal case in which a radiologist (call him "Radiologist D") was sued by the family of a patient whose ultimately fatal tumor had not been detected by D during a routine physical examination. At trial, plaintiffs called as an expert witness another radiologist ("Radiologist E"). E had seen the patient's x-rays just before his death, at which time the tumor was large and clearly visible. E then viewed the initial x-rays, originally inspected by D three years earlier, at which time the tumor had been considerably smaller and less visible. E asserted that, because he, E, could "detect" the tumor in the initial x-ray, D should have similarly detected it, and that D's failure to do so constituted malpractice.

Erin Harley and I reasoned that E's "perception" of the original tumor may well have been a form of hindsight bias that we dubbed *visual hindsight bias*. Although reports of such bias appear in occasional medical reports (e.g., Muhm, Miller, Fontana, Sanderson, & Uhlenhopp, 1983), it had received surprisingly little attention from the psychology community—the closest we could find were recent descriptions of "change blindness blindness," e.g., Levin, Momen, Drivdahl, & Simons, 2000; Levin, 2002. Accordingly, we carried out several projects to investigate visual hindsight bias. The general procedure was to show pictures of celebrities. Each picture began so blurred as to be unrecognizable, then gradually de-blurred. We measured the degree of blur at which observers recognized the celebrity. This unbiased recognition point was compared to corresponding points measured when observers (1) knew who the celebrity was to begin with or (2) were later asked to indicate the blurriness point at which they had originally recognized the celebrity. We found visual hindsight in abundance: Observers claimed to have recognized celebrities at a blurrier point when they knew beforehand who the celebrity was ([9]; [13, A8]). We replicated this effect with young children using to-be-identified Snodgrass & Vanderwart drawings ([11, A6]; [16]).

B.2.i. Developmental Work

In conjunction with Andy Meltzoff and Danny Bernstein, I am carrying out developmental work with 3-5 year old children. In particular, as just mentioned, we have measured the developmental course of visual hindsight bias ([11, A6]). We have also measured the developmental course of degraded object identification and the Bruner & Potter (1964) perceptual-interference effect ([11, A6]; [16]). As described in these articles, we have developed numerous computer programs for performing this work as well as techniques for interpreting its results and quantifying developmental growth rates.

B.2.j. Laboratory Renovations (and Consequences)

One of the proposed projects for the current funding period was to transform our productive but creaky, 8-observer, 5-slide projector, visual-memory laboratory into a sleek, 21st century model based on a Macintosh G4, running under MATLAB, controlling a single LCD projector. We accomplished this goal (described in [17]), but for a variety of reasons, the transition was (shockingly) quite a bit slower and more hassle-laden than we had anticipated. Many days during the first year and a half of the funding period were thus agonizingly data-free (although I did take advantage of much of this down time developing theory and writing a major treatise on statistics and data presentation, published as [6, A3]).

Transition problems now an unpleasant but distant memory, the new laboratory has run almost entirely without difficulty for 3 years, is very efficient (running, if not 24/7, at least 8/5) and, as I write, has generated more than 2 million observer responses. Generation, manipulation, and display of stimuli under MATLAB allows considerable flexibility: Any kind of relevant image processing, e.g., spatial filtering, contrast manipulation, color manipulation, size manipulation, or superimposition of different images, can be done with a few minutes of programming time. Our lab computer is fast enough that reasonable sized images, e.g., 500 x 500 pixels, can be easily transferred to video memory within a single screen refresh. Analysis and theory fits can be accomplished instantly following data collection. We have amassed a large collection of library routines for accomplishing all this.

B.3. Grant-Supported Manuscripts

Below I list manuscripts from the current funding period. If a listed manuscript is included as an appendix, the appendix number follows in parentheses. The square-bracketed symbols following each manuscript reference indicate the manuscript's topic matter using the following keys: GTI: General theoretical issues; ET: Equivalence techniques; MM: Mathematical models; SRIA: SRIA Theory; FP: Face processing; SFD: Spatial-frequency decomposition; C: Contrast effects; GLP: Global/local processing; CA: Confidence and accuracy; SDP: Statistics and data presentation; L: Laboratory techniques; VHB: Visual hindsight bias; D: Developmental work.

1. Loftus, G.R. & McLean, J.E. (1999). A front end to a theory of picture recognition. *Psychonomic Bulletin & Review,* 6, 394-411. (Appendix 1), [MM, SRIA, C].
2. Busey, T. (1999). Localization and identification rely on different temporal frequencies. *Vision Research, 39*, 513-532. [MM, SRIA].
3. Busey, T.A., Tunnicliff, J., Loftus, G.R. & Loftus, E.F. (2000). Accounts of the confidence-accuracy relation in recognition memory. *Psychonomic Bulletin & Review*, *7*, 26-48. (Appendix 2), [ET, FP, C, CA].
4. Harley, E. M., & Loftus, G. R. (2000). MATLAB and graphical user interfaces: Tools for experimental management. *Behavior Research Methods, Instruments, and Computers*, *32*, 290-296. [L].
5. Busey, T.A. & Townsend, J. (2001). Independent sampling vs. inter-item dependencies in whole report processing: Contributions of processing architecture and variable attention. *Journal of Mathematical Psychology*, 45, 283-323. [MM].
6. Loftus, G.R. (2002). Analysis, interpretation, and visual presentation of data. *Stevens' Handbook of Experimental Psychology, Third Edition*, *Vol 4*. New York: John Wiley and Sons, 339-390. (Appendix 3), [GTI, ET, MM, SDP].
7. Loftus, G.R. (2003). What do we know about facial cognition? What should we do with this knowledge? *Contemporary Psychology*, *48*, 503-507. (Appendix 4), [FP].
8. Masson, M.E.J. & Loftus, G.R. (2003). Using confidence intervals for graphically based data interpretation. *Canadian Journal of Experimental Psychology*, *57*, 203-220. [SDP].
9. Harley, E.M. (2004). Demonstrations of visual hindsight bias. Dissertation submitted to the University of Washington. [VHB].
10. Loftus, G.R. & Harley, E.M. (2004). How different spatial-frequency components contribute to visual information acquisition. *Journal of Experimental*

Psychology: Human Perception and Performance, *30*, 104–118. (Appendix 5), [ET, MM, SRIA, SFD, GLP].

11. Bernstein, D.M., Atance, C., Loftus, G.R, & Meltzoff, A.N. (2004). We saw it all along: Visual hindsight bias in children and adults. *Psychological Science*, 15, 264-267. (Appendix 6), [SFD, VHB, D].
12. Harley, E.M., Dillon, A.M., & Loftus, G.R. (2004). Why it's difficult to see in the fog: How contrast affects visual perception and visual memory. *Psychonomic Bulletin & Review*, *11*, 197-231. (Appendix 7), [GTI, ET, MM, SRIA, FP, C, CA].
13. Harley, E.M., Carlsen, K.A., & Loftus, G.R. (2004). The " I saw it all along" effect: Demonstrations of visual hindsight bias. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, in press. (Appendix 8), [FP, SFD, VHB].
14. Loftus, G.R., Oberg, M.A., & Dillon, A.M. (2004). Linear theory, dimensional theory, and the face-inversion effect. *Psychological Review*, in press. (Appendix 9), [GTI, ET, MM, FP, SDP].
15. Loftus, G.R. & Harley, E.M. (2004). Why is it easier to recognize someone close than far away? *Psychonomic Bulletin & Review*, in press. (Appendix 10), [MM, FP, SFD].
16. Bernstein, D.M., Loftus, G.R., & Meltzoff, A.N. (2005). Object identification in toddlers and adults. *Developmental Science* (in press). [SFD, VHB, D].
17. Loftus, G.R. & Chen, J. A MATLAB-based visual-perception and visual-memory laboratory. Under revision for *Behavior Research Methods, Instrumentation, and Computers*. [SRIA, L].
18. Bernstein, D.M., Chen, J., & Loftus, G.R. On the perceptual representation of stimulus duration and stimulus contrast (manuscript in preparation), [GTI, ET, C].

D. RESEARCH DESIGNS AND METHODS

The research that has been supported for the past 18 years has addressed various questions about visual processing and visual memory. Five research strategies, alluded to above in varying degrees, have proved to be quite useful, and will continue to be emphasized. First, we have been constructing theories of relatively simple situations that concern specific aspects of the psychological activities involved in visual perception and visual memory. Common to these theories are (a) a unidimensional construct, loosely termed "Information" or "Strength," (b) a set of rules by which the value on this dimension is established by the visual-perceptual-cognitive system in a particular set of experimental circumstances, and (c) a set of rules linking the value of "Strength" to observable performance. Second, we have carefully worked out sets of such theories such that each successive theory in the set is a stronger version, i.e., a special case of the previous one and we have demonstrated specific data patterns that imply confirmation or disconfirmation of each theory in the set ([12, A7, pp. 198-200]; [14, A9, p. 29]). Third, we have formulated the stronger theories as mathematical equations such that the fit of theory to data can be characterized precisely and unambiguously. Fourth, we have tried to bypass the usual statistical machinery of psychological research by collecting data with sufficient power that statistical error becomes largely irrelevant (our standard goal is that the error bars be largely obscured by the curve symbols, as in Figures 2-3, pp. 24 and 26 above). Fifth, we have begun to investigate more complex situations in which unidimensional theory is rejected by the data, and multidimensional theories are required (e.g., [14, A9, pp. 21-25]).

Of central importance in past and planned research is formal and precise theory. Our theories begin with a description of the independent variables, progress through specific, quantitatively defined assumed processes, and end with either a specific function relating some relevant internal construct to the dependent variable, or equivalence equations that specify circumstances under which the dependent variable(s) should have equal values. This research strategy forces us to be explicit about assumptions, and forestalls ambiguity in predictions.

There is, compared to most research proposals, a somewhat unusual feature of this one: This is that I have never found it useful to propose a series of rigidly-planned experiments, and I don't do so here. Instead, I describe relatively few genuinely planned and designed experiments, with full knowledge that the nature of subsequent experiments will be dictated by (often unexpected) outcomes of the ones actually proposed. Therefore, descriptions below of proposed experiments will often assert something like, "Theory T implies Y [where Y is some quantitative outcome, e.g., 'two curves are horizontally parallel on a log-duration scale']. Outcome Y thereby confirms Theory T. Outcome not-Y, while disconfirming Theory T, is consistent with numerous possibilities, and subsequent experiments will depend on which of them actually occurred." It has been true throughout my research career that most research projects have blossomed from some experimental outcome that I never could have imagined when I wrote the proposal describing whatever experiment yielded the outcome. On a related note, it is difficult to predict the actual number of experiments that will be carried out during the proposed funding period. The current-period manuscripts listed above incorporate 33 experiments. Approximately 30 more were run either as pilot experiments or as experiments that have not yet been written up.

In the remainder of this section, I first provide a brief overview of relevant experimental methodology (Section D.1). I then describe proposed research in four content areas (Sections D.2-D.5) that correspond to Specific Aims 1-4 above. Proposed research relevant to Specific Aim 5 (eye fixations) is described in conjunction with contrast effects (Section D.2). Proposed research relevant to Specific Aims 6 and 7 is distributed throughout this section.

D.1. Experimental Methodology

Methodological details (luminances, display sizes, counterbalancing, testing, analysis and theory-fitting procedures, along with descriptions of stimulus sets for most of the proposed experiments) are described in various of the Appendices. In particular, for picture-recognition procedures, see [14, A9]; for confidence-rating procedures, [12, A7]; for spatial-filtering techniques, [10, A5], [15, A10]; and for developmental work, [11, A6]. Generally speaking, over the past 34 years I have worked out methodological details for visual-memory experiments quite thoroughly.

D.1.a. Data-Analysis Techniques

We design our experiments to yield substantial statistical power. For example, in picture-memory experiments, hit probability typically has a standard error of around 0.012. Therefore, quantitative theories can be rejected quite easily and conversely, persuasive *confirmation* of a quantitative theory requires a very good fit of the theory.

Different paradigms demand different analysis techniques. Sometimes, we use standard techniques in which mean performance values are statistically compared across experimental conditions. Other times we emphasize horizontal comparisons of psychophysical functions (e.g., performance as a function of duration or distance) in order to test for additive or multiplicative effects. Here we have two, non-mutually-exclusive options. First, as described, we can collect data with sufficient statistical power to distinguish unambiguously among the relevant competing hypotheses. Second, performance curves can often be fit by a standard function (e.g., a cumulative normal, as in Loftus, et al., 1986, or an exponential as in Busey & Loftus, 1994). Here, the function is fit to individual subject data, and statistical analyses are performed on the estimated function parameters.

D.1.b. Theory-Fitting Techniques

We have several techniques for fitting our theories to data. When the theory is capable of predicting exact observed performance, we use optimization routines (of which MATLAB has many) to find parameter values that minimize some criterion statistic, such as observed-predicted root mean square error over conditions. When the theory is capable of predicting only some unobservable construct presumed to be monotonically related to observed performance, we use analogous procedures to find the parameter values that maximize some appropriate non-parametric correlation coefficient between observed performance and the predicted measure.

D.2. Stimulus Contrast

Although there are many ways in which visual stimuli may be degraded, a large body of research indicates that stimulus *contrast*, defined as some variant of the ratio of foreground to background luminance, is critical in determining the fundamental response of the visual system. This effect can be seen in the cat's visual system, wherein retinal ganglion cells are considerably more sensitive to stimulus contrast than to absolute light levels (e.g., Wandell, 1995, pp. 139). The effect continues up through experiments investigating human sensitivity wherein contrast sensitivity varies over a range of approximately 20:1 as absolute light level varies over a range of more than 1,000,000:1 (e.g., Van Nes & Bouman, 1967).

Stimulus contrast is often the key experimental measure in vision science. This is largely because unlike stimulus intensity where linearity fails, a high degree of linearity is observed in neuronal responses when intensity is fixed and stimulus contrast is treated as the input variable. This linearity extends beyond physiology to perception. For example, Ginsburg, Cannon, and Nelson (1980) demonstrated that perceived contrast is a linear function of stimulus contrast for sine-wave gratings, and Olds and Engel (1998) showed that object identification is predicted well by the SRIA Theory, within whose context responses to different spatial-frequency components of independently varying contrasts are simply summed to determine the overall response.

As described earlier, while there exists a large body of research investigating contrast effects on low-level sensory processes, there has been considerably less research investigating contrast effects on higher-level cognitive processes. Recent work in our lab has been aimed at determining whether some of the fundamental laws that characterize simple stimuli in simple situations (e.g., detection of a monochromatic light patch) may be extended to more complex stimuli in more complex situations (e.g., face recognition). A guiding meta-hypothesis is that low-level contrast effects, which are generally well understood, underlie higher-level effects in ways that are amenable to precise theory and to unambiguous empirical test.

We have used two kinds of stimuli. *Biluminant stimuli*, characterized by having only two luminance levels, consist of a dark stimulus on a lighter background, e.g., digits, random forms, or line drawings. Here a single contrast value can be defined such as the ratio of foreground-minus-background luminance difference to background luminance. Such stimuli, while limited, are useful, in that strong quantitative theories, such the SRIA theory, can be tested. When the SRIA theory provides satisfactory fits to the data, the parameters have meaningful values (see Table 1) which allow specific, quantitative interpretations of various effects (see, e.g., Busey & Loftus, 1998), and constitutes confirmation of the underlying Bloch's-Law nature of the duration-contrast relation, as discussed on p. 20 above.

In other experiments, we use *multiluminant stimuli*—typically natural images, whose luminance composition encompasses the entire grayscale range (see, e.g., [14, A9, Figure 11, p. 18]). As described by Peli (1990) the definition of contrast is somewhat arbitrary in grayscale pictures. Commonly used is *mean contrast energy,* the average squared deviation between individual-pixel and mean luminance. Another definition offered by Peli is *band-limited contrast* which is average contrast energy computed at successive, nonoverlapping spatial frequency bands.

D.2.a. Testing for Identical Contrast Effects

We have entertained the proposition that stimulus contrast is a low-level—what we have termed a *fundamental*—variable, whose effect on perceptual processing is entirely automatic. By this I mean that contrast effects are immune to conscious influence and are the same for different levels of any manipulation. So far we have confirmed this proposition for a number of such manipulations. In [12, A7] for example, we confirm it for different task difficulty levels, different stimulus-task combinations (immediate digit recall versus random-form recognition), different stimulus types (e.g., unfamiliar versus celebrity faces), and different testing procedures (prospective confidence at study versus retrospective confidence at recognition).

To carry out these tests, we have used a visual-memory paradigm in which contrast and duration are varied at study along with some other focal variable (e.g., stimulus-task combination—digit recall versus random-form recognition). The equal-contrast-effect proposition is then tested using state-trace analysis, as described in Section B.2.e.ii.(d), wherein performance for one focal-variable level (digit recall in this example) is plotted against performance for the other level (form recognition) with different scatterplot points corresponding to the different duration-contrast conditions. The equal-contrast-effect proposition implies this scatterplot to be monotonic, as in Figure 2C, p. 24 above; see [12, A7, Figure 4C, p. 208] for the actual plot. A non-monotonic scatterplot implies rejection of the equal-contrast-effect proposition, and the exact nature of the nonmonotonicity reveals the nature of the different contrast effects on one focal-variable level versus the other—just as in Figure 2E above, the relation of the inverted to the upright data points implies a FIE, and specifically a FIE wherein inversion is more detrimental to face processing than to house processing.

D.2.a.i. Developmental Effects. McKee's First Law of child development is: "Everything gets better over age." Generally, this is true in our work along with everyone else's. In [11, A6], for instance, we report that ability to recognize degraded objects increases dramatically from ages 3 to 5.

However, if contrast is a fundamental variable, then a plausible hypothesis is that its effect is age-invariant. Most fundamental visual processes are relatively fixed at an early age, e.g., approximately 6 months for color vision and 3-5 years for visual acuity (see Teller, 1997, for a summary). These properties are, however, fixed in ways that may be characterized simply by settling at specific, adult values of continuous-valued parameters—e.g., parameters corresponding to some contrast-sensitivity function (CSF) in the case of acuity, or to cone-receptor distributions or cone response functions in the case of color vision. A plausible hypothesis about contrast however, is that it is fundamentally fixed in a *qualitative* manner, i.e., by Bloch's Law: As discussed on p. 20 above, our research is consistent with the possibility that, fundamentally, the ratio of two processing rates corresponding to two contrasts is equal to the ratio of the contrasts themselves. If contrast truly operates in such a Bloch's-Law manner, then there is no obvious route by which it would develop from some other state—which leads to the hypothesis that it is fixed at a very early age, perhaps at birth.

In conjunction with Davida Teller and Andy Meltzoff, I plant to investigate these issues. I have developed and piloted methodology to investigate contrast effects in young children. The paradigm is logically equivalent to a digit-recall paradigm that we have successfully used in many venues (e.g., Busey & Loftus, 1994; [10, A5]) but that uses kid-friendly stimuli: Ten line drawings (an elephant, a cat, a kite, etc.) are used in place of the 10 digits. On each of a number of trials, a single object is presented for a specified duration and contrast level, and the child attempts to name it. The experimenter then types in a single letter ("e" for elephant, "k" for kite, etc.). Brief but entertaining mini-events, e.g., one face morphing into another, serve as rewards for correct responses. Such data will be collected for several age ranges—as a start, for 3-year olds and adults. We will test relatively small numbers of observers, with large amounts of data per kid, in order to estimate effects for individual children[2].

As described, we test the equal-contrast-effect proposition using state-trace analysis (see Figure 2, p. 24 above; substitute children/adults for houses/faces and high/low contrast for upright/inverted). Given what we have discovered about contrast effects we anticipate that such effects will be identical for children and adults, even though we expect absolute performance to differ considerably. Any other outcome would be surprising but interesting, and would trigger a series of parametric studies whose designs would depend on the exact nature of the single-dimension theory violation. Given confirmation of a single-dimension theory, we would be in a position to evaluate stronger theories: multiplicative theory, the SRIA Theory, and Bloch's Law.

D.2.a.ii. General Familiarity/Specific Object. In past work, I have investigated the subjective bases of picture-recognition responses (e.g., Loftus, 1972; Loftus & Bell, 1975; Loftus & Kallman, 1979). This work has indicated (at least) two such bases. The first basis is a *specific feature* (e.g., "I saw this picture because I remember the rocking horse on the porch" or "I didn't see this picture because I would have remembered the Volkswagen"). The second basis is *general familiarity* ("I saw this picture because it looks familiar" or "I didn't see this picture because it looks unfamiliar"). This distinction is similar to the "remember-know" distinction (see e.g., Tulving, 1985; Gardiner, 1988). We have suggested that these two responses reflect two qualitatively different kinds of information in visual memory; indeed the Loftus & Bell article was entitled "Two kinds of information in picture memory."

What is meant by "qualitatively different"? We never directly addressed this question. Traditionally, one would attempt to answer such a question using *dissociation* (e.g., Jacoby, 1991)—i.e., one would seek variables that cause one effect for specific-feature information, and no effect or an opposite effect for general-familiarity information, or vice-versa. Contrast is a candidate such variable. However as Dunn & Kirsner (1988) have persuasively shown, the logic underlying such dissociation techniques is both logically flawed and needlessly demanding. Using state-trace analysis we can, as we have repeatedly demonstrated, unequivocally test whether a variable does or does not have differential effects in different situations even when the variable's qualitative effect appears superficially to be the same (e.g., compare Figures 2AB, p. 24 above with Figures 2DE). Finding identical contrast effects for the two types

[2] Pilot testing indicates that 3-5 year old children view this as a wildly enjoyable computer game and beg to play it incessantly. Also, by tailoring the particular 10 stimuli used for a particular child to the known vocabulary of that very child, very young, just post-verbal children can be tested in the paradigm.

of information would add support and generality to the equal-contrast-effect proposition. Finding different contrast effects would provide useful clues as to the nature of the difference between the two information types: For instance, a finding of a greater contrast effect on general-familiarity information would suggest that general-familiarity information is primarily *visual* and is thereby influenced more contrast than is specific-feature information which might be primarily verbal (e.g., Nelson, Metzler, & Reed, 1974; Paivio, 1971; 1991). Such speculations would then be crafted into specific, quantitative, to-be-tested hypotheses and additional experiments.

D.2.b. Extension to Eye Fixations

Loftus (1972) showed that effects of exposure duration on picture recognition are mediated by number of eye fixations made on the picture at study. For instance, later recognition is better if twelve 250-ms fixations are made on the picture during a 3-sec study exposure than if six 500-ms fixations are made; likewise, for instance, ten fixations on a picture produced the same recognition performance whether the ten fixations averaged 300 ms per fixation during a 3-sec presentation, or 500 ms per fixation during a 5-sec presentation.

D.2.b.i. Quantum Theory. This result can be accounted for by the proposition that a given fixation is designed to acquire some "quantum" of information from the picture. For many reasons, different such quanta require different amounts of time to acquire, but an acquired quantum's contribution to subsequent recognition doesn't depend on how long it took to acquire it. If this is true, then one could experimentally manipulate eye-fixation duration, keeping numbers of fixations constant, without an attendant effect on subsequent memory performance.

D.2.b.i.(a). Contrast, Eye Fixations and Visual Memory. David Irwin and I plan a project involving eye movements and visual memory. The first experimental series will involve investigations of stimulus contrast as a means of manipulating eye fixation duration. Prior work has shown that eye-fixation duration is monotonically related to stimulus contrast in a free-viewing situation (Loftus, et al., 1990) and that, as discussed at length above, duration and contrast interact multiplicatively in a picture-recognition paradigm. In an initial experiment, we will pull these results together. We show pictures in a recognition procedure. During the study phase, contrast is manipulated and eye movements are recorded. A stimulus picture vanishes immediately after some number of fixations, e.g., 1, 2, or 3 have been made. The most general predictions are that (a) fixation durations will be longer for low-contrast than for high-contrast pictures, but that (b) recognition performance will depend *not* on contrast or total duration, but only on number of fixations. A stronger, multiplicative, prediction is that reducing contrast by a given amount will reduce *all* fixation durations by the same factor. Yet stronger is a Bloch's-Law prediction: Lowering contrast by some factor, r_c (see Section B.2.a.i above), will increase eye-fixation durations by the same factor r_c. In either case, the factor by which duration increases as a result of lowering contrast can be compared with the r_P-value obtained in non-eye-fixation experiments wherein duration is manipulated within sub-eye-fixation-duration levels, and contrast is manipulated.

D.2.b.i.(b). Visual versus non-Visual Processing within an Eye Fixation. It is likely that the Bloch's Law prediction will fail for (at least) the following reason: Contrast would presumably affect only *visual* processing within a fixation. However, not all processing within an eye fixation is necessarily visual. For instance, in reading, there is strong evidence that eye fixations are used partly for visual information acquisition and partly for non-visual processing, e.g., integrating current information with information acquired over previous eye fixations, or verbal encoding of acquired information (see, for example, Just & Carpenter, 1975, for a theoretical account of this proposition, and Rayner, Inhoff, Morrison, Slowiaczek, & Bertera, 1981, for an empirical demonstration of it).

Suppose we wish to inquire: "During what proportion of the fixation does such purely visual processing occur?" We can start with the following assumptions. First, some percentage, x, of each eye fixation duration entails perceptual processing. Second, lowering contrast by factor r_C slows down perceptual processing by the same factor r_C. Third, contrast does not affect the duration of non-perceptual processing. Given these assumptions, it can be shown that the ratio of low- to high-contrast fixation durations is, $r_{L/H}=d_L/d_H=x(r_C-1)+1$. Such a determination provides precise information about processing within eye fixations that serves as a basis for quantitative theory.

D.2.c. Representation of Duration and Contrast in Long-Term Memory

At any given instant, a person is being bombarded with a vast amount of environmental information, only a tiny fraction of which is needed for the task at hand. Accordingly, as has been widely acknowledged, a fundamental problem faced by the sensory-perceptual-cognitive system is that of acquiring and retaining the small portion of incoming information that is needed, while ignoring and/or discarding the rest that is not. There are numerous ways of solving this problem, e.g., responding to only a tiny portion of the electromagnetic spectrum (*viz*., the visible spectrum), reducing the dimensionality of environmental information (as with color metamers), focusing attention, categorizing, and selectively forgetting.

Our past duration x contrast experiments are relevant to this issue. As described earlier, we have conducted numerous experiments involving a wide variety of stimulus categories, whose results can be accounted for by assuming that visual recognition performance is based on a single dimension that results from a (multiplicative) combination of target contrast and duration. An "information-loss hypothesis," consistent with this finding, is that individual contrast and duration values are not stored as part of a picture's long-term memory representation. Such a perceptual strategy makes sense; As I have just argued the brain is invested in conserving resources by ignoring and/or jettisoning information that is rarely needed.

Nevertheless, some recent data collected by Danny Bernstein, Janice Chen, and me [18] suggest that at least under some circumstances, duration and contrast information *is* retained in memory. We carried out three experiments, each with two phases. In the first, *inspection*, phase, pictures were shown in one of four conditions generated by combining two contrasts (low/high) with two durations (short/long). The specific contrast and duration values were selected such that, based on past data, recognition performance would be approximately equal for the low-contrast x long duration (cD) and the high-contrast x short-duration (Cd) conditions. In the second, surprise *testing* phase, we showed all pictures, and asked observers to identify either the original contrast level, or the original duration level. Our hypothesis was that both contrast and duration estimates would be based on the same single dimension that we had previously supposed to determine recognition performance. The prediction of this hypothesis is that contrast judgments and duration judgments be ordered in the same way across the four conditions.

Surprisingly, the results—an example of which is shown in Figure 4—disconfirmed this hypothesis: The scatterplot is nonmonotonic. Per the logic presented above, it cannot be true that, at the time of inspection, duration and contrast combine into a single measure which then determines both duration and contrast judgments. To see why this is so, consider the Figure-4 solid and dashed lines which represent plausible continua of points from hypothetical multiple contrast levels. Two vertically aligned points as indicated, for example, by the vertical arrow, represent two conditions—one longer duration x lower contrast, and the other shorter duration x longer contrast—that are judged to have been of the same contrast. If both duration and contrast judgments for these two conditions were determined by a single "Strength" value, as assumed by the information-loss hypothesis, then these two conditions would be inferred to have the same Strength which, in turn, would cause them have the same duration judgments. But they do not: Instead, the longer-duration condition is in fact judged to be longer. In short, the data indicate that separate representations of stimulus duration and stimulus contrast are maintained from the inspection to the test phase of the experiment. The data also indicate however, that these dimensions are not accessed independently: Given constant duration, increasing contrast leads to an increase in duration judgment, and vice-versa; for example duration as well as contrast is judged to be higher in Condition Cd compared to cd and in Condition CD compared to cD.

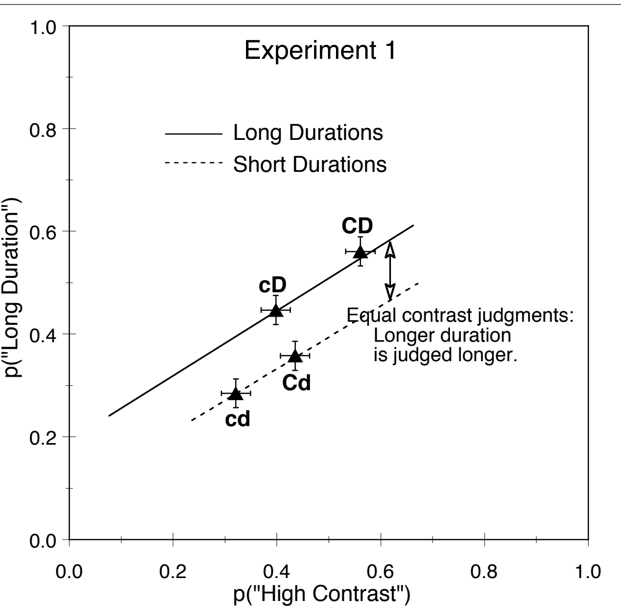

Figure 4. Bernstein, Chen, & Loftus data: Each inspection-phase condition is indicated adjacent to the appropriate point: cd (low contrast x short duration); cD (low contrast x long duration); Cd (high contrast x short duration); CD (high contrast x long duration). Dashed and solid lines connect short-duration and long-duration conditions. Error bars are standard errors.

These data provide numerous clues as to the nature of duration and contrast representation in long-term memory. In [18] we are developing formal models of the duration/contrast/recognition relations. Several follow-up experiments are required. First, our observers, who were not expecting a recognition test, may have processed the stimuli differently during inspection than in past experiments when they *were* expecting a recognition test. The experiment therefore needs to be redone with inclusion of an expected recognition test. With such a design, the single-dimension theory is that all three dependent variables—duration judgment, contrast judgment, and recognition performance—are based on a single dimension, and therefore that all three state-trace plots, each plotting one dependent variable against the other, would be monotonic. Departures from monotonicity would confirm or disconfirm various theories of what kinds of dimensional information are stored in memory and used as a basis for the various kinds of performance. Subsequent experiments would be designed to determine why and under what circumstances this seemingly wasteful strategy is used.

D.2.d. Theoretical Work with Multiluminant Stimuli

For reasons described in [12, A7, pp. 225-227], it appears that the SRIA theory is incapable of describing data based on multiluminant stimuli, i.e., normal grayscale scenes. This makes sense. The SRIA theory includes the simplifying assumption that, associated with a stimulus is a single contrast value which scales a single sensory-response function. With multiluminant stimuli there is no single contrast value. Instead, there are multiple edges at varying contrast levels which define features that have varying degrees of importance, relevance, and roles in encoding the picture for later recognition. Moreover, as contrast is reduced, some features that are low-contrast to begin with fall below threshold, while other higher-contrast features will not. It is possible that by (1) analyzing each individual picture with respect to its various internal contrast levels, (2) applying the SRIA theory simultaneously to these various levels, (3) assessing the roles of the features corresponding to the various edges defined by these varying contrast levels, and (4) using the results to generate measures of "information" that can be sensibly related to the dependent variable, the SRIA theory could be successfully applied to multiluminant stimuli on a picture-by-picture basis. As is apparent from this brief discussion, we are only at the starting phase of developing such a theory and determining ways of testing it, but this work will form a continuous background activity during the proposed funding period.

D.3. Spatial Frequencies and Global-to-Local Processing

Research reported in [10, A5] was designed to distinguish among three theories—independence theories, global-precedence theories, and global-to-local interactive theories—of the relation between global and local processes in a somewhat restricted situation: immediate object identification and digit recall. The results of this work disconfirmed independence and interactive theories. Accordingly,we modified the SRIA Theory to change it from an independence theory to a global-precedence theory: Global information acquisition precedes local information acquisition, but the two kinds of information still combine additively.

In particular, the original SRIA Theory, applied to this paradigm by Olds and Engel (1998), posited separate sensory-response functions corresponding to global and local information. The overall sensory-response function was then the weighted sum of the global and local sensory-response functions with weights w_L and w_H=1-w_L (see Table 1, p. 27 above). In our modification, which entailed no increase in the number of free parameters, the weights were allowed to vary over time, t, since stimulus onset; specifically $w_L(t)=e^{-kt}$, and $w_H(t)=1-w_L(t)$. This adjustment implied a global-precedence theory wherein global information acquisition decreased over stimulus presence compared to local information acquisition. This modified theory afforded excellent fits to the two experiments reported in [10, A5; see Figure 4, p. 111] and to three experiments reported by Olds and Engel (1998).

D.3.a. Distinguishing Among Global-to-Local Theories with More Complex Stimuli

Disconfirmation of an interactive theory was a surprise both to Olds and Engel (1998) and to Harley and me [10, A5]. Sanocki (1993), in providing a compelling rationale for global-local interactions, reiterates the oft-noted fact that objects in the world can appear in an infinitude of orientations, sizes, shapes, colors, etc., and underscores the obvious implication: "If during object identification, the perceptual system considered such factors for an unconstrained set of alternatives, the enormous number of combinations of stimulus features and feature-object mappings would create a combinatorial explosion" (p. 878). Sanocki notes that an obvious means of reducing what would be an otherwise impossible information-processing task is to use early information to constrain the interpretation of later information. Sanocki reports considerable evidence favoring this proposition.

As noted, both Olds and Engel's and our data involved quite simple stimuli—digits and objects—which may not be quite so prone to the kind of cataclysmic informational explosion that Sanocki described. I propose a series of experiments to test the three theory classes described above, but using complex scenes as stimuli. An example is the following. I will use natural scenes. In quest of generalization (and concomitantly, detection of any interesting stimulus dependencies), variants of the experiment use more specific stimulus classes, e.g., faces, houses, or cityscapes. Low spatial-frequency (L), high spatial-frequency (H) and normal (L+H) versions of each picture are created such that, as described by Olds and Engel (1998) and [10, A5] the (L+H) versions are the pixel-by-pixel contrast sums of the L and H versions. Relatively high-contrast versions of each of the three picture types are shown at varying durations in picture-recognition experiments. In the next sections, I describe formal predictions of independence, global-precedence, and interactive theories.

D.3.a.i. Independence Theories An independence theory is the conjunction of the following assumptions.

1. There is a quantity called "integrated response," i.e., a sensory response integrated over time, which I term R, that is proportional to stimulus duration. This is an implication of any linear theory, such as the SRIA theory, within whose context a response is generated by convolving the stimulus temporal waveform with some non-negative impulse-response function.
2. Information-acquisition rate for information types L and H differ by a factor of k (k>0). Denote $R_X(d)$ as the total signal issuing from some information type X $\in$ {L, H, (L+H)}, following duration d.
3. Responses combine additively, i.e., the total information from the (L+H) stimulus is $R_{L+H}(d)=R_L(d)+R_H(d)$.
4. Performance, p, e.g., percent correct recognition, or d', is a monotonic function of total response.

The implications of such a theory are worked through in Table 2. Of central importance, Rows D and E provide the *log-parallel* and *reciprocal-additivity* predictions, which are shown in Figure 5. By the log-parallel prediction, performance curves are horizontally parallel when plotted on a log-duration axis: As indicated in Row D and Figure 5A, the separations between the L and H, the L and L+H and H and L+H curves are ln(k), ln(k+1), and [ln(k+1)-ln(k)] respectively. By the reciprocal additivity prediction, the L and H curves add horizontally to the L+H curve when plotted on a 1/d axis: As indicated in Table 2, Row E and in Figure 5B, the duration reciprocal required

Table 2. Implications of an additive independence theory.

	Stimulus contains…		
	Information L	Information H	Information L+H
A) Information-Acquisition Rate	r(t)	kr(t)	(k+1)r(t)
B) Total signal at duration d	R(d)	kR(d)	(k+1)R(d)
C) Required duration for signal level R_0	$d_L = d_0$	$d_H = d_0/k$	$d_{L+H} = d_0/(k+1)$
D) ln (required duration for signal level R_0)	$\ln(d_0)$	$\ln(d_0) - \ln(k)$	$\ln(d_0) - \ln(k+1)$
E) Reciprocal of required duration for signal level R_0	$1/d_0$	k/d_0	$(1+k)/d_0 = 1/d_0+k/d_0= 1/d_0+ k/d_0$

Note: Response R_0 is assumed to imply performance $p_0 = m(R_0)$ where m is monotonic. Therefore all rules for determining levels of R_0 are, *ipso facto*, rules for determining levels of p_0.

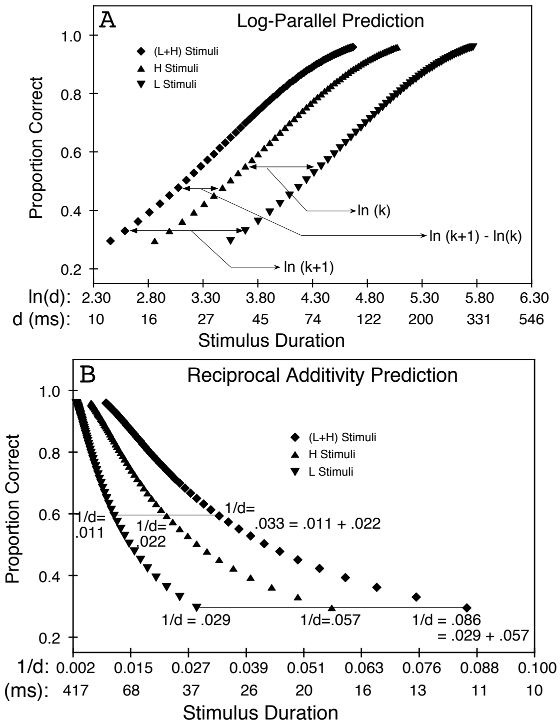

Figure 5. Predictions of the additive independence theory. Panel A: Curves are parallel on a log-duration axis. Panel B: Curves are horizontally additive on a reciprocal axis. Note that duration scales are both in ms and in ln (ms) (top panel) and 1/ms (bottom panel).

to achieve performance p_0 given stimulus type L+H is $1/d_0+k/d_0$, i.e., the sum of the corresponding required duration reciprocals given stimulus types L and H alone.

D.3.a.ii. Global-Precedence Theories. By a global-precedence theory, acquisition of global information precedes acquisition of local information, but the two information types still add to produce total information. The prediction becomes: Log-parallelism fails but reciprocal additivity still holds. Space limitations preclude here a mathematical proof of this prediction (or of the interactive-theory predictions described next). Two intuitions that may aid the reader are these. First, consider curves corresponding to L- and H-stimuli only. A global-precedence theory allows a standard crossover interaction between stimulus-type and stimulus duration: At short durations, L-stimulus performance can exceed H-stimulus performance, and vice versa at longer durations (see [10, A5, Figure 4, p. 111], for an example). A standard (vertical) crossover interaction implies a horizontal crossover interaction as well, which is *a fortiori* inconsistent with horizontal parallelness. Second, reciprocal additivity in terms of duration is a signature of additivity in terms of integrated signal, and L and H information are still additive by a global-precedence theory.

D.3.a.iii. Interactive Theories By an interactive theory, L and H information are no longer additive: The more L information available, the greater the contribution of the H information. This means that reciprocal additivity will fail. Specifically there should be *superadditivity*: The L+H curve therefore falls to the right of the independence prediction shown in Figure 5B. Should such superadditivity be observed, its exact pattern will imply constraints on viable quantitative theories.

D.3.b. Experiments to Distinguish Among the Theories

This theoretical machinery forms the foundation for numerous experiments to distinguish amongst the three global-to-local theories. Here are two examples.

D.3.b.i. Natural Pictures. As a start we will simply replicate experiments reported by Olds and Engel (1998) and by [10, A5], using natural pictures rather than objects or digits. Here, three types of pictures, L, H, and (L+H), are created. On each study trial of a recognition paradigm, a target picture is shown in a condition defined by combining spatial-frequency type with stimulus duration. Recognition memory is then measured. Predictions of the independence theory are as shown in Figure 5, and specific departures from the independence predictions correspond to predictions of the global-precedence and interactive theories, as just described.

D.3.b.ii. Priming with LSF Information. Sanocki (2001) provided strong evidence for interactive theories using a paradigm in which a target picture (a simple line drawing of a house or a vehicle) was presented to an observer who was then required to distinguish the target from a same-shape distracter. Either just prior to or just following target presentation, there briefly appeared one of two kinds of *prime*. *Large-scale* primes depicted the global outline of the target while *small-scale* primes depicted small interior details of the target. In the most compelling of Sanocki's (2001) experiments, the large-scale prime provided no information that would allow the observer to distinguish the target from the distracter. Nevertheless the large-scale prime, when presented prior to the target, improved performance. Sanocki concluded that the large-scale prime provided a perceptual framework within which target information could be interpreted.

While persuasive as to the validity of an interactive theory, Sanocki's data are insufficient for testing quantitative predictions. I propose building on Sanocki's work as follows. Complete, i.e., (L+H) target pictures are shown at varying durations in the study phase of a recognition procedure. Each picture is preceded either by a LSF version of the same picture, a HSF version, or a row of X's (no prime). Performance curves are plotted for the three priming conditions. Of central interest is the relation between the LSF ("global") prime and the no-prime conditions. By an interactive theory, the LSF prime speeds up processing, implying the LSF-primed and unprimed curves to diverge horizontally; that is, the (horizontally compared) slope of the LSF-primed curve would exceed the slope of the unprimed curve. The HSF primed curves, in contrast, are predicted to be horizontally parallel to the no-prime curve. If these predictions are not met, I will entertain the possibility that "global" and "local" as defined by LSF and HSF stimuli do not trigger the same perceptual processes as do Sanocki's "large-scale" and "small-scale" primes. I would then repeat the experiment using stimuli similar or identical to Sanocki's.

D.3.c. LSF-HSF Composite Experiments

Schyns and his colleagues have reported a variety of re-

Figure 6. Composite Celebrities: From close up, with normal vision, you see the HSF version of each picture: Russell Crowe, left and Cameron Diaz, right. From across the room, or if you can blur the image, you see the LSF versions, and the celebrities reverse positions.

sults based on *composite stimuli* similar to those in Figure 6: a LSF version of one stimulus superimposed on a HSF version of another (please follow instructions in the caption). In particular, Schyns and Oliva (1994) showed observers composite scenes either at a short duration (30 ms) or at a long duration (150 ms). At the short duration, observers tended to perceive the LSF scene, while at the longer duration they tended to perceive the HSF scene. Thus the data confirmed global-precedence theories: Low spatial-frequency information is acquired first, followed by high spatial-frequency information.

This elegant paradigm provides a foundation for proposed parametric experiments in which composite celebrities are shown for durations ranging from short (say 17 ms) to long (say 200 ms). Many variants of such an experiment can be run. Two of them are these.

D.3.c.i. Immediate Celebrity Recognition. After each display, the observer is given a 2AFC test as to whom they saw (Russell Crowe/Cameron Diaz in the Figure-6 example). A global-precedence theory predicts that, with increasing duration, a greater proportion of choices be of the HSF celebrity. Confirmation of this prediction would both replicate the Oliva & Schyns data, and would provide a parametric, empirical basis for fitting quantitative theories such as the modified SRIA Theory.

D.3.c.ii. Additivity of LSF and HSF Information from Composites? A basic finding from vision science is that simple stimuli—sine-wave gratings—of very different spatial frequencies are processed independently (e.g., Blakemore & Campbell, 1969; Campbell & Robson, 196l). When the stimuli are complex pictures and, as is normally true, the different spatial frequencies come from the same picture, it is reasonable to expect that such independence will fail: Based on past data, and for theoretical reasons elucidated by Sanocki and others, one expects that when LSF, HSF, and (LSF+HSF) versions of pictures are compared, one would confirm an interactive—in particular a superadditive—theory.

Suppose, however that LSF and HSF information were presented simultaneously (as is usual) but from *different celebrities*, i.e., from composites. Would independence hold then? To address this question, composites are shown along with both LSF and HSF noncomposite pictures in the study phase of a recognition procedure: For instance, ten composites (which contain, of course, two celebrities per composite) are shown, intermixed with ten LSF noncomposites and 10 HSF noncomposites for a total of 40 different individual target celebrities[3]. All pictures are then tested in a later recognition procedure comprising 80 pictures—normal versions of all 40 target pictures, plus 40 distracters. The independence prediction is that performance for a given target picture is the same whether the target appeared alone or as part of a composite. Confirmation of the independence theory would provide a remarkable link between low-level and higher-level visual performance, as it would indicate that a particular kind of spatial-frequency information can be gotten as easily from a picture that is part of a composite as from the picture shown by itself. One can, however, think of many reasons why the independence theory might fail: For instance, unlike the simple stimuli in the low-level vision experiments, the two pictures in a composite compete for the attention required for storing them in long-term memory, thereby implying *sub*-additivity. In any event, as already discussed, any particular manner in which the independence theory failed would provide useful information as to how LSF and HSF information is acquired and processed.

D.3.d. Gist Detection Versus Recognition

Numerous researchers have investigated the relation between gist identification of a picture and later recognition performance (e.g., Boyce & Pollatsek, 1992; Potter, 1975; 1976; Intraub, 1980; 1981). However, few experiments have specifically investigated the degree to which the same or different information underlies the two tasks.

A reasonable hypothesis is that LSF information is more important for gist acquisition while HSF information is more important for later recognition (particularly when the stimuli are relatively similar to one another; see Loftus, Nelson, & Kallman, 1983). An experiment designed to investigate this issue is as follows. Stimuli are natural pictures drawn from various perceptually distinct categories (say 12 categories, such as seascapes, kitchens, skylines and so on with, say 24 instances of each category). LSF and HSF versions of each picture are prepared. In the study phase of a recognition experiment, half the members of each category are shown for varying durations (say 6 durations) at each of the two spatial frequencies. Following each study trial, gist knowledge is tested. In the later test phase, the intact versions of all pictures are tested in a 2AFC recognition test wherein each test trial entails a target picture plus a previously unseen member of the target's category.

We can begin with the hypothesis that HSF and LSF information are equally useful for gist perception and recognition. To test this hypothesis, we construct a scatterplot of recognition performance against gist performance over

[3] Two procedural notes: First, care would have to be taken that contrast energy is the same for the individual components of the composites and the noncomposites. Second any stimulus class, i.e., not necessarily celebrity pictures could be used in this experiment.

all 6 (durations) x 2 (spatial frequencies) = 12 study conditions, analogous to Figures 2CF (p. 24 above). If HSF and LSF information are equally important for the two tasks, the scatterplot points will be monotonic. If not, the specific nature of the monotonicity failure provides information about the nature of the relative differential effects. For instance, if LSF information is indeed more important for gist acquisition, then LSF points will be displaced to the right compared to HSF points: That is, considering two duration x SF conditions that produce equal recognition performance, the LSF condition will produce better gist performance.

D.3.e. Spatial Frequency and Contrast

Using similar logic, one can ask: Does contrast affect high and low spatial frequency channels in the same way? The pertinent experiment entails a 6 (exposure duration) x 2 (contrast) x 2 (high/low spatial frequency) design. Different versions of the experiment would examine gist identification and long-term recognition. The data-analysis logic is analogous to that described in the previous paragraph, but now HSF performance is plotted against LSF performance over the 12 duration x contrast conditions: A monotonic state-trace plot implies identical contrast effects for both kinds of spatial-frequency information. As discussed in Section D.2 above, the default prediction would be of equal contrast effects for both HSF and LSF information types. Any specific failure of this prediction would provide useful clues about how HSF and LSF information differentially affect various kinds of visual-memory tasks.

D.4. Face Processing

As noted earlier, face processing is increasingly assuming center stage in my research. In previous sections of this proposal, I have described several research areas in which face processing is at least tangentially involved. In this section, I describe several proposed projects wherein face processing is the central topic.

D.4.a. Face Processing and Spatial Frequencies

In Section B.2.a.ii.(b), I described experiments in which observer-face distance was simulated by low-pass filtering the face. Here I describe details of how that was done, and propose additional experiments.

In Section B.2.a.ii.(b), I demonstrated that the equation relating filtering, defined in terms of f in c/face to distance, D, was $M(f) = M[Fx(43/D)]$ where F is spatial frequency in terms of c/deg, and M is a filter. To use this equation, the function M must be specified. For reasons described in [15, A10] it is reasonable to suppose M is low-pass. There are many ways of characterizing a low-pass filter; somewhat arbitrarily, in [15, A10] we chose a filter that passes spatial frequencies perfectly (i.e., $M(F) = 1.0$) up to a *rolloff frequency* of F_0 c/deg, drops parabolically reaching zero at a *cutoff frequency* of F_1 c/deg, and then remains at zero for all $F > F_1$. The exact equations are provided in [15, A10, pp. 10-11][4]. There are two free parameters, F_0 and F_1. For reasons irrelevant to this proposal, F_0 was set to $F_1/3$. With these constraints, specifying F_1 specifies the entire filter. For expositional simplicity, I characterize the filter by F_1, or f_1. The crucial prediction for any performance measure, p, thus becomes:

$$p(1/f_1) = p[D/(43F_1)] \qquad (8)$$

That is, a face D ft away should produce performance equivalent to a face filtered by f_1, as defined by Equation 8. Given empirical confirmation of Equation 8, one can equate the observed proportionality constant relating $(1/f_1)$ and D to $1/(43F_1)$ which permits estimation of F_1, and by extension the entire human modulation-transfer function (MTF) that obtains in this situation.

In [15, A10] we report two experimental paradigms to test the Equation-8 prediction. In each, distance, D, was implemented not by varying the literal observer-image distance, but by *sizing* a face such that its visual angle equaled that of a real face D ft away. In Experiment 1, a *test face,* shown on a 10-ft distant, high-resolution monitor, was appropriately sized such that its visual angle equaled that of a real face shown at one of 6 distances ranging from 20 to 300 ft. The observer's task was to adjust the degree of filtering of a full-sized *comparison face,* shown on a second, near monitor so as to match the informational content of the test face. On each trial, the filter, f_1, of the matching comparison face was recorded. As shown in Figure 7A (next page), the measured $1/f_1$ was almost perfectly proportional to D, and F_1 was estimated to be 42 c/deg.

In Experiments 2-4, we asked observers to identify well-known celebrity faces. Each face began very small (mimicking $D \approx 500$ ft) or very filtered ($f_1 \approx 4$ c/face) and then gradually either enlarged or deblurred. On each trial, we recorded either the value of D (for enlarging trials) or of f_1 (for deblurring trials) at which the celebrity was recognized. In each of Experiments 2-4, some dichotomous *cognitive variable*—i.e., a variable that affected recognition performance but not the physical nature of the stimuli—was manipulated. For example, in Experiment 2, each to-be-recognized celebrity had either been previously *primed* with the celebrity's name, or had not been primed. The results are shown in Figure 7B (see caption for explanation). We again observed that $(1/f_1)$ was almost perfectly proportional to D: The estimated proportionality constant of 1,290 ft/(c/face) was invariant over cognitive-variable levels and across different performance levels. The estimated F_1 values ranged from 25-30 c/deg across Experiments 2-4, i.e., they were somewhat less than the $F_1 = 42$ c/deg value estimated in Experiment 1.

D.4.a.i. Follow-up Experiments. Accurate knowledge of the suprathreshold human MTF sought in these experiments would be valuable: It is a function central to everyday visual processing, analogous to the much-studied CSF that characterizes the visual system's threshold response to different spatial frequencies. The most parsimonious hypothesis is that the human MTF is a unitary entity whose form could be estimated in any relevant task wherein the physical configuration (i.e., contrast level, luminance level, degree of motion, retinal position, etc.) is held constant. A comparison of [15, A10] Experiment 1 with Experiments 2-4 suggests, as just sketched, that this is

[4] We are now using truncated cosines as bases of low-pass, band-pass and high-pass filters (see Peli, 1990). A low-pass cosine filter has a similar shape, and is governed by the same parameters, F_0 and F_1 as the parabolic filter but, for technical reasons, benefits from not having the parabolic filter's discontinuity at F_1.

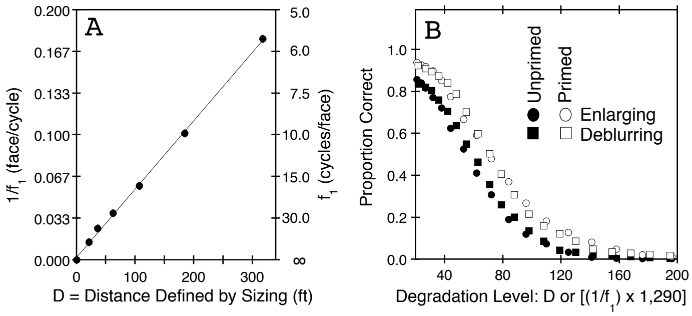

Figure 7. Left panel: Experiment 1. Mean blur setting in ($1/f_1$) units (f_1 on right-hand ordinate) as a function of distance; slope implies F_1=42 c/deg. Right panel: Experiment 2. Proportion celebrities identified as a function of degradation level. Abscissa units are interpreted as distance, D, for enlarging stimuli (circles) and as ($1/f_1$) for deblurring stimuli (squares). The ($1/f_1$) units are scaled so as to bring the deblurring curves as much as possible into alignment with the enlarging curve: The scaling factor that accomplishes this is 1,290 ft/(c/face), which represents the theoretical proportionality constant relating D to ($1/f_1$). This constant, which is the same for the primed data (open symbols) and unprimed data (solid symbols), implies F_1=30 c/deg, i.e., somewhat lower than the Experiment-1 (matching-task) estimate.

not true: The estimated F_1 value was approximately 42 c/deg in Experiment 1 (matching) but around 30 c/deg in Experiments 2-4 (identification). I propose several experiments to address this discrepancy in order to determine whether the pleasing hypothesis of a unitary human MTF must truly be rejected.

*D.4.a.i.(a). Removal of Confounding Variables***.** Experiments 1 and 2-4 were run as separate experiments. The most salient difference between them was that different stimuli were used: 64 photos of celebrity faces in Experiments 2-4, but 4 computer-generated "identikit" faces in Experiment 1 (see [15, A10, Figure 6, p. 12]). The first follow-up experiment will replicate our data using the same (celebrity) pictures in both the identification and the matching paradigms: Observers first perform the celebrity identification task, and then perform the matching task with the same celebrities that they had just seen. Appropriate control experiments, in which matching-identification task order is manipulated with different celebrities in the two tasks, will be run to ensure that there are no order effects (based on pilot work I don't expect any). Two related questions will be addressed: First, is the higher F_1 estimate in the matching compared to the identification task replicated? Second to what degree are the F_1 estimates from the two tasks correlated over observers? A positive correlation would be expected if the same filter underlies the two tasks, but leads to different F_1 estimates because of some kind of systematic bias engaged in by observers in one or both of the two tasks.

D.4.a.i.(b). Faces Versus "Eye Charts." We noticed that observers in the matching experiment tended to concentrate on high spatial-frequency details. For instance, they might look at the test face, observe that they could just barely perceive that two strands of hair were distinct, then choose the comparison face for which the same was true. That is, observers in the matching task appeared to treat the faces (which were, as noted, computer generated and somewhat unrealistic to begin with) as a form of an eye chart, that didn't require any actual face processing. Such could not be true in the identification experiments, where face identification was at the core of the task. Perhaps this accounted for the difference in the estimated MTF's.

Numerous experiments could be carried out to test the proposition that the purported "specialness" of face processing underlies the difference between the estimated filters from the matching versus the identification task. Here is one: The experiments just described are repeated using non-face stimuli such as vehicles. The matching task carries over directly. In the identification task, we ask the observers to identify, for instance, whether a vehicle is (a) a sedan, (b) a station wagon, (c) a SUV, or (d) a convertible. Exactly as in [15, A10] the MTF can be estimated for both tasks. If the estimated MTF is determined to be the same for the two tasks, we would tentatively conclude that the difference found in our original face experiments reflect differences between face processing tasks (identification) and non-face processing tasks (matching). If the same difference is found, we would conclude that some intrinsic, non-face-related difference between the tasks is responsible for the difference in estimated MTFs.

D.4.a.ii. Encoding of unfamiliar faces for recognition. We have carried out face-recognition experiments comparing familiar to unfamiliar faces. Whereas some variables, e.g., contrast, have identical effects on familiar and unfamiliar faces ([12, A7]) , other variables, e.g., inversion have quite different effects ([14, A9]; see Figure 2, p. 24 above). In the identification task investigating distance effects, we needed to use familiar (celebrity) faces in order that observers be able to perform the task. I propose experiments in which either degree of filtering (f_1) or distance (D) is manipulated in the study phase of an old-new face-recognition experiment using unfamiliar faces. In such an experiment, there is some number, e.g., 6 f_1 levels and corresponding D levels (D again defined in terms of stimulus size). Eventual face recognition is then measured as functions of f_1 and of D. As in [15, A10] comparison of these functions allows another estimate of the MTF, this time as it relates to encoding of unfamiliar faces rather than identification of familiar faces. The simplest prediction would issue from the proposition that the filter under investigation affects only the initial representation of the stimulus, not any subsequent perceptual or cognitive processing. If so, the same estimated filter (i.e., an F_1 value of around 30 c/deg) found for celebrity identification would also be found for encoding of unfamiliar faces. Any different finding would indicate a more complex configuration of different filters for different kinds of eventual processing and would be followed up on appropriately.

D.4.a.iii. Face Identification with Band-Passed Images. In many experiments, band-passed images have been constructed to investigate the roles of different spatial-frequency regions on processing of various sorts. In one such experiment, Hayes, Morrone, and Burr (1986) reported a face-identification task: Target faces, band-passed at various image frequencies, were presented to observers who attempted to identify them. The filters, 1.5 octaves wide, were centered at one of five image-frequency

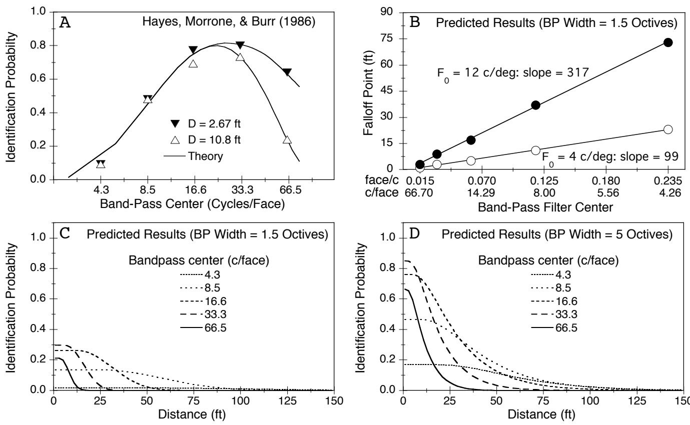

Figure 8. Panel A: Hayes et al. data along with Figure-9 theory. Panels C-D: Predictions for new experiments described in the text. Panel B: "Falloff point" (point at which Panels-C predicted curves begin to descend) as a function of band-pass center frequency for two possible F_0 values.

values ranging from 4.3 to 66.5 c/face. The faces appeared at either 2.7 or 10.8 ft from the observer, which implied absolute spatial frequencies that differed by a factor of 4 for the two distances. As shown in Figure 8A (ignore for the moment the Panel A theory predictions and Panels B-D), Hayes at al. found that identification performance depended strongly on image frequency composition, i.e., on filter center frequency, but depended strongly on viewing distance only with the highest image-frequency filter, 66.5 c/face (see Parish & Sperling, 1991, for a similar result with letter stimuli)[5].

These data can be explained by the assumptions that (1) performance is determined by the visual system's representation of spatial frequency in terms of c/face and (2) the human MTF in this situation is low-pass—it passes absolute spatial frequencies perfectly up to some rolloff spatial frequency, F_0, before beginning to drop. Of importance here is the value of F_0. Suppose for the sake of argument that F_0 were 6 c/deg. Now consider one of Hayes et al.'s lower-frequency filters, e.g., the one centered at 4.3 c/face. For a large range of distances, all spatial frequencies that would be affected by the distance—i.e., those greater than F_0=6 c/deg—would already have been removed by the band-pass filter. For high-enough-frequency band-pass filters however, high spatial frequencies would still be present following the filtering, and the low-pass filtering effect of distance would become manifest.

To endow this general account with some quantitative teeth, I developed a quick, back-of-the-envelope quantitative incarnation of it which is shown, applied to one of the Hayes et al. conditions—the 33.3 c/face filter x 10.8 ft—in Figure 9. I began with a single image, of Julia Roberts which, along with its contrast-energy spectrum (averaged over orientations) is shown in Row 1. Row 2 incorporates an idea, proposed by many, that there is a specific spatial-frequency region maximally efficient for identifying faces (see Morrison & Schyns, 2001, pp. 454-456 for a summary). This region is implemented as the band-pass filter in the left cell: The resulting filtered "face identification energy"—the product of the filter and the Row-1, original spectrum—is shown as the frequency spectrum and resulting image in the two right cells. In Row 3 the image is further filtered by the experimentally-imposed, 1.5-octave wide filter centered at 33.3 c/face. Finally, in Row 4, the experimentally-imposed distance (10.8 ft) entails a further low-pass filter with parameters $f_0 = F_0$ x (43/10.8) and $f_1 = F_1$ x (43/10.8) which diminishes the remaining contrast energy (although only slightly; 10.8 ft isn't all that far). Finally, I made the (generally dubious but for the

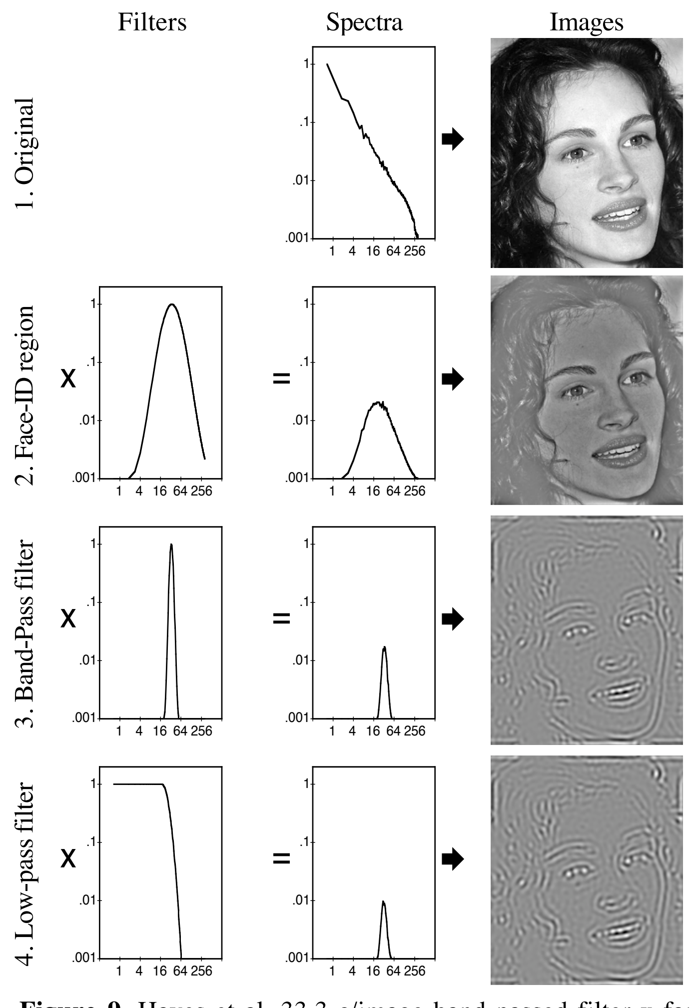

Figure 9. Hayes et al. 33.3 c/image band-passed filter x far distance condition. Theoretical representation: Amplitude scale factor (left column) or relative contrast energy (middle column) plotted against spatial frequency in c/face. Left columns: Assumed filters that operate on the image. Middle column: Results of applying successive filters to original image power spectrum, i.e., images in frequency space. Right column: Images, i.e., middle-column representations inverse-Fourier-transformed back to image space.

[5] Four notes: 1) Hayes et al. did not technically use an identification task, as their observers matched each test face to one of 4, perpetually available possible targets. Processing may be different for matching and identification tasks (see Morrison & Schyns, 2001) so the relevance of these data may be limited. 2) Hayes et al. measured image frequency in c/face *width*; I have translated into c/face *height* which we use in our research. 3) The distances of 2.7 and 10.8 ft were not the literal distances used in the experiment. Instead, they are the distances corresponding to the visual angles that would be subtended by real faces given the actual image sizes and distances used in the experiment. 4) I have corrected the Hayes et al. data for the 25% guessing rate.

moment workable) assumption that proportion correct identification is proportional to the "final contrast energy," i.e., the area remaining under the spectral energy function after all the filters have been applied (Figure 9, bottom middle cell). This theory thus had four free parameters, all of which are quantitatively meaningful and important with respect to face processing: the center and width of the putative "face-identification frequency band," plus F_0 and F_1, the parameters of the low-pass filter that governs size and distance effects. This theory was fit to the Hayes et al. data which yielded the theoretical curves shown in Figure 8A. Despite the theory's sketchy nature, the fit is not bad. Note, of course, that this demonstration was based only on a single celebrity (Ms. Roberts). In actual experiments, the predictions would be generated for, say, 60 celebrities, and the theory thereby fit to individual celebrity data.

Based on this reasoning, a variety of experiments suggest themselves. A typical one would be as follows. As in [15, A10, Experiments 2-4], to-be identified pictures of celebrities are presented (again on a distant, high-resolution screen to avoid loss-of-pixels effects). The pictures begin very small, simulating a distance of, say, D=300 ft and gradually increase in size, i.e., "move closer." Thus proportion identified celebrities can be measured as a function of distance.

The new manipulation is that, as in the Hayes et al. experiment, the celebrity pictures are band-passed at varying image-frequency centers. Based on the best-fitting parameters of the theory sketched in Figure 9, I calculated predictions for outcomes of such an experiment. They are provided in Figures 8CD which show proportion identified celebrities as functions of distance for pictures bandpass-filtered at various center frequencies, for two filter widths: 1.5 octaves (Figure 8C) and 5 octaves (Figure 8D).

This, and related experiments are analyzed in several ways. First, variants of the theory just described (Figure 9) can be fit to the data, and best-fitting values of the four parameters thereby recovered. Second, weaker versions of the theory can be fit, e.g., without the questionable assumption that proportion correct is proportional to area. In particular, the data from this experiment are highly sensitive to F_0, the theoretical rolloff frequency. To demonstrate this sensitivity, I created versions of the Figure-8C predicted data assuming different F_0 values and, for each bandpass center value, calculated the "falloff point," i.e., the distance at which each curve begins to descend from its left-hand asymptote. These falloff points are predicted to be proportional to the reciprocal of band-pass center, i.e., to faces/cycle, as is shown in Figure 8B for two F_0 values. As can be seen in the Figure-8B example, the slope (proportionality constant) of this function depends strongly on F_0; indeed for reasons too complex to describe here, these slopes are themselves proportional to F_0 with a proportionality constant that depends on band-pass filter width and which, in the Figure-8B example (filter width = 1.5 octaves), is approximately 26 ft/(face/deg). These techniques will therefore allow very precise estimates of F_0, along with reasonably precise estimates of F_1 and the presumed "face-processing frequency band."

D.4.a.iv. Face Identification versus Other Face-Processing Tasks. So far the bulk of completed and proposed experiments in this topic area involve face *identification*. As Schyns and his colleagues have persuasively demonstrated, however, different tasks, e.g., gender or expression identification probably rely on different spatial-frequency regions (Schyns & Oliva, 1999; Gosselin & Schyns, 2001). Accordingly, I will adapt many of these paradigms, particularly the band-pass paradigm just described to these other tasks. The predictions would be that (1) the distance-influencing low-pass filter (i.e., F_0 and F_1) would not change; however the spatial-frequency band relevant to the task would change in systematic ways. Thus we would use a new paradigm both to confirm Schyns' findings and to provide additional quantitative estimates of which spatial-frequency regions are used for what kinds of face-processing tasks.

D.4.b. The Face-Inversion Effect

In [14, A9] we investigated a suggestion by Valentine (1988) that a FIE obtains when familiar faces are retrieved from memory but not when unfamiliar faces are stored in memory (in anticipation, say, of a subsequent recognition test). As already described in Section B.2.e.ii.(c), we have carried out experiments in which either unfamiliar (computer-generated) faces or familiar (celebrity) faces were compared with houses. As indicated in Figure 2 (p. 24 above), we found a clear FIE for familiar but not for unfamiliar faces, thereby confirming Valentine's suggestion. However, as we described in [14, A9, pp. 29-30], our procedures did not allow unambiguous conclusions for three reasons.

1. Lack of a direct comparison: We never compared familiar and unfamiliar faces directly; rather, as just noted, we compared familiar and unfamiliar faces to houses in separate experiments.

2. Stimulus differences: Our familiar faces were celebrity photos, obtained from glossy magazines and the internet. Our unfamiliar faces were computer-generated "Identikit" pictures that, while moderately realistic, were obviously artificial.

3. Confounding between faces and familiarity: We claimed a FIE for familiar faces compared to houses. However, our data allowed the interpretation that *any* familiar (or nameable) stimulus suffers more from inversion than an unfamiliar stimulus. Based on much past data, it has been concluded that a FIE occurs for stimuli in which the observer has expertise (e.g., Diamond & Carey, 1986; Gauthier, et al., 2003). However having expertise with respect to some stimulus class is not the same as being familiar with individual members of the class; e.g., while most people can recognize a picture of Julia Roberts as someone familiar, dog experts would not generally recognize a particular dog (as in, "Oh, it's Lassie!") that appeared in the Diamond and Carey (1986) study.

These impediments to unambiguous interpretation suggest several experiments which are sufficiently obvious that I describe each only briefly.

D.4.b.i. Direct Comparison of Familiar and Unfamiliar Faces. Either familiar (celebrity) or unfamiliar faces are shown, upright or inverted, for varying durations in the study phase of a recognition procedure. The unfamiliar faces are drawn from the same sources as the celebrities (glossy magazines; the internet). State-trace plots are generated as in Figures 2F (p. 24 above) where "unfamiliar face recognition" is substituted for "house recognition." If inversion affects retrieval of familiar faces more than encoding of unfamiliar faces, the state-trace plot will resemble Figure 2F. If inversion affects face storage and face retrieval equally, it will resemble Figure 2C.

D.4.b.ii. A Building-Inversion Effect? To test the proposition that recognizing and being able to name faces is responsible for the difference between [14, A9 Experiments 1 and 2], I propose an experiment in which familiar buildings are compared to unfamiliar houses (i.e., an experiment like [14, A9, Experiment 2] except that nameable "celebrity buildings" are used in place of celebrity faces). Lorena Chavez and I have collected a set of such buildings. They include obvious candidates such as the Empire State Building, as well as local Seattle and University of Washington buildings, familiar to UW student participants. State-trace plots are generated as in Figures 2CF where "Familiar buildings" is substituted for "Celebrity faces." If the FIE of [14, A9, Experiment 2] is due to general familiarity/nameability, the state-trace plot will resemble Figure 2F, while if the effect is unique to faces, it will resemble Figure 2C.

D.4.c. Configural and Featural Processing

Data from the just-described (and other) experiments, will be fit by a two-dimensional theory which, as described in [14, A9, pp. 21-25], was driven primarily by three considerations. First, it incorporated the oft-discussed dimensions of "featural" and "configural" strength. Second, it was one of a quite successful class of information-processing theories, variants of which have been described by numerous investigators (e.g., Loftus, Busey & Senders, 1993; Massaro, 1970; Rumelhart, 1970; Shibuya & Bundesen, 1988), that assume random sampling over time of information from a visual stimulus. Such theories imply some internal measure, e.g., "Strength," and/or observed performance to increase with stimulus duration by the function $(1–e^{-kd})$ where d is duration and k is a constant.

The third consideration issues from the data in Figure 2 (p. 24 above). I have demonstrated why the monotonic state-trace plot in Figure 2C and the nonmonotonic state-trace plot in Figure 2F confirm a unidimensional theory for unfamiliar faces and imply a multi-dimensional theory for familiar faces, respectively. However there is additional information in these state-trace plots that allows stronger inferences: Both the upright and the inverted functions are approximately *linear*, and the curves corresponding to the inverted conditions have approximately zero intercepts. Accordingly we made the highly constraining decision to restrict our choice of quantitative theories to those that imply these characteristics.

In particular, featural strength SF_{ij}, in duration condition i and orientation condition j was defined to be,

$$SF_{ij} = \begin{cases} (1 - e^{-d_i/b}) \text{ x } Y_U & \text{for upright stimuli} \\ (1 - e^{-d_i/b}) \text{ x } Y_I & \text{for inverted stimuli} \end{cases} \qquad (9)$$

where d_i is duration. The parameter b is an exponential growth rate common to all stimuli; it may be viewed as representing a low-level characteristic of the system that is ignorant of stimulus meaning. The parameters Y_U and Y_I, constrained to fall between 0 and 1, reflect asymptotic featural strength that can differ for upright compared to inverted stimuli. Note that SF_{ij} must fall between 0 and 1 and can therefore be treated as a probability.

Configural strength, SC_{jk}, for orientation j and stimulus type k, ($k \in \{F, H\}$) was defined to be

$$SC_{jk} = \begin{cases} C_{Uk} & \text{for upright stimuli} \\ C_{IF} = 0 & \text{for Inverted faces} \\ C_{IH} & \text{for inverted houses} \end{cases} \qquad (10)$$

where the C_{jk} are free parameters, constrained to fall between 0 and 1, and therefore interpretable as probabilities[6]. The assumption embodied in Equation 10 that $C_{IF} = 0$ means that no configural strength is acquired from inverted faces. This assumption was motivated in part by Valentine's (1988) observation that, "...configural information is seen as a means of encoding upright faces, but configural information cannot be extracted from an inverted face" p. 480). Equation 10 also incorporates the idea that configural strength can be different for upright faces compared to upright houses; that is C_{UF} does not necessarily equal C_{UH}. In short, featural strength is the same for faces and houses while configural strength can differ in systematic ways for the two stimulus types.

We assume, as suggested by Collinshaw & Hole (2000) that recognition can be carried out independently on the basis of either featural or configural strength. The equation for response probability is thus,

$$p_{ijk} = \begin{cases} [SF_{ij} + (1 - SF_{ij})SC_{jF}]Y_F & \text{for faces} \\ [SF_{ij} + (1 - SF_{ij})SC_{jH}]Y_H & \text{for houses} \end{cases} \qquad (11)$$

where the asymptotes, Y_k, are free parameters between 0 and 1.

In [14, A9], we fit this theory to data from three experiments. The fit, shown in Figure 2 above, was reasonably good. As shown in [14, A9, Table 4, p. 24], the parameter estimates were informative. Most notably, configural strength was estimated to be zero for all inverted stimuli (that is, for inverted faces, where it was *constrained* to be zero, plus inverted houses and inverted cityscapes where it was unconstrained). As noted I plan to apply this theory to all relevant proposed experiments. This process will entail several activities: determining where the theory does not fit (e.g., long experiment durations as in Figure 2), modifying the theory if possible to extend its domain, and making use of the estimated theory parameters as an aid to understanding face processing in general.

D.5. Confidence and Accuracy in Visual Memory

As noted earlier, we have carried out numerous investigations of the relation between confidence and accuracy in visual memory. I propose a number of continuing studies in this domain.

[6] Lack of a duration term in Equation 10 implies that configural strength is acquired instantaneously. In the limit of course, this assumption must be false; *some* time must be required to acquire any kind of information from a stimulus. Realistically, this assumption is that all the configural strength that will ever be acquired can be acquired from our briefest experimental exposures (17 ms).

D.5.a. Cognitive versus Sensory Variables

In our investigations of the confidence/accuracy relation, we have used a prospective confidence/recognition performance design in which, during the study phase of a yes-no recognition experiment, two variables are manipulated: duration and some two-level focal variable. Two such variables are *contrast* and *rehearsal*: In one experiment ([3, A2]), observers were either required to rehearse, or prevented from rehearsing, the just-seen target picture for 15 sec following picture offset. In other experiments ([12, A7]), pictures were shown at either low or high contrast. Following each study trial, in both sets of studies, observers were asked to rate their *prospective confidence* that they would eventually be able to recognize the picture. State-trace plots were constructed in which actual recognition performance was plotted against prospective confidence. A monotonic state-trace plot indicates that observers are able to accurately assess the focal variable's effect—both confidence and accuracy would be inferred to be based on the same internal measure—while a nonmonotonic state-trace plot indicates error in observers' assessment of the focal variable's effect in that prospective confidence and recognition performance would be inferred to be based on different internal data. We found that the effect of contrast, a low-level variable, was assessed almost perfectly via the prospective confidence rating ([12, A7]). However the effect of post-exposure rehearsal, a higher-level variable, was assessed incorrectly: At study, observers strongly overrated the degree to which having just rehearsed the target picture would eventually boost recognition performance [3, A2].

A possible (seemingly paradoxical) reason for this finding is that information about the state of a low-level variable, such as contrast, is lost early: We have found good evidence for the unidimensional theory that contrast and duration combine (multiplicatively) very early, perhaps during perception, thereby leaving only a value on a single dimension ("Strength"). In other words, an observer expecting a recognition test may, by default, not encode whether a just-seen target is a low- or a high-contrast picture. The only information available to the observer is thus Strength, whose value does not include the original duration and contrast values that produced it. This single Strength measure then forms the basis for both the prospective confidence judgments and for recognition performance, thereby ensuring that contrast's effect on recognition—which is mediated by Strength—is accurately captured in the prospective confidence judgments.

Higher-level variables such as rehearsal, however, do not act this way: It is obvious based on common experience, that an observer is entirely aware following a study trial whether s/he has just rehearsed the picture. This allows the use of metacognitive strategies—or in our lingo, additional dimensions—that affect the prospective confidence judgment. For instance, in [3, A2], we proposed two internal dimensions affected by a target stimulus: "Strength" is affected by both duration and rehearsal, while "Certainty" is affected only by rehearsal. At study, prospective confidence is a positive function of both Strength and Certainty, while at test, recognition performance is a function only of Strength. This means that two duration-rehearsal conditions that are equal in Strength will have the same recognition performance values; however, the shorter-duration x rehearsal condition will produce the higher Certainty value and therefore the higher prospective confidence value (see [3, A2], Figure 3E, p. 34).

I propose experiments to test this general idea. In two parallel recognition experiments, contrast and rehearsal are combined with duration at study. For each experiment, there is an additional between-subjects variable: Following each study trial, observers are either told or not told the contrast (or rehearsal) level of the target picture that they had just seen. This puts contrast and rehearsal on an equal footing in that for each focal variable, observers know unequivocally which condition they were in when they make their prospective confidence rating. This knowledge is, obviously, most relevant for contrast; rehearsal level will almost certainly be apparent anyway. In any event, if knowledge of focal-variable level prompts use of information on additional dimensions in making the prospective confidence judgment, then observers—as indicated by the prospective confidence-recognition performance state-trace plot—will no longer accurately assess contrast's effect on eventual memory (thereby providing yet another confirmation of Alexander Pope's, 1711, assertion that, "A little learning is a dangerous thing.")

D.5.b. Responses Made on Specific Features or General Familiarity

Earlier, I described experiments in which subjective bases for picture-recognition responses, in the form of either a specific feature, or general familiarity, are measured. Paul Jaye and I collected some pilot data investigating the degree to which observers are able to accurately assess the eventual value of encoding a specific feature for eventual recognition.

In Jaye's and my data, increasing exposure duration, or responding on the basis of a specific feature rather than general familiarity, led to increased accuracy and to increased retrospective confidence, as shown in Figures 10AB. These findings are not especially surprising, and are consistent with past data issuing from similar procedures (e.g., Dobbins, Kroll, & Liu, 1998; Loftus, 1972; Loftus & Bell, 1975; Loftus & Kallman, 1979). What is noteworthy however is that, as shown in Figure 10C, a specific feature increased confidence "more than it should have" given its effect on accuracy: That is, when two duration x response-basis "conditions"—a shorter-duration "feature" response and a longer-duration "familiarity" response—led to the same accuracy, the feature response produced higher confidence. Of importance for reasons described below, the converse is also true: Considering two such "conditions" with identical *confidence*, the "general familiarity" response is more accurate.

This result has several implications. First, in the basic-science domain, it indicates that more than a single memory dimension is necessary to account for this pattern of confidence-accuracy relations, thereby adding to the litany of studies identifying the circumstances under which confidence and accuracy are based on different memory dimensions (e.g., Chandler, 1994; Dobbins, et al., 1998; Glanzer & Adams, 1990; Nelson & Dunlosky, 1991;

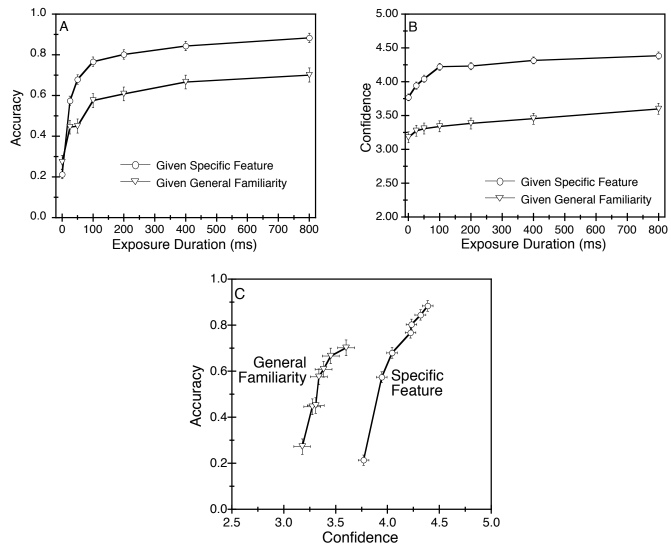

Figure 10. Jaye & Loftus data. Panels A and B are retrospective confidence and recognition performance as functions of study duration for test trials yielding "specific feature" or "general familiarity" responses. Panel C is the state-trace plot. Error bars are standard errors.

Tulving, 1981; Wells, Lindsay, & Ferguson, 1979), and suggesting profitable theoretical strategies for naming and elucidating the properties of such dimensions. In the practical (forensic) domain, it is noteworthy for the following reason. Numerous investigators (e.g., Cutler, Penrod, & Stuve, 1988) have shown that witness confidence is a critical determinant of jurors' belief in eyewitness testimony. In addition, Bell and E. Loftus (1988) have shown that jurors tend to believe witness reports more strongly when such reports contain specific details than when they do not (see also Johnson, Bush, & Mitchell, 1998). Now consider two witnesses reporting conflicting versions of some event, each reporting the same confidence, but one witness reporting details and the other witness reporting only "general familiarity." My work with Jaye just sketched indicates that the "general familiarity" witness will more likely be accurate, while, the Bell & Loftus and Johnson et al. data indicate that the "specific detail" witness will more likely be believed.

Several investigations of the specific feature/general familiarity work are proposed. The first is to replicate the results with faces rather than scenes—both to establish replicability and generality, and because faces are more forensically relevant than scenes. Second, in the Loftus & Jaye study, reporting of a specific feature was determined by the observer rather than being a genuine, manipulated, independent variable, which limits the strength of the resulting conclusions. I proposed to remedy this shortcoming by creating stimuli in which bland pictures (scenes and/or faces) are modified using Photoshop or the Faces Identikit application, to produce a version with an obvious specific feature; thus there is a "bland" and a "specific feature" version of all stimuli. Third we will induce encoding of specific details using a manipulation reported by Loftus & Kallman (1979) in which, during the study phase of a picture-recognition experiment, observers were or were not instructed during a post-stimulus interval to write down the name of a specific object that they thought would assist them in eventually recognizing the picture.

E. HUMAN SUBJECTS

E.1. Risks to Subjects

E.1.a. Human Subjects involvement and Characteristics. Adult and child human subjects will be involved in all empirical aspects of the proposed research. Child subjects fall into two categories: undergraduates 17-20 years old defined by NIH to be "children" and 3-5 year old children. For ease of exposition, I will, in what follows, lump the former children and the adults into one group and call them "adults." I will refer to the 3-5 year old children as "children." Although it is difficult to predict exactly how many subjects we will use, it will be on the order of 15,000 over five years. Of these 15,000, approximately 100 will be children, all run at the University of Washington. Of the total 15,000 subjects, approximately 50 will be run at the University of Illinois where they will have eye movements recorded. The remainder will be run at the University of Washington. No subject run at the University of Washington will have eye movements recorded.

Adult subjects will be required to sit for an hour or so at a time and press keys corresponding to perception or memory decisions. In some of the experiments, eye movements will be recorded. When children are used as subjects, they will be asked to try to identify pictures of common objects (e.g., "dog") and call out their names.

E.1.b. Sources of Research Material. Subjects will provide perceptual or recognition responses. Data will be collected by computer and will then be summarized prior to being analyzed by humans. Data will be used only for research purposes.

E.1.c. Potential risks. The risks in the non-eye movement experiments (i.e., the majority of planned experiments) are essentially nonexistent. Observers will be required to sit in seats for an hour at most, view visual materials (scenes or text), attempt to perceive and remember them and type in responses.

For the eye-move experiments to be run at the University of Illinois (only adults involved), risks are similarly low. During the experiments subjects will be required to wear an eye tracker, an EyeLink II. The EyeLink II system consists of three miniature cameras mounted on a comfortable leather-padded headband. Two eye cameras allow binocular eye tracking or selection of the subject's dominant eye. Each camera has built-in illuminators that shine on the eye, and the EyeLink II software identifies the location of the pupil and tracks it during an experiment. An optical head-tracking camera integrated into the headband allows accurate tracking of the subject's point of gaze without the need for a bite bar. Note that no electrical equipment is attached to the subject. The amount of light absorbed by the retina is less than 7.5% of the suggested Maximum Permissible Exposure for continuous sources of infrared light given by Sliney and Freasier (1973). This level of light is comparable to what one would receive on a bright, sunny day. Subjects will wear the monitor for no more than 60 minutes per session, and for no more than 10 sessions. There should be no harmful cumulative effects from wearing the eye tracker for this period of time. Irwin has conducted eye tracking experiments for 25 years and over this period of time he have worn eye tracking devices of this kind for well over 1200 hours, with no ill effects. Furthermore, over 400 subjects have participated in Irwin's eye tracking experiments over the last 25 years, most of them for longer than 600 minutes, and none of them have experienced any problems. The method of eye tracking that Irwin will be using is one of the most widely-used in the world; it has been used with both children and adults in a variety of settings for a variety of purposes. Neither Irwin nor I know of a single case where damage has occurred to any person. So, the risk to subjects from wearing the eye tracking device is minimal.

E.2. Adequacy of Protection against Risks.

E.2.a. Recruitment and Informed Consent. Adult subjects are obtained in two ways. First, some come from the University of Washington Psychology Department subject pool which operates in the usual subject-pool manner. Second, paid subjects are sometimes recruited by messages on bulletin boards.. When subjects appear for an experiment, the procedures are explained to them, they are given consent forms to sign, and they are assured that they are free to leave if they wish.

In some experiments, we propose to use younger (3-5 year old) children. Criteria for admission into the study are that a child has no known physical, sensory, or mental handicap.

All 3-5 year old child subjects are recruited through the University of Washington Child Subject Pool, a computerized subject record that has been created by researchers on campus. The goal of the subject pool is to create a sample that includes approximately equal numbers of males and females and accurately reflects the distribution of minorities in the population of the greater Seattle area. The Child Subject Pool obtains complete birth records from all the local hospitals and then mails letters to new parents describing the research at the University of Washington and soliciting participation. Parents indicate interest by returning a self-addressed, stamped envelope that is included in the packet. Research staff from this project then telephone prospective participants to describe the details of an individual study and schedule appointments. When parents arrive in the laboratory they are given an IRB-approved informed consent form and invited to ask further questions about the research. After the test is completed research staff commonly spend time talking to parents and highlighting interesting reactions that occurred during the test. In our experience, parents find the visit to the laboratory interesting and rewarding, as manifest by the fact that they often recommend it to other friends with children.

E.2.b. Protection Against Risks. There are essentially no risks whatsoever in the proposed research except perhaps for becoming bored or uncomfortable sitting in the same place for an hour. We protect against this by assuring subjects that they are free to leave at any time.

E.3. Potential Benefits of the Proposed Research to the Subjects And Others

In our debriefing, we explain that, while there are no direct benefits to the subjects in our experiments, there is potential long-term benefit for a variety of scientific and practical reasons.

Table 3. Targeted/Planned Enrollment

	Gender		
Ethnic Categories	Female	Male	Total
Hispanic or Latino	322	175	497
Not Hispanic or Latino	8,869	4,237	13,106
Ethnic Category: Total of all subjects	9,191	4,412	13,603
Racial Categories			
American Indian/Native	125	59	184
Asian	1,978	959	2,937
Native Hawaiian	0	0	0
Black or African American	361	165	526
White	6,727	3,229	9,956
Racial Categories: Total	9,191	4,412	13,603

E.4. Importance of the Knowledge to be Gained

As discussed above, the risks are minimal to nonexistent, and the potential benefits are considerable.

E.5. Collaborating Sites

The OHRP assurance number for the University or Illinois is xx.

E.6. Women and Minority Inclusion

Table 3 provides the gender/minority breakdown.

E.6.a. Inclusion of Women. Subjects will be from the University of Washington and from University of Illinois. The male/female distribution should resemble the male/female distributions of the university populations.

E.6.a. Inclusion of Minorities. The approximately 14,950 subjects run at the University of Washington and approximately 50 subjects run at the University of Illinois will be selected semi-randomly from the university populations. The percentages of minorities is therefore expected to mirror the university proportions, as shown in Table 3.

E.7. Inclusion of Children

As I have indicated, 17-20 year old University of Washington and University of Illinois students, who technically are children, will be included in the research. As described above, 3-5 year old children are also included for specifically developmental research.

F. VERTEBRATE ANIMALS: N/A

G. LITERATURE CITED

Anderson, N.H. (1974). Information integration theory: A brief survey. In *Contemporary Developments in Mathematical Psychology, Vol 2*. New York: Freeman.

Bamber, D. (l979). State trace analysis: A method of testing simple theories of causation. *Journal of Mathematical Psychology, 19*, 137-181.

Bell, B. E. & Loftus E. F. (1988). Degree of detail of eyewitness testimony and mock juror judgments. *Journal of Applied Social Psychology, 18*, 1171-1192.

Bernstein, D.M., Atance, C., Loftus, G.R, & Meltzoff, A.N. (2004). We saw it all along: Visual hindsight bias in children and adults. *Psychological Science*, 15, 264-267.

Bernstein, D.M., Loftus, G.R., & Meltzoff, A.N. (2005). Object identification in toddlers and adults. *Developmental Science* (in press).

Blakemore, C., & Campbell, F.W. (1969). On the existence of neurons in the human visual system selectively sensitive to the orientation and size of retinal images. *Journal of Physiology, 203*, 237-260.

Bogartz, R. S. (1976). On the meaning of statistical interactions. *Journal of Experimental Child Psychology, 22*, 178-183.

Boyce, S.J. & Pollatsek, A. (1992). Identification of objects in scenes: The role of scene background. *Journal of Experimental Psychology*: *Learning, Memory, & Cognition*, *18*, 531-543.

Bradshaw, J.L. & Wallace, G. (1971), Models for the processing and identification of faces. *Perception & Psychophysics, 9*, 443-448.

Bradshaw, J.L., Taylor, M.J., Patterson, K., & Nettleton, N.C. (1980). Upright and inverted faces, and housefronts in two visual fields. *Jouranl of Clinical Neuropsychology, 2*, 245-257.

Bruce, V., Henderson, Z., Newman, C., & Burton, A.M. (2001). Matching identities of familiar and unfamiliar faces caught on CCTV images. *Journal of Experimental Psychology*: *Applied, 7*, 207-218.

Bruner, J.S., & Potter, M.C., (1964). Interference in visual search. *Science, 144*, 424-425.

Busemeyer, J.R. & Jones, L.E. (1983). Analysis of multiplicative combination rules when the causal variables are measured with error. *Psychological Bulletin*, *88,* 237-244.

Busey, T.A., Tunnicliff, J., Loftus, G.R. & Loftus, E.F. (2000). Accounts of the confidence-accuracy relation in recognition memory. *Psychonomic Bulletin & Review*, *7*, 26-48.

Campbell, F. & Robson, J. (1968). Application of fourier analysis to the visibility of gratings. *Journal of Physiology, 197*, 551-566.

Carey, S. & Diamond, R. (1977). From piecemeal to Configural representation of faces. *Science, 195*, 312-314,

Chandler, C. C. (1994). Studying related pictures can reduce accuracy, but increase confidence, in a modified recognition test. *Memory and Cognition, 3*, 273-280.

Christianson, S., Loftus, E.F., Loftus, G.R., & Hoffman, H. (1991). Eye fixations and accuracy in detail memory of emotional versus neutral events. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 17*, 693-701.

Collinshaw. S.M. & Hole, G.J. (2000). Featural and configural processes in the recognition of faces of different familiarity. *Perception, 29*, 893-909.

Costen, N.P., Parker, D.M., & Craw, I. (1994). Spatial content and spatial quantization effects in face recognition. *Perception, 23*, 129-146.

Costen, N.P., Parker, D.M., & Craw, I. (1996). Effects of high-pass and low-pass spatial filtering on face identification. *Perception & Psychophysics, 58*, 602-612.

Cutler, B.L., Penrod, S.D., & Stuve, T.E. (1988). Juror decision making in eyewitness identification cases. *Law and Human Behavior, 12*, 41-55.

De Valois, R.L., & De Valois, K.K. (1980). Spatial vision. *Annual Review of Psychology, 31*, 309-341,

De Valois, R.L., & De Valois, K.K. (1988). *Spatial Vision*. New York: Oxford University Press, 1988.

Deffenbacher, K. (1980). Eyewitness accuracy and confidence: Can we infer anything about their relationship? *Law and Human Behavior, 4*, 243-260.

Diamond, R. & Carey, S. (1986). Why faces are and are not special: An effect of expertise. *Journal of Experimental Psychology: General, 115, 107-117*.

Dobbins, I.G., Kroll, N.E.A. & Liu, Q. (1998). Confidence accuracy inversions in scene recognition: A remember know analysis. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 24*, 1306-1315.

Dunn, J.C. (2004). Remember-Know: A matter of confidence. *Psychological Review*, in press.

Dunn, J.C. & James, R.N. (2003). Signed difference analysis: Theory and application. *Journal of Mathematical Psychology, 47*, 389-416.

Dunn, J.C. & Kirsner, K. (1988). Discovering functionally independent mental processes: The principle of reversed association. *Psychological Review*, *95*, 91-101.

Ellis, H. D & Shepherd, J.W. (1975). Recognition of upright and inverted faces presented in the left and right visual fields. *Cortex*, *11*, 3-7.

Farah, M.J., Tanaka, J.N. & Drain, M. (1995). What causes the face inversion effect. *Journal of Experimental Psychology*: *Human Perception & Performance, 21*, 628-634.

Farah, M.J., Wilson, K.D., Drain, M., & Tanaka, J.N. (1998). What is “special” about face perception? *Psychological Review*, *105*, 482-498.

Fiorentini, A., Maffei, L., & Sandini, G. (1983). The role of high spatial frequencies in face perception, *Perception*, 12, 195-201.

Fischhoff, B. (1975). Hindsight ≠ foresight: The effect of outcome knowledge on judgment under uncertainty. Journal of Experimental Psychology: Human Perception and Performance, 1, 288-299.

Gardiner, J.M. (1988). Functional aspects of ecollective experience. *Memory & Cognition, 16*, 309-313.

Garner, W.R. (1974). *The processing of structure and information*. New York: Wiley.

Gauthier, I, Curran, T, Curby, K.M., & Collins, D. (2003). Perceptual interference supports a non-modular account of face processing. *Nature-Neuroscience, 6, 428-432*.

Georgeson, M.A. & Sullivan, G.D. (1975). Contrast constancy: Deblurring in human vision by spatial frequency channels. *Journal of Physiology, 252*, 627-656.

Ginsburg, A.P., Cannon, M.W., & Nelson, M.A. (1980). Suprathreshold processing of complex visual stimuli: Evidence for linearity in contrast perception. *Science, 208*, 619-621.

Glanzer, M. & Adams, J.K. (1990). The mirror effect in recognition memory: Data and theory. *Journal of Experimental Psychology: Learning, Memory, & Cognition, 16*, 5-16.

Gorea, A., & Tyler, C. W. (1986). New look at Block’s law for contrast. *Journal of the Optical Society of America A: Optics and Image Science, 3*(1), 52-61.

Gosselin, F., & Schyns, P. (2001). Bubbles: A technique to reveal the use of information in recognition tasks. *Vision Research, 41*, 2261-2271.

Graham, N. (1989). *Visual pattern analyzers*. New York: Oxford.

Hancock, P.J.B., Bruce, V., & Burton, A.M. (2000). Recognition of unfamiliar faces. *Trends in Cognitive Science, 4*, 330-337.

Harley, E. M., & Loftus, G. R. (2000). MATLAB and graphical user interfaces: Tools for experimental management. *Behavior Research Methods, Instruments, and Computers*, *32*, 290-296.

Harley, E.M., Carlsen, K.A., & Loftus, G.R. (2004). The "I saw it all along" effect: Demonstrations of visual hindsight bias. *Journal of Experimental Psychology: Learning, Memory, & Cognition*, in press.

Harley, E.M., Dillon, A.M., & Loftus, G.R. (2004). Why it's difficult to see in the fog: How contrast affects visual perception and visual memory. *Psychonomic Bulletin & Review*, *11*, 197-231.

Hayes, T., Morrone, M.C., & Burr, D.C. (1986). Recognition of positive and negative bandpass-filtered images. *Perception, 15*, 595-602.

Hays, W. (1973). *Statistics for the Social Sciences (second edition).* New York: Holt.

Henderson, J.M., & Hollingworth, a. (1998). Eye movements during scene viewing: An overview. In G. Underwood (Ed.), *Eye guidance in reading and scene perception* (pp. 269-283), Oxford, England: Elsevier.

Hollingworth, A. (2004) Constructing visual representations of natural scenes: The roles of short and long-term visual memory (*Journal of Experimental Psychology*: *Human Perception and Performance*, in press.

Hood, D. C. & Finkelstein, M. A. (1986) Sensitivity to light. In K. R. Boff, L. Kaufman, and J. P. Thomas (Eds.), *Handbook of Perception and Human Performance (Vol. I).* New York: Wiley.

Hughes, H.C., Nozawa, G., & Ketterle, F. (1996). Global precedence, spatial frequency channels, and the statistics of natural images. *Journal of Cognitive Neuroscience, 8*, 197-230.

Intraub, H. (1980). Presentation rate and the representation of briefly glimpsed pictures in memory. *Journal of Experimental Psychology: Human Learning and Memory, 6*, 1-12.

Intraub, H. (1981). Identification and processing of briefly glimpsed visual scenes. In Fisher, D.E., Monty, R.A. and Senders, J.W. (Eds) *Eye Movements: Cognition and Visual Perception.* Hillsdale NJ: Erlbaum Associates.

Irwin, D. E. (1991) Information integration across saccadic eye movements. *Cognitive Psychology, 23*, 420-456.

Jacoby, L.L. (1991). A process dissociation framework: Separating automatic from intentional uses of memory. *Journal of Memory & Language, 30*, 513-541.

Johnson, M.K., Bush, J.G., & Mitchell, K.J. (1998). Interpersonal reality monitoring: Judging the sources of other people's memories. *Social Cognition, 16*, 199-224.

Just, M.A. & Carpenter, P.A. (1976). Eye fixations and cognitive processes. *Cognitive Psychology, 8*, 441-480.

Just, M.A. & Carpenter, P.A. (1980). A theory of reading: From eye fixations to comprehension. *Psychological Review, 87*, 329-354.

Kanwisher, N., McDermott, J., & Chun, M.M. (1997). The fusiform face area: A module in human extrastriate cortex specialized for face perception, *Journal of Neuroscience, 17*, 4302-4311.

Kanwisher, N., Tong, F., & Nakayama, K. (1998). The effect of face inversion on the human fusiform face area. *Cognition, 68*, B1-B11.

Krantz, D. H. & Tversky, A. (1971). Conjoint-measurement analysis of composition rules in psychology. *Psychological Review, 78*, 151-169.

Krantz, D. H., Luce, R. D., Suppes, P., & Tversky, A. (1971). *Foundations of Measurement*. New York: Academic Press.

Kruskal, J.B. (1964). Multidimensional Scaling: A numerical method. *Psychometrica, 29,* 115-129.

Leehey, S., Carey, S., Diamond, R., & Cahn, A. (1978). Upright and inverted faces: The right hemisphere knows the difference. *Cortex. 14*, 411-419

Legge, G. E., Pelli, D.G., Rubin, G.S., & Schleske. M.M. (1985) Psychophysics of reading: I. Normal vision. *Vision Research, 25*, 239-252.

Levin, D. T. (2002). Change blindness blindness as visual metacognition. *Journal of Consciousness Studies, 9,* 111-130.

Levin, D. T., Drivdahl, S. B., Momen, N., & Beck, M. R. (2002). False predictions about the detectability of visual changes: The role of beliefs about attention, memory, and the continuity of attended objects in causing change blindness blindness. *Consciousness & Cognition: An International Journal, 11*, 507-527.

Loftus, G.R. (1972). Eye fixations and recognition memory for pictures. *Cognitive Psychology, 3*, 525-551.

Loftus, G.R. (1976). A framework for a theory of picture memory. In R.A. Monty & J.W. Senders (eds.), *Eye movements and psychological processes. Hillsdale*, N.J.: Erlbaum.

Loftus, G. R. (1978). On interpretation of interactions. *Memory and Cognition, 6*, 312-319.

Loftus, G. R. (1985). Evaluating forgetting curves. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 11*, 396-405. (a)

Loftus, G.R. (1985). Consistency and confoundings: Reply to Slamecka. *Journal of Experimental Psychology: Learning, Memory and Cognition, 11*, 817-820. (b)

Loftus, G. R. (1985). Picture perception: Effects of luminance level on available information and information-extraction rate. *Journal of Experimental Psychology: General, 114*, 342-356. (c)

Loftus, G.R. (1991). On the tyranny of hypothesis testing in the social sciences. *Contemporary Psychology*. *36*, 102-105.

Loftus, G.R. (1996). Psychology will be a much better science when we change the way we analyze data. *Current Directions in Psychological Science*, 161-171.

Loftus, G.R. (2002). Analysis, interpretation, and visual presentation of data. *Stevens' Handbook of Experimental Psychology, Third Edition*, *Vol 4*. New York: John Wiley and Sons, 339-390.

Loftus, G.R. (2003). What do we know about facial cognition? What should we do with this knowledge? *Contemporary Psychology*, *48*, 503-507. (Appendix 4),

Loftus, G. R., Johnson, C. A., & Shimamura, A. P. (1985). How much is an icon worth? *Journal of Experimental Psychology: Human Perception and Performance, 11*, 1-13.

Loftus, G. R., Nelson, W. W. & Truax, P. E. (1986). Age-related differences in visual information processing: Quantitative of qualitative? In C. Schooler and W. Schaie (Eds.) *Cognitive Functioning and Social Structure over the Life Course*. Norwood, NJ: Ablex.

Loftus, G.R. & Bamber, D. (1990) Learning-forgetting independence: Unidimensional memory models and feature models: Comment on Bogartz (1990). *Journal of Experimental Psychology: Learning, Memory, and Cognition, 16*, 916-926.

Loftus, G.R. & Bell, S.M. (1975). Two types of information in picture memory. *Journal of Experimental Psychology: Human Learning and Memory, 104*, 103-113.

Loftus, G.R. & Harley, E.M. (2004). How different spatial-frequency components contribute to visual information acquisition. *Journal of Experimental Psychology: Human Perception and Performance*, *30*, 104–118.

Loftus, G.R. & Harley, E.M. (2004). Why is it easier to recognize someone close than far away? *Psychonomic Bulletin & Review*, in press.

Loftus, G.R. & McLean, J.E. (1999). A front end to a theory of picture recognition. *Psychonomic Bulletin & Review,* 6, 394-411. (Appendix 1), [MM, SRIA, C].

Loftus, G.R. and Masson, M.E.J. (1994) Using confidence intervals in within subjects designs. *Psychonomic Bulletin & Review*, *1*, 476-490.

Loftus, G.R., & Kallman, H.J. (1979). Encoding and use of detail information in picture recognition. *Journal of Experimental Psychology: Human Learning and Memory, 5*, 197-211.

Loftus, G.R., Duncan, J. & Gehrig, P. (1992). On the time course of perceptual information that results from a brief visual presentation. *Journal of Experimental Psychology: Human Perception and Performance*, *18*, 530-549.

Loftus, G.R., Kaufman, L., Nishimoto, T., & Ruthruff, E. (1990). Why is it annoying to look at slides with the room lights turned off? Effects of visual stimulus degradation on perceptual processing an long term memory. In K. Rayner (Ed.) *Eye Movements and Cognitive Processes*, pp. 203-226.

Loftus, G.R., Nelson, W.W. & Kallman, H.J. (1983). Differential acquisition rates for different types of information from pictures. *Quarterly Journal of Experimental Psychology, 35A*, 187-198.

Loftus, G.R., Oberg, M.A., & Dillon, A.M. (2004). Linear theory, dimensional theory, and the face-inversion effect. *Psychological Review*, in press.

Massaro, D.W. (1970). Perceptual processes and forgetting in memory tasks. Psychological Review, 77, 557-567.

Masson, M.E.J. & Loftus, G.R. (2003). Using confidence intervals for graphically based data interpretation. *Canadian Journal of Experimental Psychology*, *57*, 203-220.

Morrison, D.J. & Schyns, P.G. (2001). Usage of spatial scales for the categorization of faces, objects, and scenes. *Psychonomic Bulletin & Review, 8*, 434-469.

Muhm, J.R., Miller, W.E., Fontana, R.S., Sanderson, D.R., & Uhlenhopp, M.A. (1983). Lung cancer detected during a screening program using four month chest radiographs. *Radiology, 148*, 609-615.

Musselwhite, M.J., & Jeffreys, D.A. (1982). Pattern-evoked potentials and Bloch's Law. *Vision Research, 22*, 897-903.

Navon, D. (1977). Forest before trees: The precedence of global features in visual perception, *Cognitive Psychology, 9*, 353-383.

Neisser, U. (1967). *Cognitive Psychology*, New York: Appleton-Century-Crofts.

Nelson, T. O., & Dunlosky, J. (1991). When people's judgments of learning (JOLs) are extremely accurate at predicting subsequent recall: The "delayed JOL effect". *Psychological Science*, *2*, 267-270.

Nelson, T.O., Metzler J. & Reed, D.A. (1974). Role of details in the long term recognition of pictures and verbal descriptions. *Journal of Experimental Psychology, 102*, 184-186.

Olds, E. S. & Engel, S. A. (1998). Linearity across spatial frequency in object recognition. *Vision Research, 38*, 2109-2118.

Olzak, L. A. & Thomas, J. P. (1986). Seeing spatial patterns. In K. R. Boff, L. Kaufman, and J. P. Thomas (Eds.), *Handbook of Perception and Human Performance (Vol. I)*. New York: Wiley.

Paivio, A. (1971). *Imagery and verbal processes*. New York: Holt, Rinehart, & Winston.

Paivio, A. (1991). Dual coding theory: Retrospect and current status. *Canadian Journal of Psychology, 45*, 255-287.

Palmer, J. (1986). Mechanisms of displacement discrimination with and without perceived movement. *Journal of Experimental Psychology: Human Perception and Performance, 12*, 411-421. (a)

Palmer, J. (1986). Mechanisms of displacement discrimination with a visual reference. *Vision Research, 26*, 1939-1947. (b)

Parish, D. H. & Sperling, G. (1991). Object spatial frequencies, retinal spatial frequencies, noise, and the efficiency of letter discrimination. *Vision Research, 31*, 1399-1415.

Parker, D.M. & Costen, N.P. (1999). One extreme or ther other or perhaps the golden mean? Issues of spatial resolution in face perception. *Current Psychology, 19*, 118-127.

Peli, E. (1990). Contrast in complex images. Journal of the Optical Society of America, 7, 2032-2040.

Pelli, D. G. (1997). The videotoolbox software for visual psychophysics: transforming numbers into movies. *Spatial Vision, 10*, 437-442.

Phelps, M.T. & Roberts, W.A., (1994). Memory for pictures of upright and inverted primate faces in humans (Homo sapiens), squirrel monkeys (Saimiri sciureus), and pigeons (Columba livia). *Journal of Comparative Psychology, 108*, 114-125.

Phillips, R.J. & Rawles, R.E. (1979). Recognition of upright and inverted faces: A correlational study. *Perception. 8*, 577-583.

Pinker, S. (1997). *How the Mind Works*. New York: Norton.

Pope, Alexander (1711). *An Essay on Criticism*. London: Collins.

Potter, M.C. (1975). Meaning in visual search. *Science, 187*, 965-966.

Potter, M.C. (1976). Short-term conceptual memory for pictures. *Journal of Experimental Psychology: Human Learning and Memory 2*, 509-522.

Rakover, S. (2001). *Face Recognition*. Amsterdam: John Benjamins.

Rayner, K., Inhoff, A. W., Morrison, R. E., Slowiaczek, M. L. & Bertera, J. H. (1981). Masking of foveal and parafoveal visions during eye fixations in reading. *Journal of Experimental Psychology: Human Perception & Performance, 7*, 167-179.

Reinitz, M. T., Wright, E., & Loftus, G. R. (1989). The effects of semantic priming on visual encoding of pictures. *Journal of Experimental Psychology: General 118*, 280-297.

Rhodes, G. (1988). Looking at faces: First-order and second-order features as determinants of facial appearance. *Perception*, *17*, 43-63.

Rossion, B. & Gauthier, I (2002). How does the brain process upright and inverted faces? *Behavioral and Cognitive Neuroscience Review*. 1, 62-74.

Rumelhart, D.E. (1970). A multicomponent theory of the perception of briefly exposed visual displays. *Journal of Mathematical Psychology, 7*, 191-218.

Sanocki, T. (1991). Effects of early common features on form perception. *Perception & Psychophysics, 50*, 490-497.

Sanocki, T. (1993). Time course of object identification: Evidence for a global to local contingency. *Journal of Experimental Psychology: Human Perception & Performance, 19*, 878-898.

Sanocki, T. (1997). Structural contingencies and object based shifts of attention during object recognition. *Journal of Experimental Psychology: Human Perception & Performance, 23*, 780-807.

Sanocki, T. (2001). Interaction of scale and time during object identification. *Journal of Experimental Psychology: Human Perception & Performance, 27*, 290-302.

Sargent, J. (1984). An investigation into component and configural processes underlying face perception. *British Journal of Psychology*, *75*, 221-242.

Schyns, P. G. & Oliva, A. (1994). From blobs to boundary edges: Evidence for time- and spatial-scale-dependent scene recognition. *Psychological Science, 5*, 195-200.

Shepard, R.N. (1962). The analysis of proximities: Multidimensional scaling with an unknown distance function. *Psychometrica, 27*, 125-140.

Shibuya, H. & Bundesen, C. (1988). Visual selection from multielement displays: Measuring and modeling effects of exposure duration. *Journal of Experimental Psychology: Human Perception and Performance, 14*, 591-600.

Solomon, J. A. & Pelli, D.G. (1994). The visual filter mediating letter identification. *Nature, 369*, 395-397.

Spekreijse, H., Van der Tweel, L.H., & Zuidema, Th. (1973). Contrast evoked responses in man. *Vision Research, 13*, 1577-1601.

Sperling, G. (1960). The information available in brief visual presentations. *Psychological Monographs, 74*, 1-29.

Teller, D.Y. (1997). First glances: The vision of infants. *Investigative Ophthalmology & Vision Science, 38*, 2183-2204.

Tulving, E. (1981). Similarity relations in recognition. *Journal of Verbal Learning and Verbal Behavior, 20,* 479-496.

Tulving, E. (1985). Memory and consciousness. *Canadian Psychology*, *26*, 1-12.

Tversky, A., & Russo, J. E. (1969). Substitutibility and similarity in binary choices. Journal of Mathematical Psychology, 6, 1-12.

Valentine, T. (1988). Upside-down faces: A review of the effect of inversion upon face recognition. *British Journal of Psychology, 79,* 471-491.

Valentine, T., & Bruce, V. (1986). The effect of race, inversion and encoding activity upon face recognition. *Acta Psychologica. 61*, 259-273

van Nes, R.L. & Bouman, M.A. (1967). Spatial modulation transfer in the human eye. *Journal of the Optical Society of America*, 57, 401-406.

Wandell, B.A. (1995). *Foundations of Vision* Sunderland, MA: Sindaur Associates.

Watson, A.B. (1986). Temporal sensitivity. In K.R. Boff, L. Kaufman, and J.P. Thomas (Eds.), *Handbook of Perception and Human Performance (Vol I* pp. 6-1 6-43*)*. New York: Wiley.

Watson, A. B., & Pelli, D. G. (1983). QUEST: A Bayesian adaptive psychometric method. Perception & Psychophysics, 33, 113-120.

Watt, R.J. (1987). Scanning from course to fine spatial scales in the human visual system after the onset of a stimulus *Journal of the Optical Society of America, 4, 2006-2021.*

Wells, G. L., Ferguson, T. J., & Lindsay, R. C. L. (1981). The tractability of eyewitness confidence and its implication for triers of fact. *Journal of Applied Psychology, 66*, 688-696.

Yin, R.K. (1969). Looking at upside-down faces. *Journal of Experimental Psychology*, *81*, 141-145.

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