

Seeing Changes: How Familiarity Alters Our Perception of Change

by

Mark Tovey

A thesis submitted to the Faculty of Graduate and Postdoctoral Affairs in partial
fulfillment of the requirements for the degree of

Doctor of Philosophy

in

Cognitive Science

Carleton University
Ottawa, Canada

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Your file *Votre référence*
ISBN: 978-0-494-81557-1
Our file *Notre référence*
ISBN: 978-0-494-81557-1

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Seeing Changes: How Familiarity Alters Our Perception of Change

Mark Tovey

Abstract

Change blindness is a phenomenon where individuals have difficulty detecting seemingly obvious changes in their environment. The objective of this dissertation was to assess the impact of the familiarity of objects on change blindness. Familiarity was operationalized by manipulating the Orientation (upright vs. inverted) of letters: Upright letters formed familiar stimuli whereas inverted letters (i.e., reflecting the stimuli across the horizontal axis) produced unfamiliar stimuli. Three experiments were conducted. In all three experiments Orientation was shown to affect the ability to detect change. In Experiment 1, the Orientation effect was independent of the number of distractors (Set Size), suggesting that Orientation and Set Size affect separate processing stages. The results of Experiment 2 suggested that Set Size, which interacts with Stimulus Quality, has its effects early in processing, whereas Orientation has an effect on a later stages of processing. Experiment 3 provides further evidence in support of a stage model of change blindness. A stage model of change blindness is proposed in which large changes are detected at a early Feature Extraction stage, while small changes require comparison at a later Identification stage.

For my parents, Ted and Edith Tovey.

Acknowledgements

A dissertation is a group effort. There are many people who contributed to the success of this project, including family, friends, and colleagues.

To start with, huge thanks are due to my supervisor, Chris M. Herdman, for his enthusiasm, his curiosity, his thoughtfulness, his ability to communicate challenging ideas, his excitement as we explored new ones, his generous support of my efforts, his kind words when they were needed, and for always being there for me when it counted.

Jo-Anne Lefevre and Robert West, the other members of my committee, gave me a lot of their time and effort. Their encouragement and attention to detail is very much appreciated. My internal-external, Gabriel Wainer, and my external, Steve Joordens, deserve special thanks for carefully engaging with my dissertation and asking probing questions.

Matthew Brown thoughtfully commented on many drafts of my dissertation, and cheerfully fielded my many questions about statistics and research design. I both enjoyed, and learned a great deal from our ongoing conversations.

My deep thanks also go to Judith Runnels and Alex Theus for thoughtful feedback, and for many stimulating conversations. It has been a pleasure working with them.

My “mock-defense” committee, Colin Henein, Ian Mclean, Nicole Robert, Richard Webster, and Jen Schellinck, deserve special thanks for their time and penetrating questions.

Many thanks also go to Kathryn O'Hara, and the students in her science journalism class, who gave me the opportunity to discuss my experiments at length, and who questioned me closely on them.

The members of the Advanced Cognitive Engineering lab, past and present, including Jolie Bell, Lisa Hagen, Jerzy Jarmasz, Kamilla Run Jóhannsdóttir, Ana Mileska, Derek Pasma, Kishore Raheja, Kathy Van Bentham, and Yun Zhang, who offered timely help, stimulation, and thoughtfulness, and generally made the lab a congenial place to work and think.

For equipment, software, stimulating conversation, sound advice, timely intervention, and understanding over and beyond the call of duty, I want to acknowledge the competence, cheerfulness, and professionalism of the technical team in the ACE lab, especially Dan Bleichman, Murray Gamble, Andy Staples, and Jon Wade.

Warm thanks go to Lianne Dubreuil, Colleen Fulton, and May Hyde for being consistently friendly and helpful, and being there for me when I needed it.

Perry Bamji, Roxy Hamilton, Lucy Keating, and the rest of the Ontario Centres of Excellence VAP team, gave me tools and skills which made the whole process easier. Many thanks.

Monique Sénéchal and Deepthi Kamawar both made timely loans of experimental equipment which have been a boon to this project, and which are very much appreciated.

The following people made contributions at various times during this process by giving crucial advice, support, accomodation, inspiration and encouragement, for which I am truly grateful. They may not remember, but I do!

Eva Amsen, Dale Armstrong, Intisar Awisse, Timothy Bisha, Roman Blaszczyk, Stefanie Bowles, Andrew Brook, Nancy Brooks, Vernon Brooks, Sanjay Chandrasekesharan, Emily Chung, Chet Creider, Jody Culham, Jim Davies, Steven Davis, Peter Denny, Megan DePutter, Jen Dodd, Ranpal Dosanjh, Jay Drydyk, Lianne Dubreuil, Craig Eby, Robert Erickson, Jordy Gold, Rhys Goldstein, Mel Goodale, Andrea Gormley, Noëlle Hansen, David Heap, Kathy Hoos, Keith Humphrey, May Hyde, Zoltan Jakab, Francis Jeanson, Walter Joyce, Shamima Khan, David Kirsh, Mark Klein, Christine Koggel, Alan Kosaric, Naim Kosaric, Carla Krachun, Julien Lamarche, Tracey Lauriault, Stuart Lee, Joseph Lella, Marc Léonard, John Logan, Derek Lomas, Heidi Maibom, Hassan Masum, David Matheson, Emily McCarthy, Jim McGinley, Brad McMillan, Bob Mercer, David Morgan, Robert Murray, Sheila Murray, Michael Nielsen, Thomas Papathomas, André Paquette, Carlene Paquette, Marcie Penner-Wilger, David Pierre Leibovitz, Aryn Pyke, Michael Reade, Moira Reade, James Redekop, Dominic Rossi, Matthew Rutledge-Taylor, Leslie Santibañez, Jane Simm, Rob Spekkens, Marc Stamos, Robert Steele, Giulia Stefani, Terry Stewart, Stephen Stich, Michelle Syba, Leo Trottier, Tutis Vilis, Angela White, David Whitney, Greg Wilson, and Lisa Zeitz.

I also want to thank my family, as well as other friends and colleagues who gave me support throughout this process. To all of you, my sincere thanks!

I gratefully acknowledge financial support from the Province of Ontario through the Ontario Graduate Scholarships (OGS), and the Ontario Graduate Scholarships in Science and Technology (OGSST) programmes; from Carleton University through their Graduate Scholarships and through the Darbyshire Graduate Scholarship in Cognitive Science; from the Cybercartography and the New Economy project (SSHRC); and from the Ontario Centres of Excellence (OCE). Research infrastructure was supported through the Canada Foundation for Innovation (CFI).

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INTRODUCTION

The world seems to us to be highly detailed. Wherever we look, we have the experience of a rich, coherent scene. We feel as though we have complete visual access to the contents of the world around us in all its variety and fluctuation. Although the world itself may indeed be detailed, we are likely deceived, in at least some respects, in the degree to which we have full visual access to our surroundings and what goes on in them (Noë, Pessoa, & Thompson, 2000). With each fixation, our visual system can only focus on a small portion of our world (*foveal vision*) (approximately 2° of visual angle; Churchland & Ramchandran, 1996) with high visual acuity. This dictates, in part, the amount of detail we have available to process at any one moment. Moreover, the amount of information transmitted to the visual cortex from the retina is also limited by the size, or *channel capacity*, of the optic nerve itself (Lennie, 1984). Some of the information that is transduced by the photoreceptors is not passed on for further processing. Thus, although our visual world may appear to be large and complete, our real-time access to its detailed contents is restricted by the physiology of our retina and optic nerve.

Our visual access is impoverished in other ways as well. Our eyes normally saccade multiple times a second (Reichle, Rayner, & Pollatsek, 2003). However we fail to notice this movement, either because the movement is too rapid, or because our visual system temporarily shuts itself down during saccades—a phenomenon known as *saccadic suppression* (Thiele, Henning, Kubischik, & Hoffman, 2002). Thus, although our vision appears to be continuous, it is punctuated by discontinuities in our access to the visual

world. Because of saccadic suppression, it is difficult for observers to notice changes in the visual scene that occur during eye movements (Grimes, 1996). Thus, not only are the data that are available to our perceptual system limited in the ways described above, but so is our ability to attend to changes that occur during saccadic eye movements.

Changing stimuli are normally associated with visual transients. Visual transients can provide cues to our visual system, which effortlessly and exogenously guide our attention to changes in our environment (Kanai & Verstraten, 2004). However, when the transients associated with the change are surrounded by competing transients (O'Regan, Rensink, & Clark, 1999) attention can fail to be drawn to the changing object. Eye blinks (O'Regan, Deubel, Clark, & Rensink, 2000) and other externally mediated visual disruptions, such as briefly blanking a computer screen (Landman, Spekreijse, & Lamme, 2003; Pashler, 1988; Phillips, 1974; Rensink, O'Regan, & Clark, 1997) compete with visual transients.

Transients normally associated with a change may also be unavailable when the change is sufficiently gradual, which produces the blindness to change seen in gradual change studies (e.g., Simons, Franconeri, & Reimer, 2000). Change detection can also be attenuated when a number of competing transients are presented at precisely the same time as the change in the target. So-called “mudsplash” experiments, which generate multiple flashes at the same time as an object change is introduced, illustrate this phenomenon. These flashes do not have to cover up the changing object to produce an effect of change blindness (O'Regan et al., 1999). Thus their effect is a result of

competition between visual cues, rather than a question of the visual cues being occluded. In other words, these simultaneous flashes reduce awareness of the changing stimulus, not by removing the target from view but by diverting the viewer's attention with competing transients.

Regardless of the paradigm, change blindness occurs when there is no unique visual transient to cue the observer. In all of these situations, the dependence on transients to signal change suggests that when a change is detected, it is detected in very early preprocessing (Sanders, 1990) through a parallel process that immediately signals the change and orients attention and fixation towards it (Kanai & Verstraten, 2004). When a change is not detected immediately it must be detected through a subsequent search process that involves feature extraction and identification (Sanders, 1990). This basic functional division between preprocessing and search is expressed diagrammatically in Figure 1.

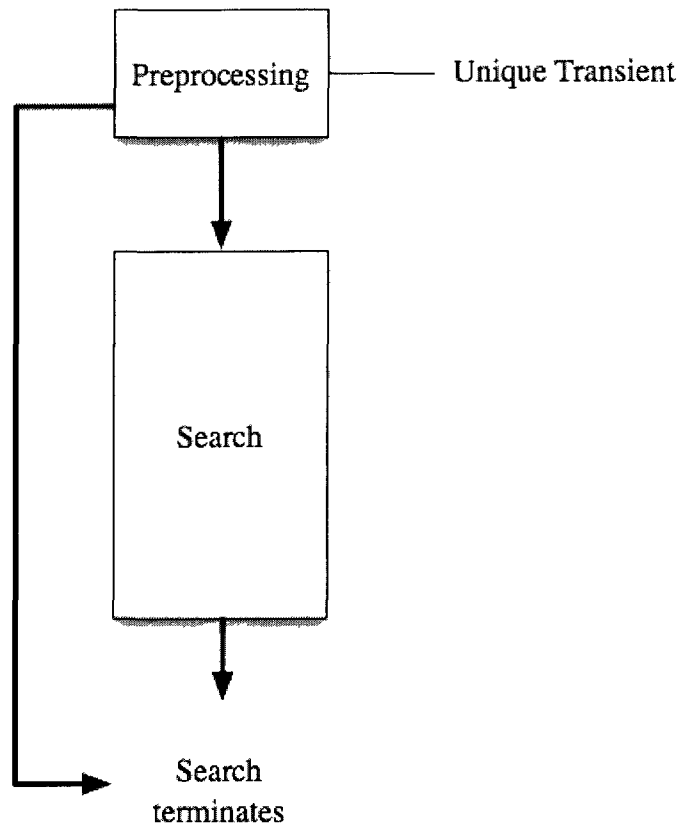


Figure 1. Unique transients cue the observer to changes. If change is detected in Preprocessing, no further search is required.

The simple model shown in Figure 1 can be expanded by appealing to a model which more finely articulates stages of mental processing. Sanders (1990), in a meta-analysis of the stages of processing for choice reaction tasks, discusses six processing stages. Sanders also outlines some of the factors, across a variety of experiments, that have been found to have effects on particular stages. The stages outlined by Sanders include three perceptual processing stages (Preprocessing, Feature Extraction, and Identification), one response choice stage (Response Selection), and three response processing stages (Motor Programming, Program Loading, and Motor Adjustment). The helpful divisions between the stages in Sanders (Perceptual Processing, Response Selection, Response Processing) are taken from Johnson and Proctor's (2004) version of Sanders stage diagram, and have been incorporated into the diagram presented in Figure 2. In the current dissertation, the perceptual stages in Sanders' model for choice reaction were applied to describe and account for perceptual performance in change blindness tasks.

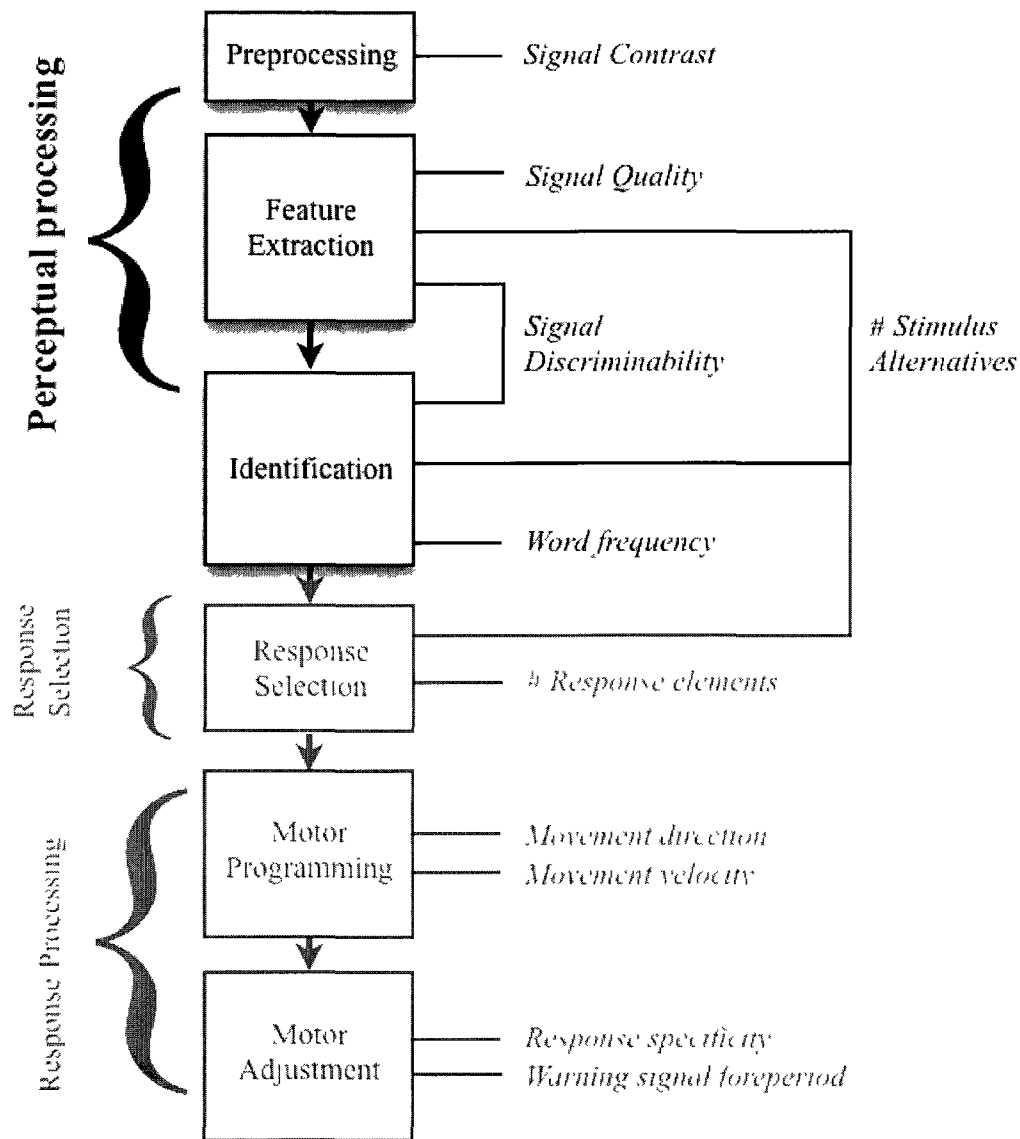


Figure 2. Stage model for choice reaction tasks, after Sanders (1990), redrawn, adapted, and simplified, with side labels for the stage groupings (on the left) taken from Johnson & Proctor's (2004) adaptation of Sanders' stage diagram. The stages of interest in the current research (the Perceptual Processing stages) are shown in gray.

Evidence for an Effect of Familiarity on Change Blindness

There has been a growing body of research related to change blindness (for reviews see Rensink, 2000a; 2002; Simons & Ambinder, 2005; Simons & Rensink, 2005). Much of this research has focused on the role played by strictly visual properties of the changing objects, using factors such as Change Size (i.e., number of features that changed in an object) and Set Size (i.e., number of objects in the display) (e.g., Fernandez-Duque & Thornton 2003; Laloyaux, Destrebecqz & Cleeremans, 2006; Mitroff & Simons, 2000; Mitroff, Simons, & Franconeri, 2002; Mitroff, Simons, & Levin, 2004; Richards, Tombu, Stolz, & Jolicoeur, 2004; Smilek, Eastwood, & Merikle, 2000; Stolz & Jolicoeur, 2005; Vierck & Kiesel, 2008). These chiefly concern the question of whether or not visual representations accumulate pre-attentively. Another group of research, often using photographs of real world scenes as stimuli, has examined the role that top-down processes play in mediating change blindness (Jones et al., 2003; Rensink et al., 1997; Werner & Thies, 2000). Much of this work has centered around showing that changes in objects of greater interest to the participant will be noticed more quickly. The interest in this dissertation is in a third group of papers, which have made attempts to examine both top-down and bottom-up processes simultaneously (Barton & Malik, 2003; Barton, Radcliffe, Cherkasova, Edelman, & Intriligator, 2006; Caplovitz, Fendrich, & Hughes, 2007; Palermo & Rhodes (2003); Pashler, 1988; Richards, 2002; Ro, Russell, & Lavie, 2001). The interest with these papers lies in whether changes in familiar objects (i.e., objects that can be readily categorized) are detected differently from

and/or more efficiently than, changes in unfamiliar objects. This remains an unsettled question. Simons and Rensink identified the extent and manner in which “long-term representations ... contribute to change-detection performance” (Simons & Rensink, 2005, p. 19) as one of the outstanding issues in the field. The current dissertation attempts to shed some light on both the extent and the manner in which long-term representations have an effect on change-detection performance, and in the process, put to rest the long-standing issue of whether or not changes in familiar objects are detected differently (and more efficiently) than those in unfamiliar objects.

The first study to directly examine the role of familiarity in change blindness was reported by Pashler (1988). A familiar object, in Pashler’s sense, is an object with a known identity, which means that it is possible to categorize it. We do not categorize an individual dot in a set of similar looking dots (Phillips, 1974), whereas we do categorize letters (e.g., ‘A’, ‘F’, or ‘L’), or numbers (e.g., ‘1’, ‘2’, or ‘3’). Pashler operationalized familiarity by inverting letters (i.e., reflecting them across the y-axis) to create unfamiliar stimuli. Under ordinary viewing conditions (i.e., where change blindness is not involved), upright letters were identified more quickly, and with fewer errors, than inverted letters. Inverting the letters to make them less familiar had the advantage of holding feature composition and complexity constant across these two levels of familiarity. Because the difference between an inverted letter and an upright one is the degree to which it is readily categorizable, or has an identity, Pashler proposed that any difference in time or accuracy must be attributable to the stimulus’s degree of familiarity. If letter

identification plays a role in change detection, one would anticipate that changes in upright letters would be detected more efficiently than changes in inverted letters.

Pashler's (1988) displays consisted of ten letters in a 2×5 matrix that were either all upright (familiar orientation) or all inverted (unfamiliar orientation). On half the trials, a letter in the first display was replaced by a different, randomly chosen letter. On the other half of the trials, the two displays were identical. Displays were separated by a blank interstimulus interval (ISI) that varied in length from 34 ms to 217 ms. Participants indicated whether or not a change occurred. Pashler reported that regardless of ISI, participants were no more accurate at detecting changes in upright displays than in inverted ones. This finding led Pashler to conclude that familiarity does not facilitate change detection. In particular, the lack of any difference in change detection accuracy between the two conditions led Pashler to claim that categorical knowledge of the objects does not affect the outcome of the detection process.

Pashler (1988) used a one-shot paradigm, where each stimulus set is only presented once in a given trial, after which participants indicate whether they saw a change or not. The one-shot paradigm is designed to test accuracy and not response time. Because the paradigm used by Pashler only measured accuracy, it is possible that the presence of a familiarity effect was missed. As summarized below, recent evidence from response time experiments suggests that there are some conditions under which change is facilitated by categorical knowledge of the identities of the objects (Jones et al., 2003; LaPoint et al., 2010), or by expertise with the contents of a scene (Werner & Thies,

2000). The single one-shot presentation of each stimulus set also limits the time available for detection, which could have hidden an effect of familiarity in Pashler's study, if present (Richards, 2002).

In contrast to Pashler (1988), a potential role of familiarity on change blindness has been suggested in several studies in which a flicker paradigm was used. The flicker paradigm is arguably more suitable for examining change blindness than the one-shot paradigm used by Pashler. In contrast to the one-shot paradigm, the flicker paradigm allows more time for participants to detect a change and it also allows for the measurement of response time. In the flicker paradigm, two displays (A and A') are repeatedly presented in a cyclical pattern, separated by a blank ISI, until the observer indicates that they notice a change (see Figure 3). Response time is measured. In some flicker paradigm experiments, the participant is also asked to indicate which element of the display changed, yielding an accuracy measurement in addition to response time.

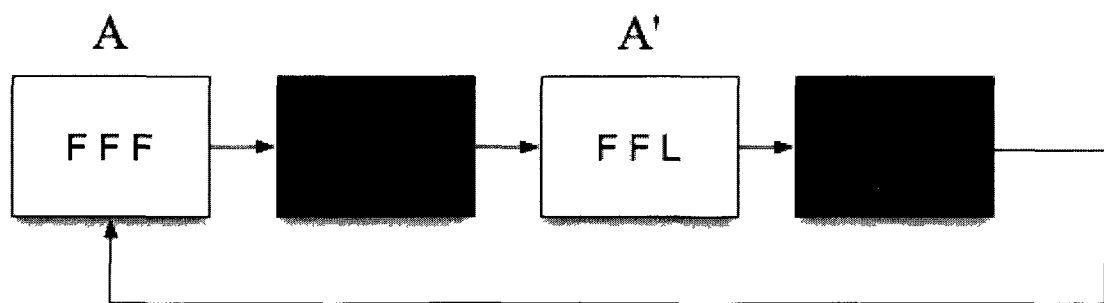


Figure 3. The flicker paradigm, showing the two displays (A and A'), repeatedly presented in a cyclical pattern, separated by a blank ISI (shown as black screens).

In a flicker paradigm experiment, Jones et al. (2003) found that heavy users of alcohol detected changes in images of alcohol bottles more quickly than changes in other kinds of objects. For the present purposes, the Jones et al. findings suggest that how we categorize an object has an effect on how well we detect changes in it. Werner and Thies (2000), also using a flicker paradigm, found that football players, when presented with two alternating images of football being played, detected changes in those images more quickly than amateurs when performance was compared to control scenes not involving football. This difference in change detection between professionals and amateurs was more pronounced in situations where the changing object in the football scene was important to the interpretation of the scene. Consistent with the conclusions of Jones et al. (2003), these results support the view that how people categorize stimuli can influence change detection.

Merely showing that categorization can be used in change detection is not sufficient to establish an effect of familiarity. The participants in Jones et al. (2003) may simply have been directing more attention to objects in a scene that interested them more (alcohol bottles, in this case). Similarly, the football players in Werner and Thies (2000) may have been more likely to examine the parts of a scene that were relevant to playing football earlier in search. These studies speak to the subjective *salience* of the objects in a scene whereby participants could have directed more attention to certain objects in a scene, or to parts of a scene that are of special interest. To establish an effect of familiarity, it is necessary to determine whether changes in readily categorizable objects

are detected more efficiently than changes in less categorizable objects in situations where salience does not play a role. The study that brings us closest to this ideal, to date, is an unpublished dissertation by Richards (2002). Using a flicker paradigm, Richards found evidence for an effect of familiarity on change blindness. However, Richards' results are subject to the criticism that his familiar stimuli (Figure 4a) are different from his unfamiliar stimuli (Figure 4b) in terms of featural composition (e.g., angled vs. vertical/horizontal) and visual complexity. Thus, it is impossible to confidently interpret the impact of familiarity in Richards' experiments because differences in performance across the familiar vs. unfamiliar stimuli may be entirely driven by the featural differences between the stimuli rather than by familiarity itself.

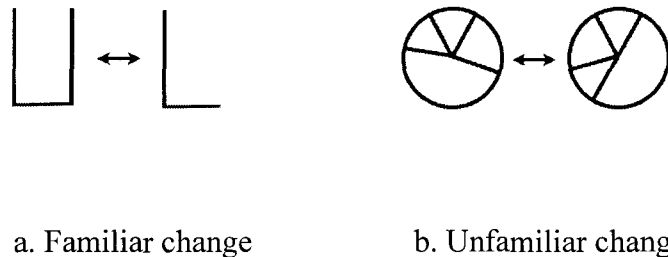


Figure 4. Two-feature change from Richards (2002).

To summarize, there is indirect evidence from Jones et al. (2003) and from Werner and Thies (2000) that categorical information can affect a person's ability to detect change in the environment. However these results cannot speak directly to the

question of whether object familiarity affects change blindness. The results from more direct examinations of familiarity on change blindness are divergent. Pashler (1988) found no effect of familiarity. Richards (2002) concludes that familiarity had an effect on detecting change, but the conclusions from that study are compromised because it was not possible to directly compare the familiar and unfamiliar stimuli.

Present Research

The objective of the present research was to examine the role of object familiarity on change blindness. Three experiments were performed in which change blindness was examined using a flicker paradigm. Familiarity was manipulated by presenting letter stimuli in an upright orientation versus an inverted orientation. Experiment 1 established a familiarity effect: changes to inverted letters took significantly longer to detect than changes to upright letters. Experiments 2 and 3 replicated this finding and provided evidence to support the development of a stage model of change blindness.

Preliminary Model

A preliminary model of change blindness using Sanders' (1990) stage approach can be outlined based on research by Smilek et al. (2000). Smilek et al. used a flicker paradigm in which alternating stimulus sets (A and A') were presented separated by a blank screen (see Figure 3). In addition to manipulating Set Size (number of stimulus alternatives), Smilek et al. varied the Change Size (i.e., the number of LED elements that changed in the target) from trial to trial. For example, L alternating with F was a large

change (3 features), whereas **F** alternating with an **E** was a small change (1 feature). An interaction between Change Size and Set Size was found. Additive factors logic, as will be elaborated on later, holds that two interacting factors in a serial processing system affect the same stage (Sternberg, 1969; see also Johnson & Proctor, 2004; Pachella, 1974; Sanders, 1998). The interaction between Change Size and Set Size in Smilek et al., therefore, suggests that these factors affect a common stage.

Richards, Tombu, Stolz, and Jolicoeur (2004) localized the effect of Change Size between the very early stages of processing, which Sanders (1990) calls the Preprocessing stage, and the attentional bottleneck, which Sanders calls Response choice, and which others refer to as the decision-making or response selection stage (Dux, Ivanoff, Asplund, & Marois, 2006). Thus, in terms of Sanders' model, Change Size has its effects on the stages between Preprocessing and Response choice, and thus in the Feature Extraction stage, or the Identification stage, or possibly both. By additive factors, the interaction between Set Size and Change Size (Smilek et al., 2000) would indicate that Set Size would also have its effects in at least one of the stages affected by Change Size (i.e., at the Feature Extraction or Identification stages). This assignment corresponds with Sanders placement of Signal Discriminability (\sim =Change Size) and Number of Alternatives (\sim =Set Size) at both the Feature Extraction and Identification stages (See Figure 5).

A preliminary attempt at locating the role of familiarity on change detection can be made by referring to Sanders (1990), who shows Word Frequency as having its effects

at the Identification stage (Figure 5). If familiarity has an effect, we might reasonably predict that familiarity would affect the same stage as Word Frequency, which also relies on the ability to categorize stimuli.

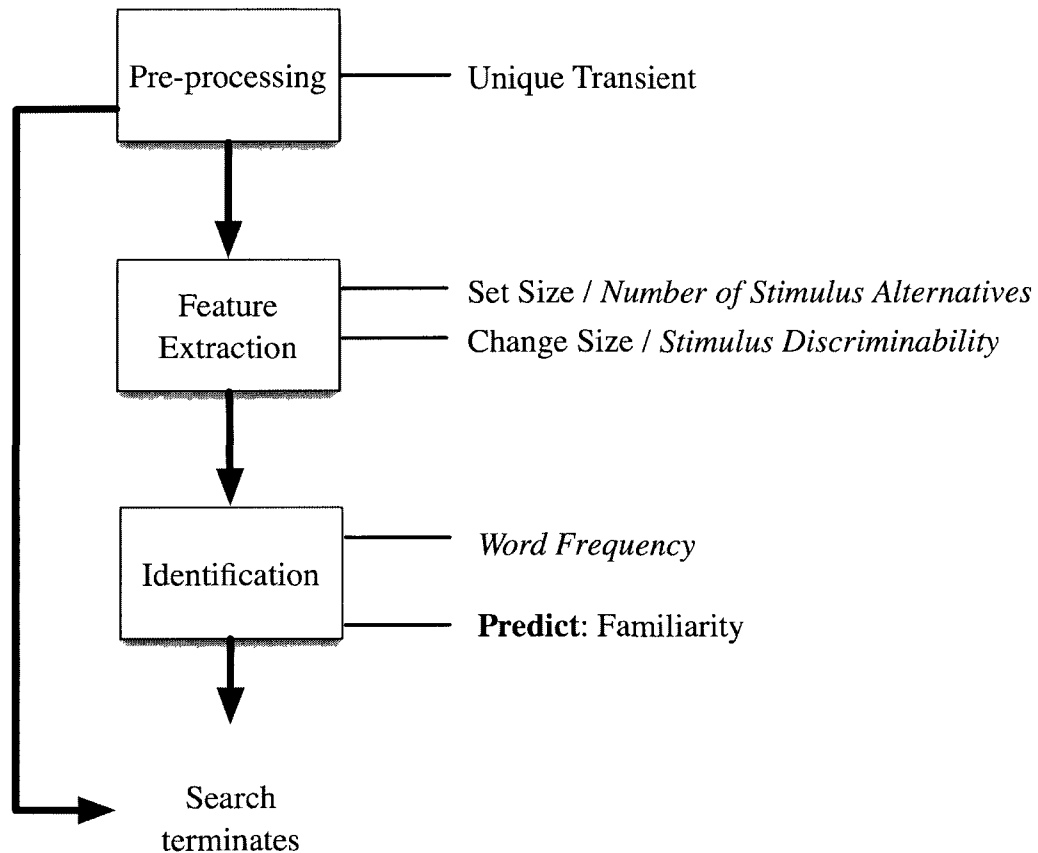


Figure 5. Preliminary stage model of change blindness. This model combines Sanders' (1990) stage model for choice reaction with results and vocabulary from Smilek et al. (2000) and Richards et al. (2004). Sanders' Identification stage showed the effect of Word Frequency, from which is predicted an effect of familiarity on the Identification stage.

EXPERIMENT ONE

Establishing the Effect of Familiarity on Letters

Experiment 1 was designed to test for an effect of familiarity on change detection. Familiarity was manipulated by presenting letter stimuli in an upright orientation versus an inverted orientation. The time required to detect a change in an upright letter surrounded by other upright letters was compared directly with the time required for detecting a change in an inverted letter surrounded by other inverted letters. The present research used a flicker paradigm (see Figure 3) based on Smilek et al. (2000) and Richards (2002). Pashler (1988) did not manipulate change size but replaced letters at random, without reference to how many elements of the letters were changing. Explicitly manipulating change size in the current experiments, as Smilek et al. (2000) and Richards (2002) did, allowed for an examination of how the size of change contributes to the effect of familiarity, while removing Change Size fluctuation as a source of variability. This difference in methodology turns out to be important, because as it is reported in this dissertation, the effect of Orientation is significant only when letters are changed in a small way, but not when they are changed in a large way.

As noted above, Richards' (2002) participants were exposed to unfamiliar stimuli which were visually quite different from the familiar stimuli, that is, familiar stimuli were square and contained exclusively horizontal and vertical lines, whereas unfamiliar stimuli were round and contained mostly diagonal lines. In addition, the familiar and unfamiliar stimuli were not matched for the surface area they covered. Richards' letters and "wagon

wheels” differed in degree of familiarity, but they also differed in form. In the current experiments, unfamiliar stimuli were visually matched as closely as possible to the familiar stimuli by inverting them. Inverting the stimuli does not change the roundness or squareness, size, configuration, surface area, or visual interest of the stimuli. It is a manipulation that isolates familiarity from other effects.

To summarize, Experiment 1 was designed to test whether familiarity plays a role in detecting visual changes. Familiarity was manipulated by varying the orientation (upright versus inverted) of the letter stimuli.

Method

Participants. Participants ($n=30$) were drawn from the undergraduate psychology pool at Carleton University and were compensated with 1% course credit towards their final grade. The number of participants chosen was based on earlier pilot research, and is typical to that used in the literature. Participants were assumed to have normal or corrected-to-normal visual acuity. No data were collected on the age or gender of participants.

Design. A 5 (Set Size: 4, 7, 10, 13, 16) \times 2 (Feature Change Size: small vs. large) \times 2 (Orientation: Upright vs. Inverted) within-subjects design was used. Set Size refers to the number of objects (i.e., letters) in the display. Each display consisted of one target and either 3, 6, 9, 12, or 15 distractors. The target was the only object in the display that changed. In keeping with Pashler (1988), the orientation of the distractors always matched the orientation of the target. Change Size is defined by the number of features

(i.e., the presence or absence of equal sized line segments) that changed in the target. In this experiment, either one or three features changed (Figure 6). Familiar displays consisted of targets and distractors that were upright, whereas targets and distractors in unfamiliar displays were all inverted. Unfamiliar stimuli were created, in keeping with Pashler's paradigm, by reflecting the upright stimuli across the horizontal axis. Each level within a factor appeared an equal number of times in each trial block of 100.

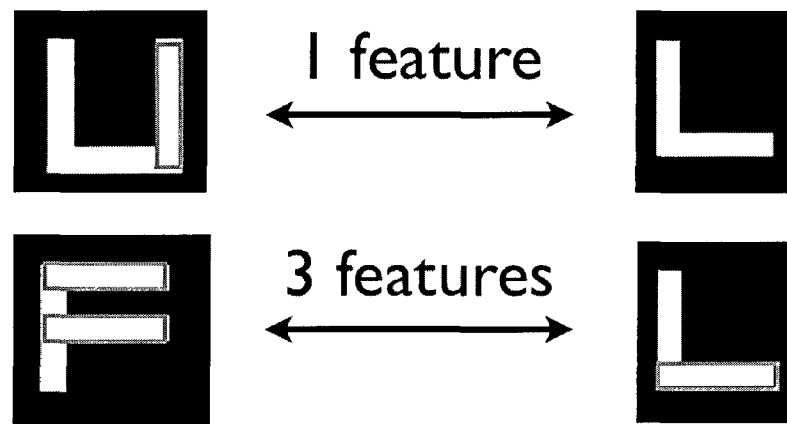


Figure 6. Illustration of sizes of feature-change in upright letters.

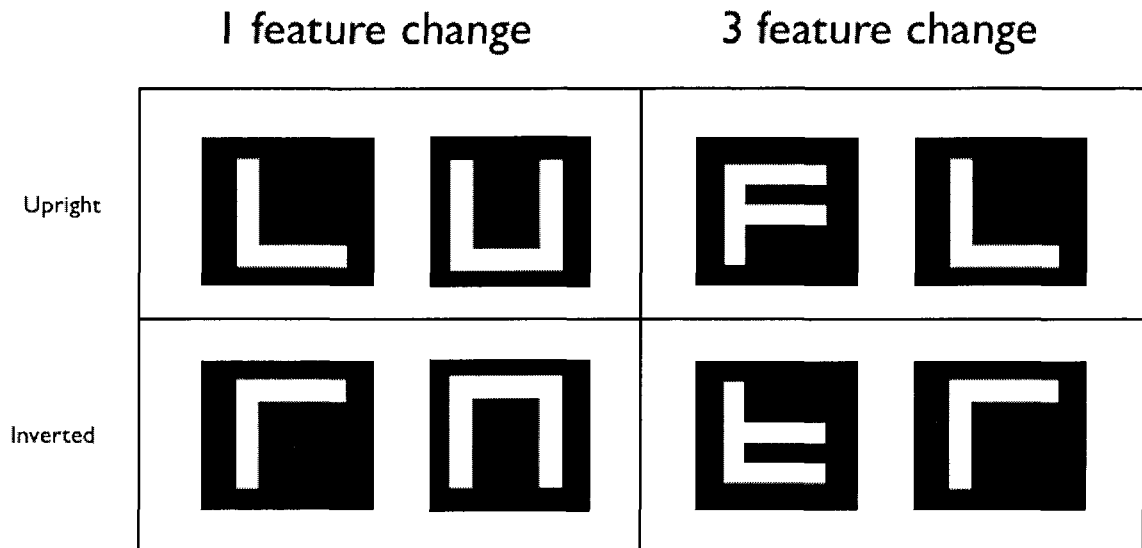


Figure 7. Comparison matrix of feature change sizes for letters, showing both familiar (upright), and unfamiliar (inverted) stimuli.

Materials/Stimuli. Stimuli were displayed on a 17" Phillips 170S LCD Monitor. The experimental box was a Macintosh Blue and White G3 with 416MB of RAM, running MacOS 9.2.2 (See Figure 8). The presentations were programmed using the PsyScript 5.1d3 experiment scripting application (Bates & D'Oliveiro, 2003), running under the AppleScript programming language, version 1.83. Equal sized line segments correspond to features. Thus $U \rightarrow L$ is a one feature alternation (small change), and $F \rightarrow L$ is a three feature alternation (large change) (see Figure 6). The letters appeared as bright white (rgb values: 65535,65535,65535) on a black (rgb values: 0,0,0) background.



Figure 8. Photograph of the experimental equipment, with author, showing a display of upright letters.

Procedure. This experiment used a flicker paradigm similar to that of Smilek et al. (2000). Within a trial, the objects were either all upright or all inverted (see Figure 7), and were randomly assigned to cells in an imaginary 6×6 grid. In each trial, displays would alternate between two screens, A and A' (separated in time by a blank screen), until the participant pressed the space bar to indicate that they had seen a change. Each cycle (after Smilek et al., 2000) consisted of an array of letters (A) displayed for 200 ms, followed by an 80 ms blank interval, followed by an second display for 200 ms (A') with one letter changed. This display was followed by another 80 ms blank interval, prior to the same A–A' cycle beginning over again (see Figure 9). This cycle repeated until the participant pressed the space bar to indicate that they had noticed a change or until 40 A–A' alternations had been presented (22400 ms).

The 6×6 imaginary grid measured 225 mm \times 225 mm onscreen, and each letter measured 27 mm \times 27 mm. Subjects viewed the screen from an approximate distance of 56 cm. Each grid square was 100 pixels by 100 pixels, and each letter was 100 pixels high \times 100 pixels across. Individual features measured 100 pixels \times 15 pixels. Grid squares were separated by 15 pixels in each direction. Thus the total size of the grid was 675 pixels \times 675 pixels ($6 \times 100 + 5 \times 15$) = 675.

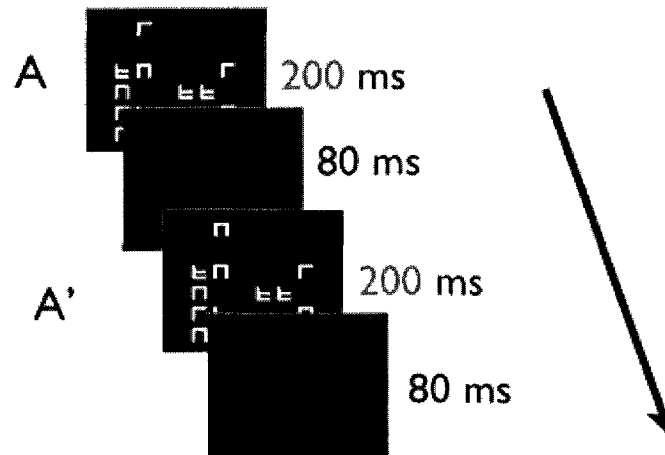


Figure 9. Example of the Flicker Paradigm used in Experiment 1. A and A' repeat until timeout has elapsed, or until space bar is pressed by participant. Note that both targets and distractors are inverted in this example.

Each participant viewed 300 trials, grouped into three blocks of 100 trials each. Within each trial block of 100, each of the 20 possible conditions (5 set sizes \times 2 change sizes \times 2 orientations) were presented 5 times. The order of the trials were randomized within each of the three blocks of 100.

The location of the target and the distractor were chosen randomly for each trial, but remained in the same locations as the display changed from A to A'. The changing target always appeared in the same place in a given trial, throughout the trial. Similarly, distractors always appeared in the same place in a given trial. Participants were instructed to press the space bar when they noticed the changing object (yielding a measure of response time) and then to select the letter that they thought had changed (yielding a measure of accuracy).

Results

Response Time Data

Response times (RTs) for correct trials were first submitted to Van Selst and Jolicoeur's (1994) Modified Recursive outlier-removal procedure. This resulted in an elimination of 2.55% of the trials. The remaining data were analysed using a 5 (Set Size: 4,7,10,13,16) \times 2 (Change Size: Small vs. Large) \times 2 (Orientation: Upright vs. Inverted) repeated measures analysis of variance (ANOVA).

There was an overall main effect of Orientation (Figure 10) where participants responded 81 ms more quickly to upright letters (1834 ms) than to inverted letters (1915 ms), $F(1,29) = 10.5$, $MSE = 94,102$, $p < .005$, $\eta_p^2 = .265$. This effect of Orientation provides straightforward evidence for an effect of letter familiarity on change blindness, an effect also demonstrated in each of the two studies that follow.

A main effect of Change Size (Figure 11) was found where large changes were detected (1637 ms) more quickly than small changes (2115 ms), $F(1,29)=230.5$, $MSE=148,843$, $p<.001$, $\eta_p^2=.888$, a difference of 478 ms. There was also a main effect of Set Size, $F(4,116)=251.4$, $MSE=214,280$, $p<.001$, $\eta_p^2=.897$, where response times increased with Set Size (1041 ms, 1448 ms, 1906 ms, 2235 ms, 2760 ms) for set sizes 4, 7, 10, 13, and 16, respectively.

The interaction between Change Size and Set Size was significant, $F(4,116)=23.4$, $MSE=121,013$, $p<.001$, $\eta_p^2=.447$. As shown in Figure 11, as Set Size increased, the effect

of Change Size also increased. The Change Size effect [small changes - large changes] was 119 ms, 296 ms, 515 ms, 546 ms, and 933 ms, for set sizes of 4, 7, 10, 13, and 16, respectively, which is the same pattern reported by Smilek et al. (2000). No other interactions were significant, suggesting additivity between Orientation and Set Size (see Figure 10) as well as between Orientation and Change Size (see Figure 12).

Error Data.

The overall error rate was 1.90%. The error data were analyzed using the same ANOVA used for the RT data. The small error rate may be the reason that no main effect of Orientation on accuracy ($F < 1$) was observed. The number of errors for small changes (2.4%) was greater than for large changes (1.3%), yielding a significant main effect of Change Size, $F(1,29)=10.7$, $MSE=.002$, $p<.005$, $\eta_p^2=.270$. There was no main effect of Set Size, $F(1, 29)=2.110$, $MSE=.006$, $p>.05$, $\eta_p^2=.068$, observed power=.611. The Orientation \times Change Size interaction (Figure 12) was significant, $F(1,29)=5.0$, $MSE=.001$, $p<.05$, $\eta_p^2=.147$, whereby Change Size had a greater impact on inverted than on upright letters. No other interactions were significant.

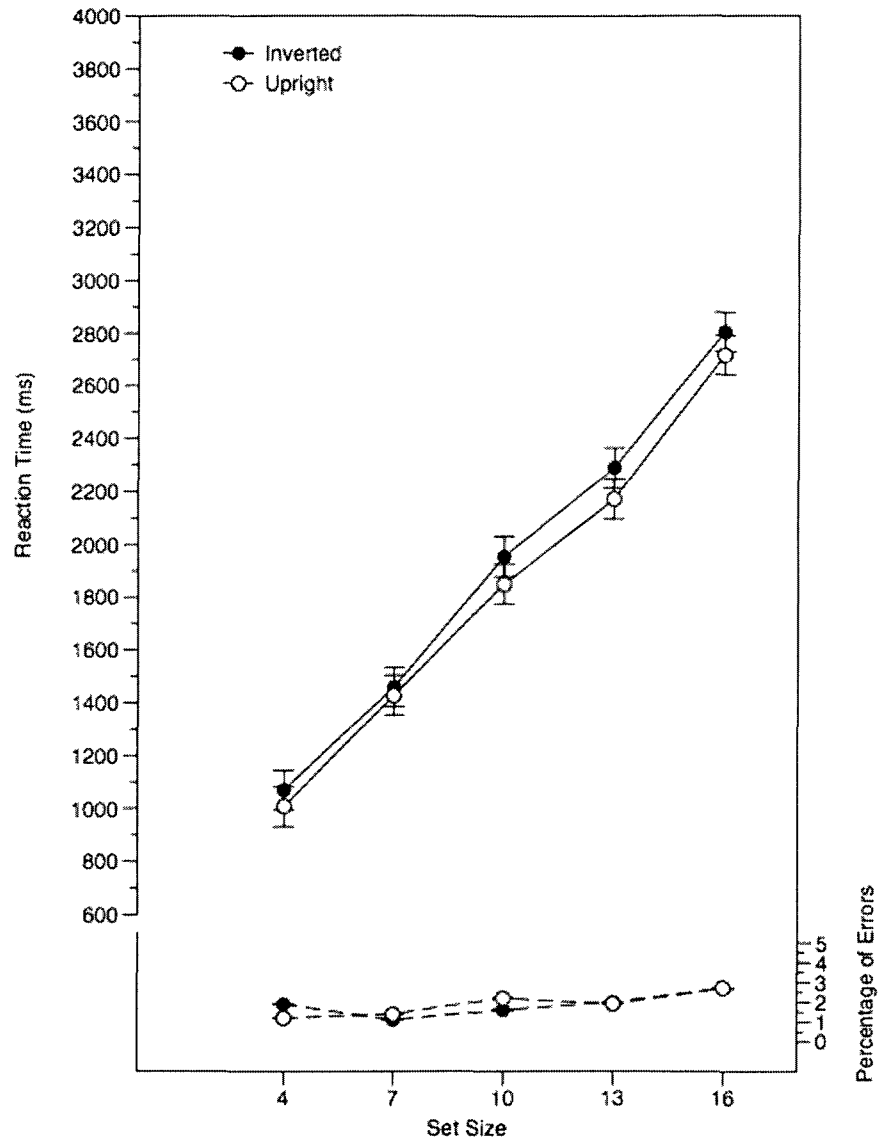


Figure 10. Response Time (in ms) and % error in Experiment 1 as a Function of Set Size and Orientation. Error bars are 95% confidence intervals.

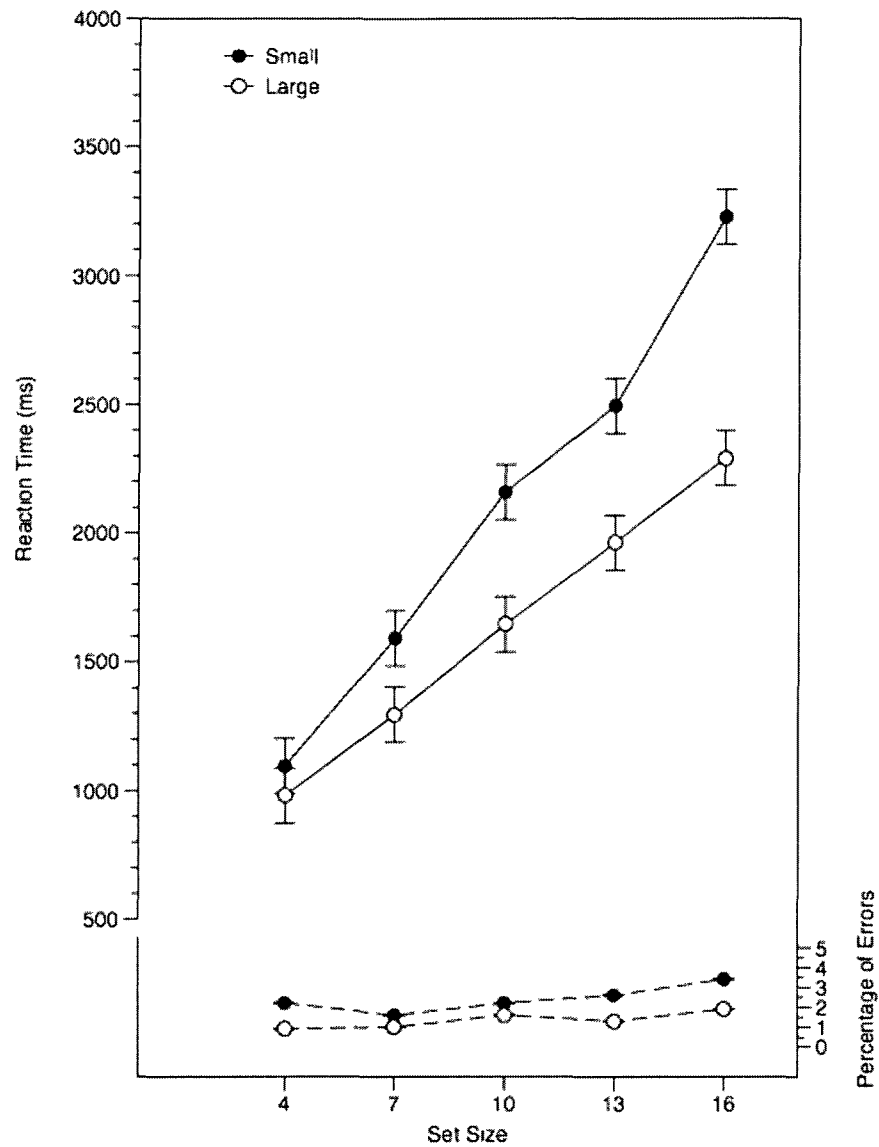


Figure 11. Response Time (in ms), and % error in Experiment 1 as a Function of Set Size and Change Size. Error bars are 95% confidence intervals.

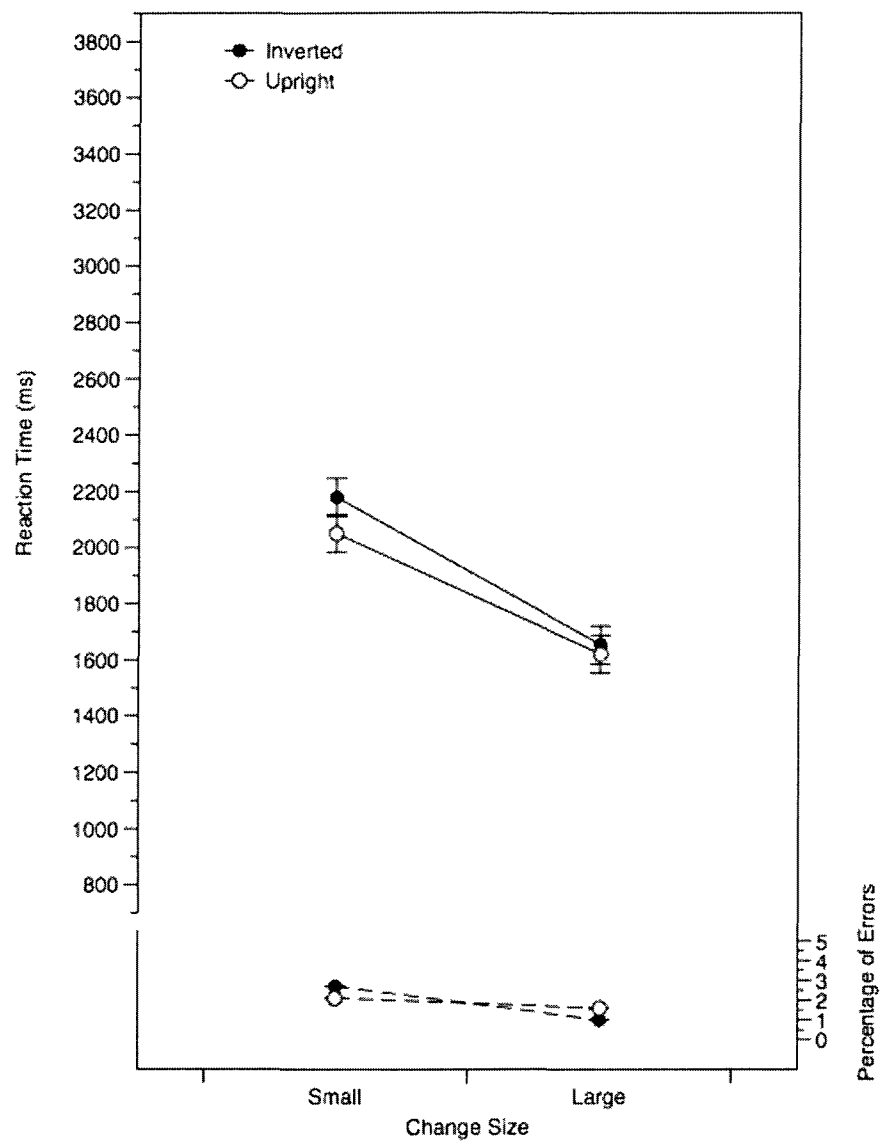


Figure 12. Response Time (in ms), and % error in Experiment 1 as a Function of Change Size and Orientation (interaction non-significant). Error bars are 95% confidence intervals.

Summary

The primary contribution of Experiment 1 is in providing clear evidence that change detection is influenced by familiarity: changes to upright letters were detected more quickly than changes to inverted letters. The effect of Orientation (upright vs. inverted) was not influenced by the number of distractors (Set Size) in the display nor by the number of features that were changed (Change Size). However, there was an interaction between Set Size and Change Size suggesting that these factors affect a common stage. In accord with a stage model, these findings suggest that Orientation affects a different stage of processing than Set Size and Change Size. This stage model will be developed as the subsequent experiments are described. At this point, two possible orderings of the stages are implied, one where Orientation has its effect in a stage after that affected by Set Size and Change Size, and the other where Orientation has its effect first. Experiments 2 and 3 were conducted to delineate the order for the stages.

EXPERIMENT TWO

Toward Localizing the Effect of Familiarity

The objective of Experiment 2 was to take steps toward localizing the effect of familiarity on change detection. To do this, three factors were examined: Orientation, Set Size and Stimulus Quality. Orientation, as before, was used as a proxy for familiarity. Stimulus Quality is known to affect early processing (Sternberg, 1969; see also Herdman et al., 1999; Meyer, Schvaneveldt, & Ruddy, 1975; Sanders, 1990). According to additive factors logic, if Stimulus Quality interacts with Orientation (but not Set Size), it would suggest that Orientation, like Stimulus Quality, has an early effect. However, if Stimulus Quality interacts with Set Size (but not Orientation), it would suggest an early role for Set Size, and a later role for Orientation.

Method

Participants. Participants ($n=19$) were drawn from the undergraduate psychology pool at Carleton University and were compensated with 1% course credit towards their final grade. Participants were assumed to have normal or corrected-to-normal visual acuity. No data were collected on the age or gender of participants.

Design. A 2 (Orientation: upright vs inverted) \times 2 (Stimulus Quality: clear vs degraded) \times 5 (Set Size: 4, 7, 10, 13, 16) within-subjects design was used.

Materials/Stimuli. The experimental conditions were similar to those in Experiment 1, except that Stimulus Quality was manipulated instead of Change Size. In this experiment, the small (one feature) change size was used throughout on the

assumption that a small change size is more likely to elicit an effect of Orientation.

Stimulus Quality was manipulated by altering the brightness of the letters. There were two levels of Stimulus Quality: clear and degraded. The stimuli in the clear condition appeared as bright white (RGB levels: 65535, 65535, 65535) on a black (RGB levels: 0, 0, 0) background, and were identical to the stimuli as used in Experiment 1. In the degraded condition, the stimuli were grey (RGB levels: 2048, 2048, 2048) on a black background.

Procedure. The procedure was identical to Experiment 1.

Results

Response Time Data

The RT data from correct trials were submitted to Van Selst and Jolicoeur's (1994) recursive outlier-removal procedure, which eliminated 2.72% of the trials. The remaining data were analyzed using a 5 (Set Size: 4,7,10,13,16) \times 2 (Orientation: Upright vs. Inverted) \times 2 (Stimulus Quality: Clear vs. Degraded) repeated measures analysis of variance (ANOVA).

Significant main effects were observed for all factors. Upright stimuli were detected more quickly (2539 ms) than inverted stimuli (2589 ms), $F(1,29)=11.8$, $MSE=135,322$, $p<.005$, $\eta_p^2=.289$, a difference of 50 ms. This effect replicated the Orientation effect already demonstrated in Experiment 1. Response times were faster for clear stimuli (2063 ms) than for degraded stimuli (3065 ms), $F(1,29)=214.2$, $MSE=209,827$, $p<.001$, $\eta_p^2=.881$, a difference of 1002 ms. As Set Size increased, so did

response times (1464 ms, 1982 ms, 2560 ms, 3091 ms, 3723 ms for set sizes of 4, 7, 10, 13, and 16, respectively), $F(4,116)=277.5$, $MSE=232,714$, $p<.001$, $\eta_p^2=.905$.

Orientation was additive with Set Size, $F(4,116)=1.2$, $MSE=163,302$, $p=.305$, $\eta_p^2=.040$, observed power = .373 (shown in Figure 13), confirming the results from Experiment 1 that Orientation and Set Size do not interact. Orientation was also additive with Stimulus Quality, $F(1,29)=3.2$, $MSE=164,033$, $p>.05$, $\eta_p^2=.102$, observed power=.418 (shown in Figure 14). The interaction between Stimulus Quality and Set Size was significant, $F(4,116)=3.5$, $MSE=145,867$, $p<.001$, $\eta_p^2=.455$. As shown in Figure 15, as Set Size increased, the effect of Stimulus Quality became more pronounced (491 ms, 696 ms, 1019 ms, 1149 ms, 1655 ms for set sizes of 4, 7, 10, 13, 16). No other interactions were significant.

Error Data

The overall error rate was 2.72%. There was a significant main effect of Stimulus Quality, $F(1,18)=5.9$, $MSE=.002$, $p=.026$, $\eta_p^2=.247$, with more errors for degraded stimuli (2.1%) than for clear stimuli (1.8%). As with Experiment 1, inverting the letters did not produce any more errors than presenting the letters right side up, $F<1$. No interactions were significant.

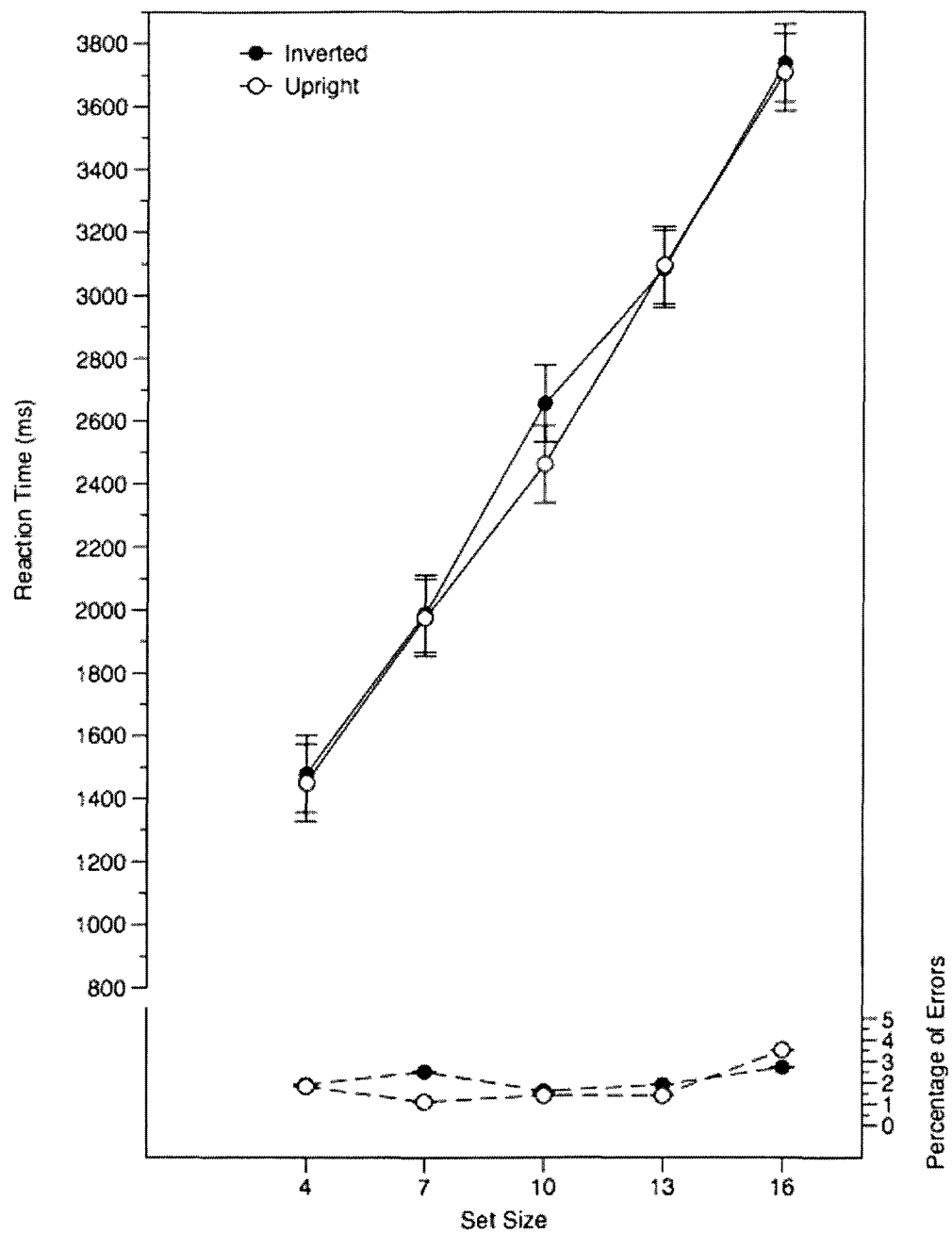


Figure 13. Response Time (in ms) and % error in Experiment 2 as a Function of Set Size and Orientation. Error bars are 95% confidence intervals.

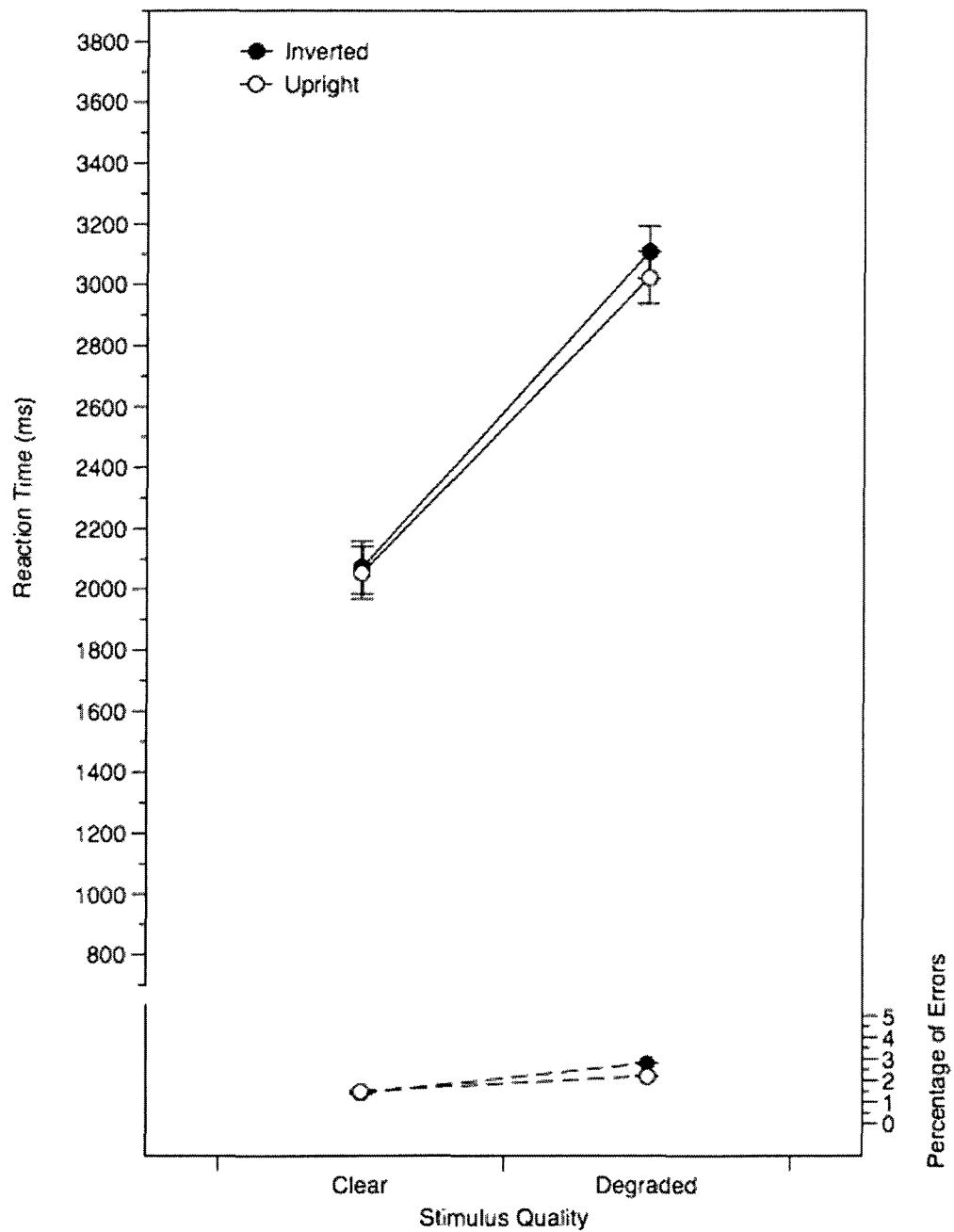


Figure 14. Response Time (in ms) and % error in Experiment 2 as a Function of Stimulus Quality and Orientation. Error bars are 95% confidence intervals.

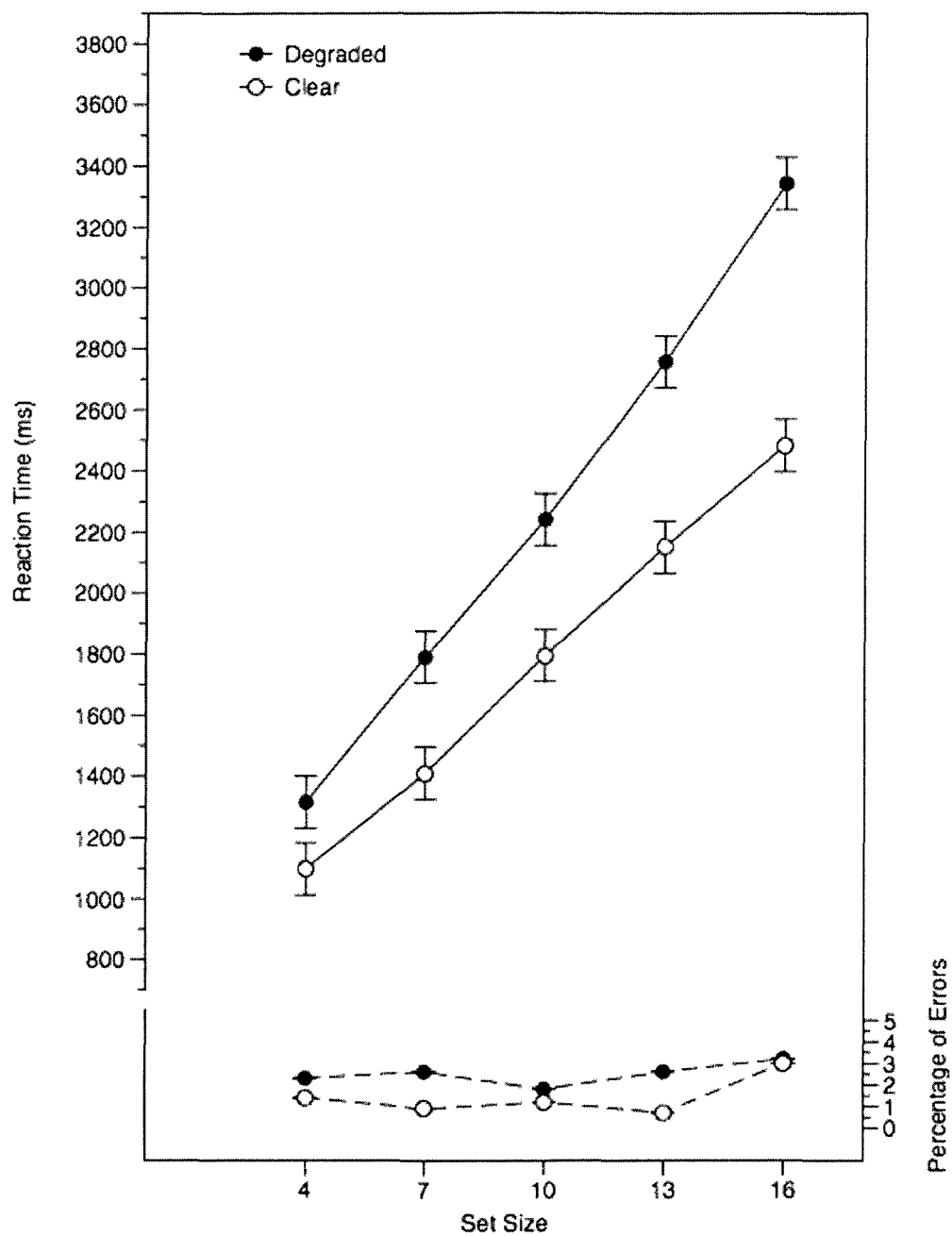


Figure 15. Response Time (in ms) and % error in Experiment 2 as a Function of Set Size and Stimulus Quality. Error bars are 95% confidence intervals.

Summary

Experiment 2 produced the same effect of Orientation that was demonstrated in Experiment 1, whereby upright letters were detected more quickly than inverted letters. As in the first experiment, Orientation and Set Size were additive suggesting that these factors affect different stages of processing. Stimulus Quality, which is known to have its effects early (Sternberg, 1969; see also Herdman et al., 1999; Meyer, Schvaneveldt, & Ruddy, 1975; Sanders, 1990), was found to interact with Set Size, but to be additive with Orientation. This pattern of results suggests that, like Stimulus Quality, Set Size has its effects at an early stage of processing. In contrast, Orientation has an effect at a later stage. In accord with Sanders (1990) and as shown in Figure 15, Stimulus Quality and Set Size are assigned to the Feature Extraction stage, and Orientation is assigned to the later Identification stage.

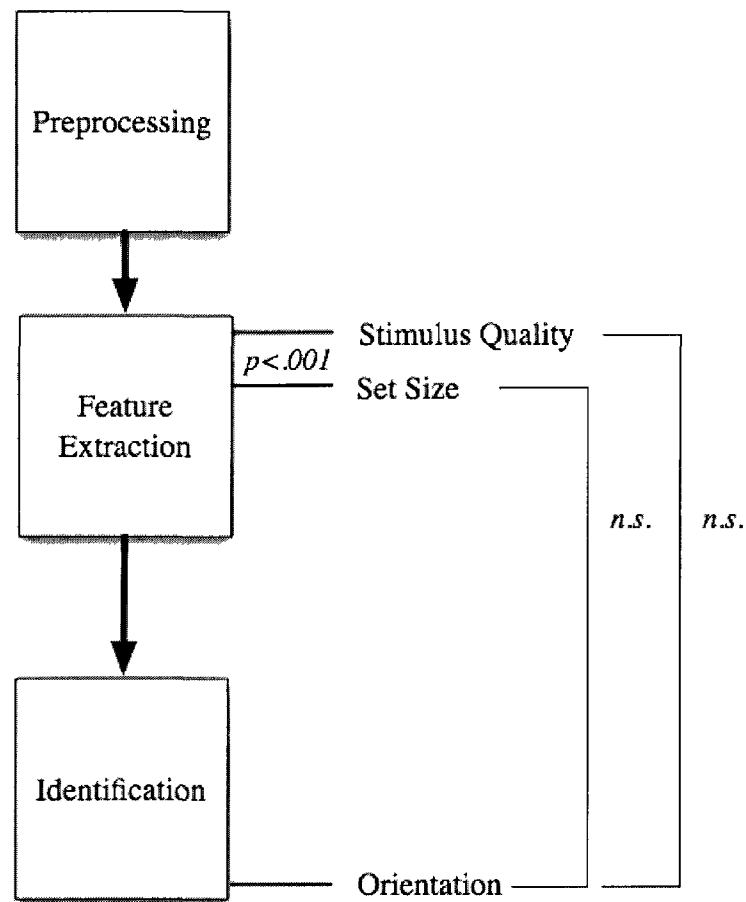


Figure 16. Two-stage model based on data from Experiment 2.

EXPERIMENT THREE

Further Evidence to Localize the Effect of Familiarity

The results of Experiment 2 suggest that Orientation does not share a stage in common with either Set Size, or Stimulus Quality and thus Orientation must have its effects at a later stage in the processing sequence. Experiment 3 was designed to further clarify the stages of processing involved in these tasks and to localize Orientation (and hence familiarity) within these stages. This was done by running a four factor experiment with a large number of participants ($n=60$), to provide enough power to clearly show the interactions and additivities among Orientation, Change Size, Set Size, and Stimulus Quality.

Method

Participants. Participants ($n=60$) were drawn from the undergraduate psychology pool at Carleton University and were compensated with 1% course credit towards their final grade. Participants were assumed to have normal or corrected-to-normal visual acuity. No data were collected on the age or gender of participants.

Design. A 2 (Orientation: upright vs. inverted) \times 2 (Stimulus Quality: clear vs. degraded) \times 2 (Change Size: small vs. large) \times 5 (Set Size: 4, 7, 10, 13, 16) within-subjects design was used. Each of the 40 possible conditions (5 set sizes \times 2 change sizes \times 2 orientations \times 2 levels of stimulus quality) were presented 5 times. The order of trials were randomized in a single block of 200.

Prior to the experimental conditions being presented, a practice block of trials was given to participants. The practice block contained 16 conditions: 2 set sizes (4 or 16 letters) \times 2 change sizes \times 2 orientations \times 2 levels of Stimulus Quality. The order of the items were randomized for each participant.

Materials/Stimuli. The experimental conditions and stimuli were identical to those in Experiment 1 (including Change Size, Set Size, and Orientation), except that in this experiment, Stimulus Quality also was manipulated as in Experiment 2.

Procedure. The procedure was identical to that used in Experiment 1.

Results

Response Time Data.

The response time data were submitted to Van Selst and Jolicoeur's (1994) recursive outlier-removal procedure, which eliminated 3.10% of the trials. The remaining data were analyzed using a 2 (Orientation: upright vs. inverted) \times 2 (Stimulus Quality: clear vs. degraded) \times 2 (Change Size: small vs. large) \times 5 (Set Size: 4, 7, 10, 13, 16) repeated measures ANOVA.

Significant main effects were observed for all factors. A significant effect of Orientation was found where upright stimuli (1977 ms) were detected more quickly than inverted stimuli (2101 ms), $F(1,59)=20.7$, $MSE=441,575$, $p<.001$, $\eta_p^2=.260$, replicating the key result in Experiments 1 and 2. On average, response times for upright stimuli differed from those for inverted stimuli by 124 ms. Clear targets (1788 ms) were responded to faster than degraded targets (2290 ms), $F(1,59)=96.7$, $MSE=1,565,600$,

$p < .001$, $\eta_p^2 = .260$, exhibiting the expected effect of Stimulus Quality. The size of this effect was 502 ms. As in the previous experiments (and as reported in Smilek et al., 2000 and Richards, 2002), participants detected large changes more quickly (1753 ms) than small changes (2325 ms), $F(1,59) = 253.9$, $MSE = 774,643$, $p < .001$, $\eta_p^2 = .811$. Similarly, response times increased as Set Size increased (1207 ms, 1600 ms, 2018 ms, 2455 ms, 2914 ms for set sizes of 4, 7, 10, 13, and 16, respectively), $F(4,236) = 274.0$, $MSE = 798,422$, $p < .001$, $\eta_p^2 = .823$.

As in Experiment 2, Orientation and Stimulus Quality were additive (Figure 17), $F(1,59) = 2.6$, $MSE = 402,340$, $p < .15$, $\eta_p^2 = .044$, observed power = .365. The interaction between Orientation and Change Size was significant, $F(1,59) = 20.0$, $MSE = 448,873$, $p < .001$, $\eta_p^2 = .253$; As shown in Figure 18, the effect of Orientation was significantly greater for small changes (245 ms) than for large changes (2 ms), showing that the orientation effect disappears when the size of change is large. This result suggests that we would have seen the same interaction in Experiment 1 if there had been sufficient power.

Stimulus Quality interacted with Change Size, $F(1,59) = 13.1$, $MSE = 292,237$, $p < .001$, $\eta_p^2 = .181$, whereby the effect of Stimulus Quality was significantly greater for small changes (582 ms) than for large changes (423 ms) (Figure 19), Stimulus Quality also interacted with Set Size $F(4,236) = 12.8$, $MSE = 554,357$, $p < .001$, $\eta_p^2 = .033$: the effect of Stimulus Quality increased with Set Size, yielding a Stimulus Quality effect of 218 ms, 380 ms, 447 ms, 606 ms, 859 ms, for set sizes of 4, 7, 10, 13, and 16 (see Figure 20). As in Smilek et al. (2000), there was an interaction between Set Size and Change Size,

$F(4,236)=26.1$, $MSE=448,642$, $p<.001$, $\eta_p^2=.307$, with the effect of Change Size increasing as Set Size increased (the Change Size effect is 152 ms, 402 ms, 581 ms, 778 ms, and 950 ms, for Set Sizes of 4, 7, 10, 13, and 16 respectively) (See Figure 21).

As in the first two experiments, Orientation did not interact with Set Size, $F(4,236)=2.015$, $MSE=421,725$, $p>.05$, $\eta_p^2=0.033$, observed power=.599 (Figure 22). None of the 3-way and 4-way interactions were significant (all $F_s<1.7$).

Error Data.

The significant main effects were in the same direction as the RT data, thus there is no concern about speed-accuracy trade-offs. The overall error rate was 2.3%. There was a significant main effect of Stimulus Quality, $F(1,59)=21.5$, $MSE=.007$, $p<.001$, $\eta_p^2=.267$, with more errors (3.1%) for degraded stimuli than for clear stimuli (1.5%). There was a significant main effect of Change Size, $F(1,59)=16.4$, $MSE=.007$, $p<.001$, $\eta_p^2=.217$, with more errors for small feature changes (3.0%) than for large feature changes (1.6%). The main effect of Set Size, $F(4,236)=6.0$, $MSE=.005$, $p<.001$, $\eta_p^2=.092$, was significant, with error rates generally increasing as Set Size increased (1.7%, 1.6%, 2.1%, 3.2%, and 3.0%), for set sizes of 4, 7, 10, 13, and 16, respectively. The main effect of Orientation was not significant ($F<1$). None of the higher order interactions were significant.

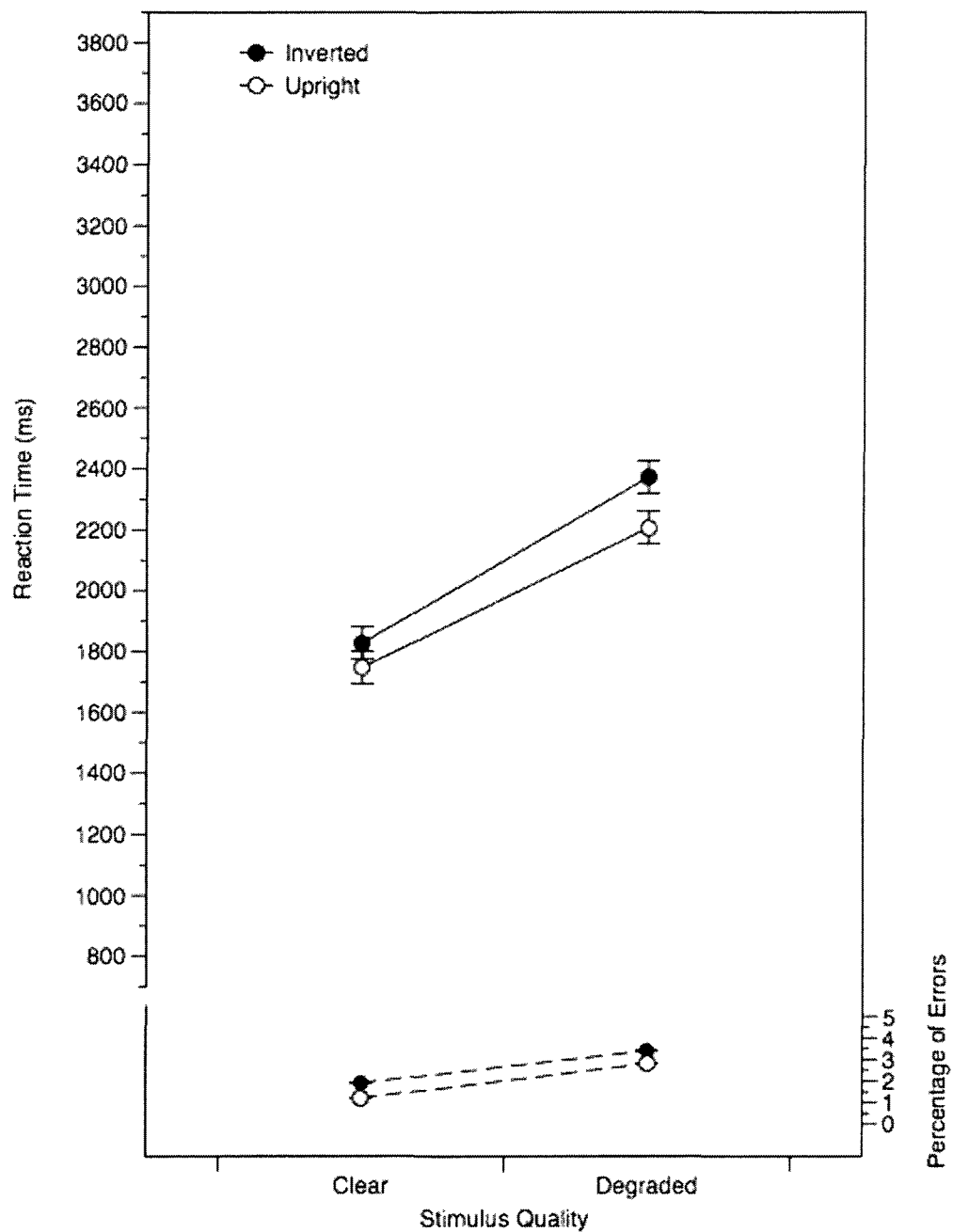


Figure 17. Response Time (in ms) and % error in Experiment 3 as a Function of Stimulus Quality and Orientation. Error bars are 95% confidence intervals.

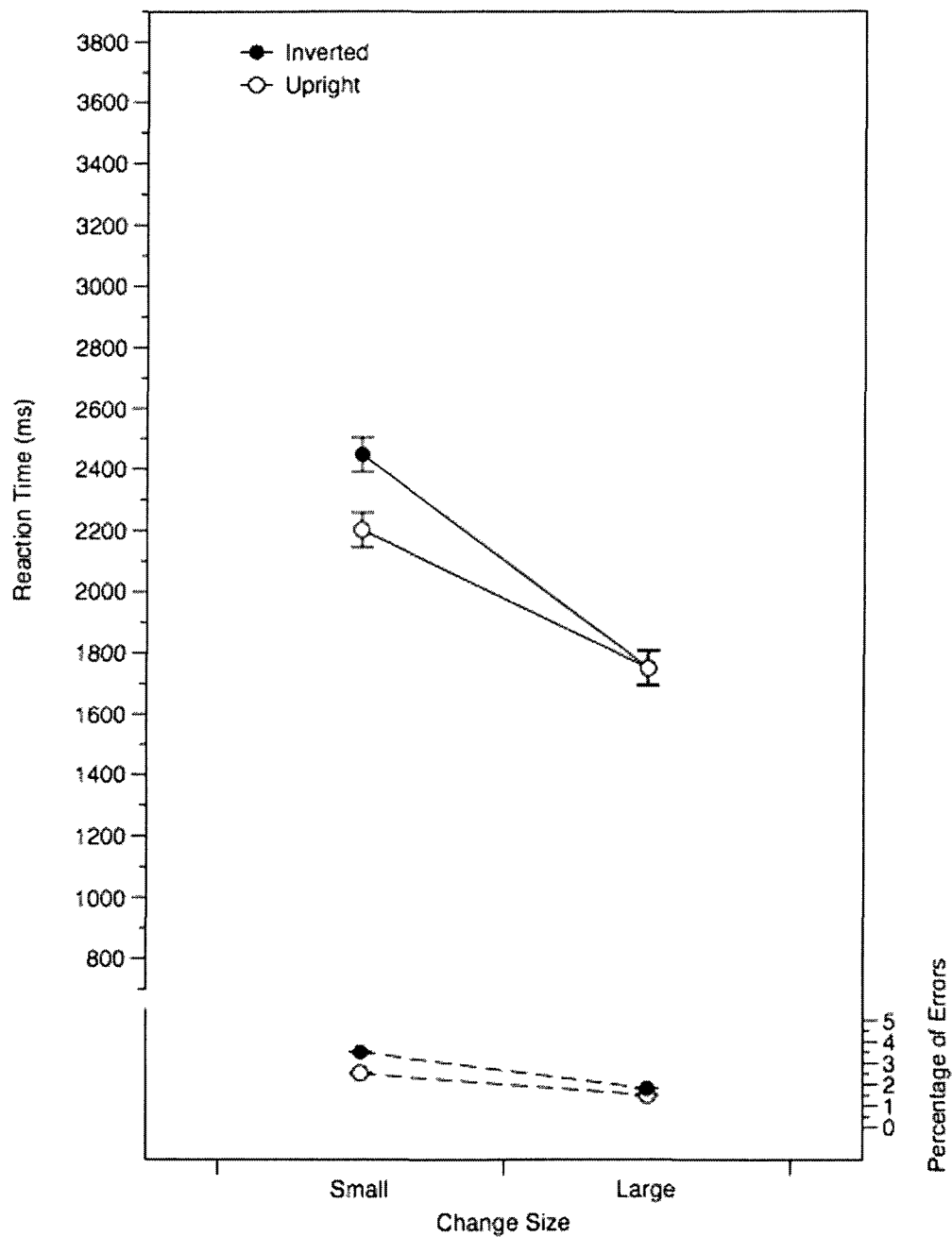


Figure 18. Response Time (in ms) and % error in Experiment 3 as a Function of Orientation and Change Size. Error bars are 95% confidence intervals.

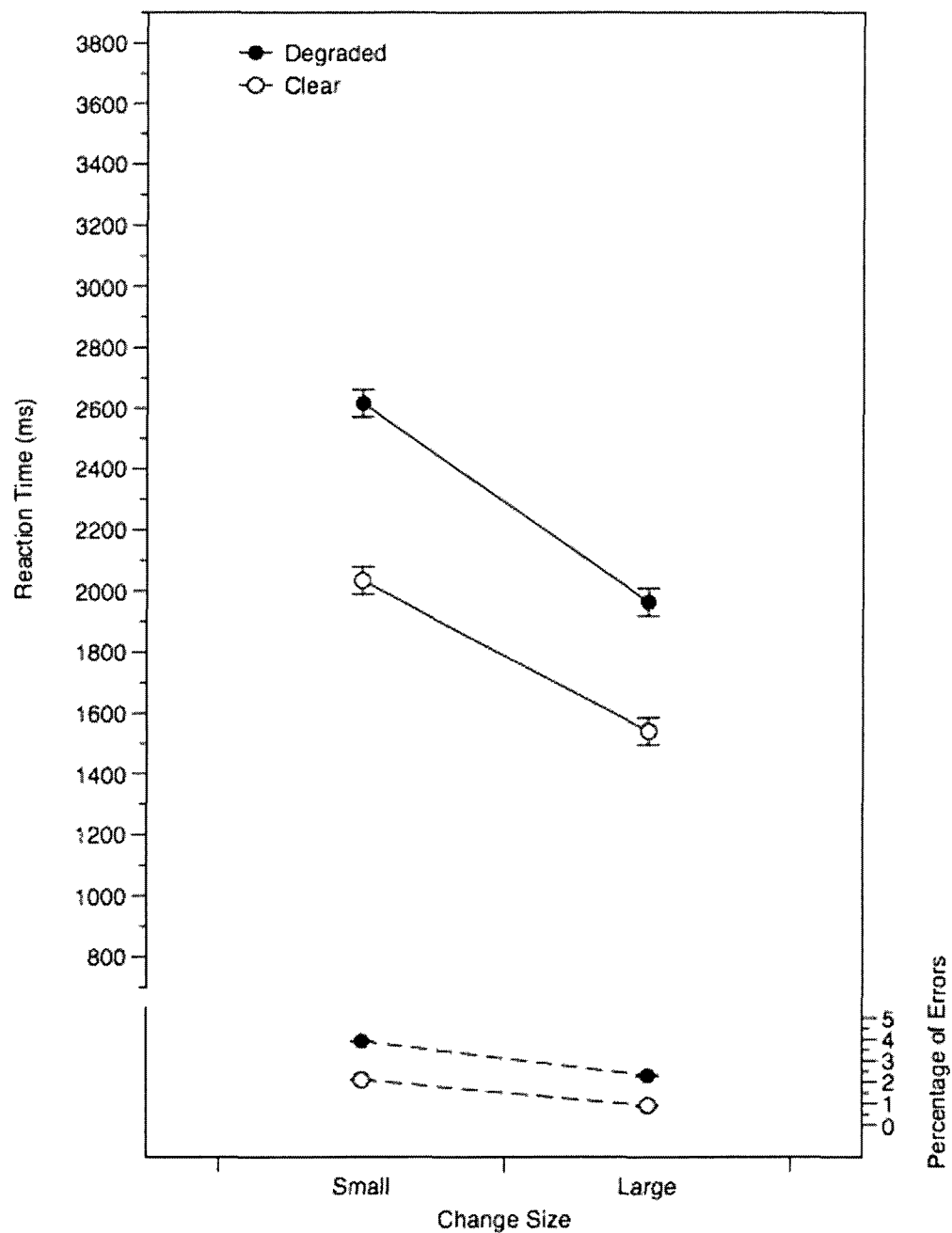


Figure 19. Response Time (in ms) and % error in Experiment 3 as a Function of Change Size and Stimulus Quality. Error bars are 95% confidence intervals.

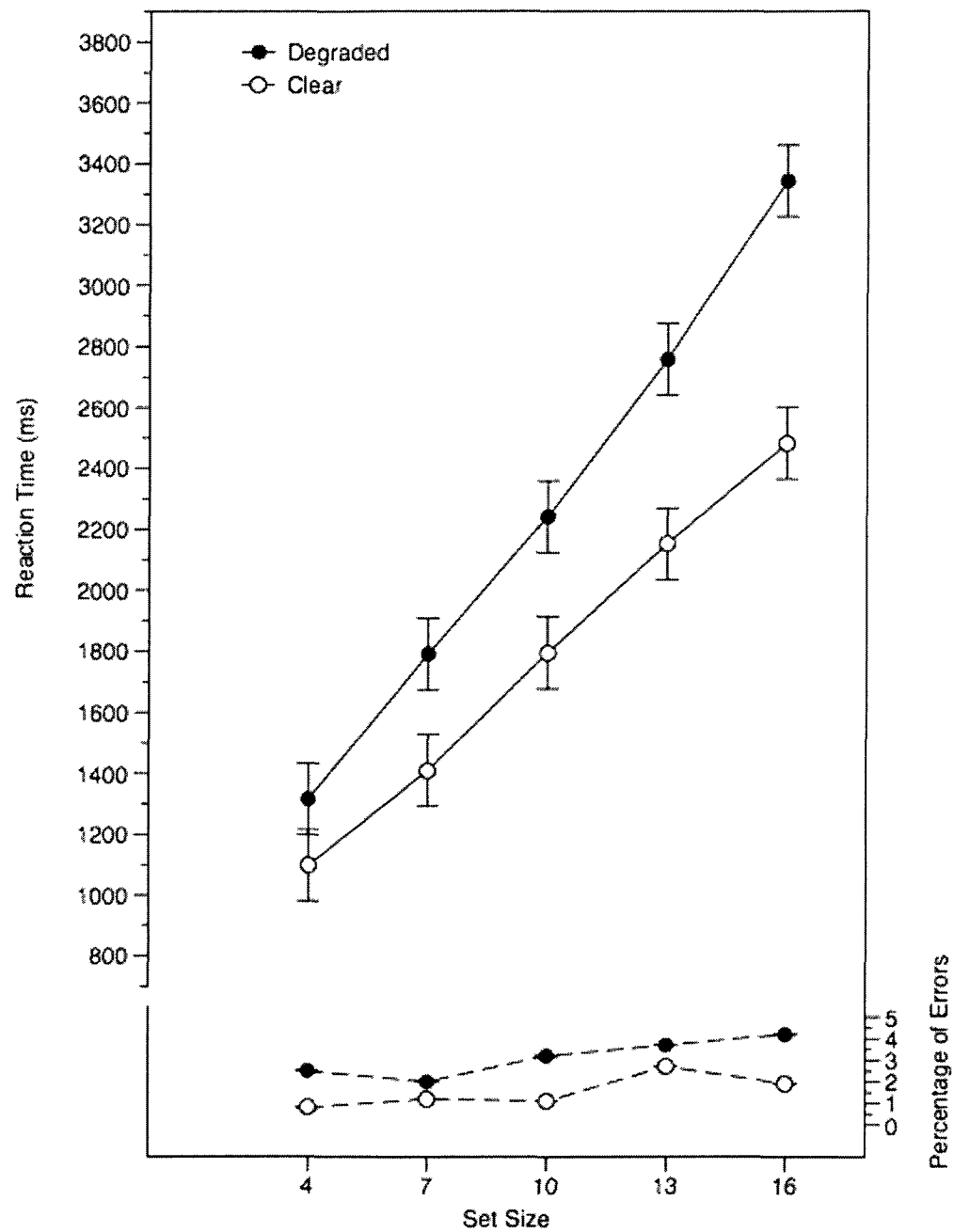


Figure 20. Response Time (in ms) and % error in Experiment 3 as a Function of Stimulus Quality and Set Size. Error bars are 95% confidence intervals.

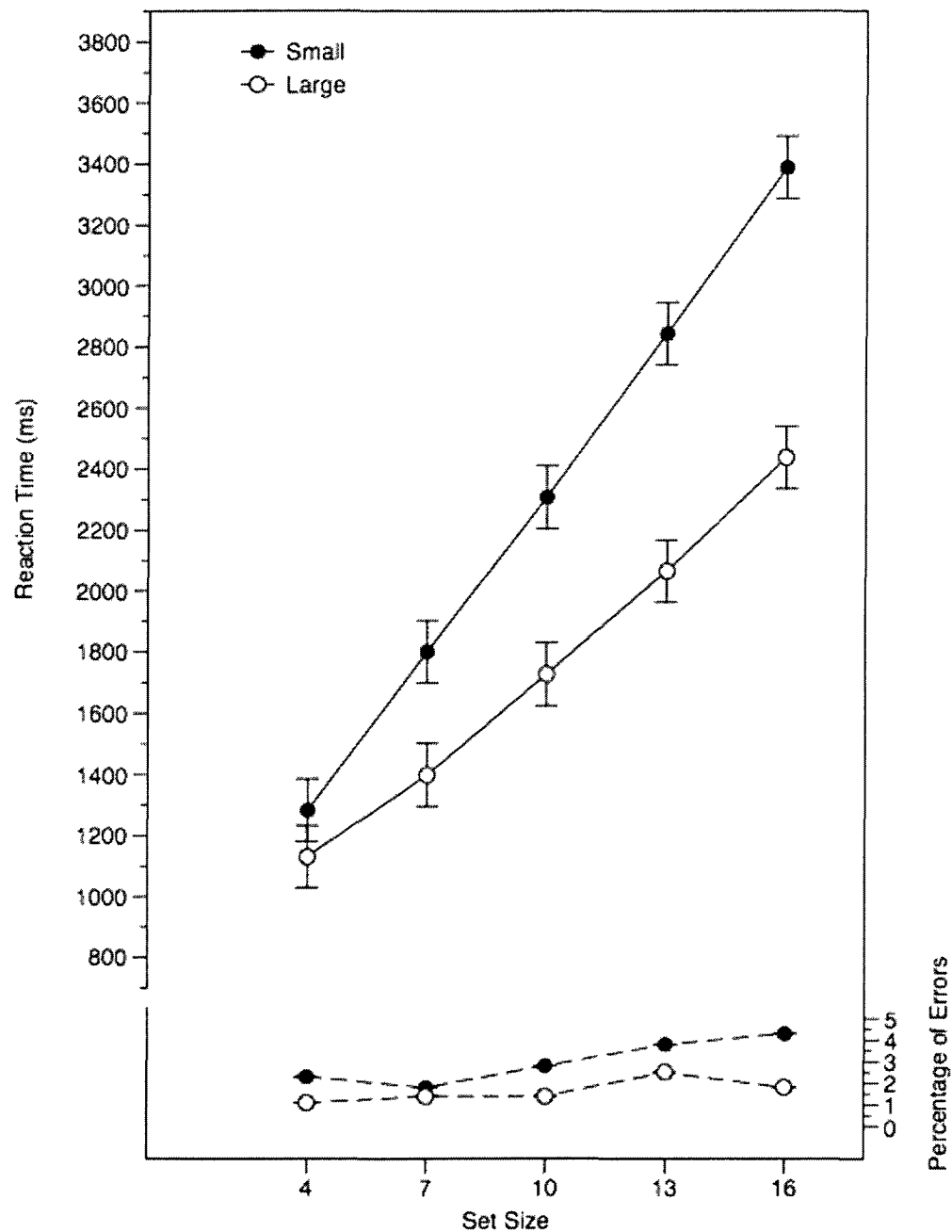


Figure 21. Response Time (in ms) and % error in Experiment 3 as a Function of Change Size and Set Size. Error bars are 95% confidence intervals.

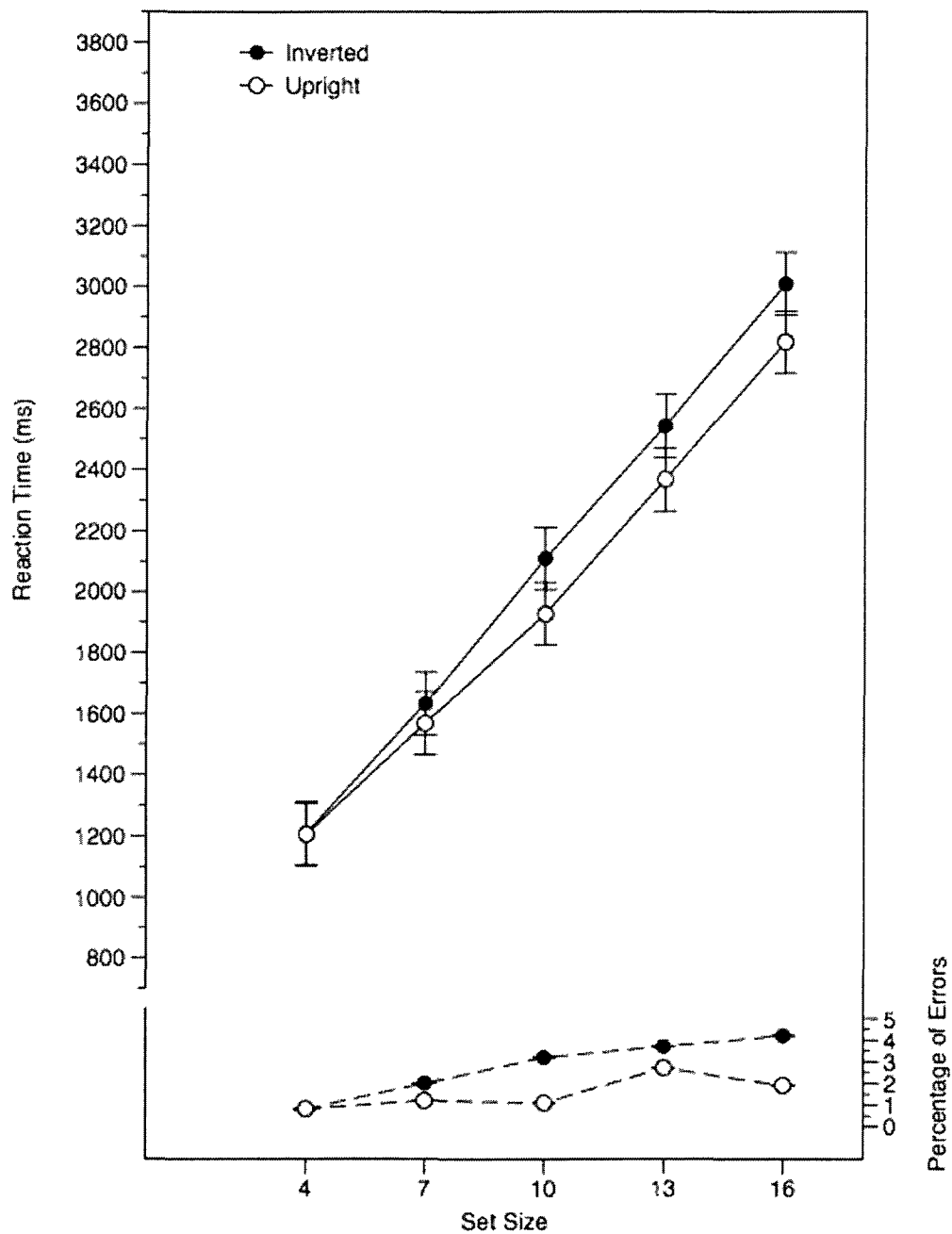


Figure 22. Response Time (in ms) and % error in Experiment 3 as a Function of Orientation and Set Size. Error bars are 95% confidence intervals.

Summary

Experiment 3 replicated the key effect of Orientation from Experiments 1 and 2, showing that changes in upright letters were detected more quickly than changes in inverted letters. Experiment 3 used a larger number of participants than the previous experiments ($n=60$). One of the reasons for increasing the number of participants in Experiment 3 was to observe whether the additivities between Orientation and Set Size, and Orientation and Stimulus Quality would persist with greater available power. They did.

Orientation was additive with Set Size, strengthening the conclusion that Set Size has its effects at a different stage of processing than Orientation. Because Stimulus Quality has its effects early (Sternberg, 1969; see also Herdman et al., 1999; Meyer, Schvaneveldt, & Ruddy, 1975; Sanders, 1990), the additivity between Orientation and Stimulus Quality (also seen in Experiment 2) reinforces the conclusion that Orientation has its effects at a later Identification stage. In contrast, the interactions of Stimulus Quality with Set Size and Change Size suggest that these factors have effects at an earlier Feature Extraction stage, in common with Stimulus Quality.

Another reason the number of participants was increased was to clarify the role being played by Change Size. In Experiment 1, Change Size and Orientation did not interact. The greater experimental power in Experiment 3 revealed a significant interaction between Change Size and Orientation for RT. This suggests that in addition to

affecting processing at a Feature Extraction stage, Change Size also exerts an effect on the Identification stage.

The results of Experiment 3 are reflected in the stage model shown in Figure 23. Stimulus Quality, Set Size and Change Size are shown as all having an impact at the Feature Extraction stage whereas Orientation is shown as affecting the Identification stage. Because Change Size interacts with all of the other three factors, Change Size is assumed to have an impact on both the Feature Extraction stage and the Identification stage.

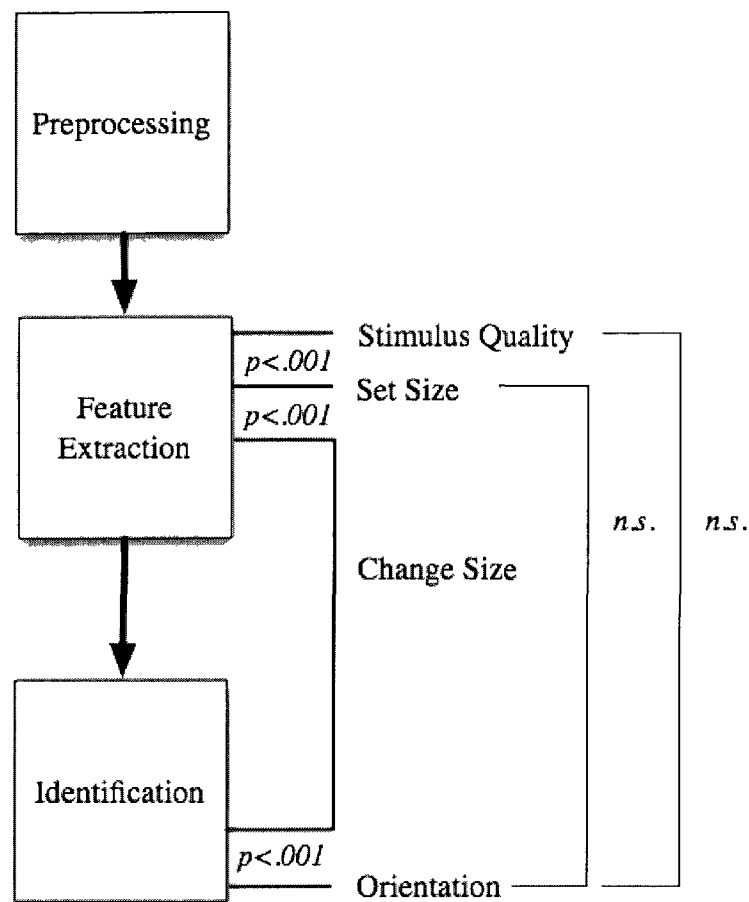


Figure 23. Stage model derived from the data in Experiment 3. Additivities illustrate the rationale for positing two separate stages (and the order in which they occur). Interactions show Change Size, Set Size and Stimulus Quality each interacting with each-other, defining the early stage. Orientation, additive with Stimulus Quality, is asserted to have its effects in the later stage. Change Size interacts with Orientation, as well as with Set Size. In the current diagram, Change Size is interpreted as having both early and late effects.

GENERAL DISCUSSION

The objective of the present research was to assess the role of object familiarity on change blindness. Three experiments were performed in which change blindness was examined using a flicker paradigm. Familiarity was manipulated by presenting letter stimuli in an upright orientation versus an inverted orientation. In all three experiments, changes to upright letters were detected more rapidly than changes to inverted letters, providing consistent evidence for a measurable effect of familiarity on change blindness.

The size of the Orientation effect did not vary with the number of objects on the display (Set Size), suggesting that Set Size and Orientation engage different processing stages. Experiments 2 and 3 showed that Orientation is additive with Stimulus Quality. Because Stimulus Quality is known to have its effects early (Sternberg, 1969; see also Herdman et al., 1999; Meyer, Schvaneveldt, & Ruddy, 1975; Sanders, 1990), these results suggest that Orientation influences processing in a later stage. Set Size and Change Size interacted with each other and both of these interacted with Stimulus Quality, suggesting that these factors all affect an early stage of processing. Change Size also interacted with Orientation, suggesting that Change Size may also influence a later stage of processing. Overall, the results can be explained using a stage model in which Stimulus Quality, Change Size, and Set Size have their effects in the first stage (Feature Extraction), and Orientation and Change Size have effects on a second stage (Identification). This model is shown in Figure 24.

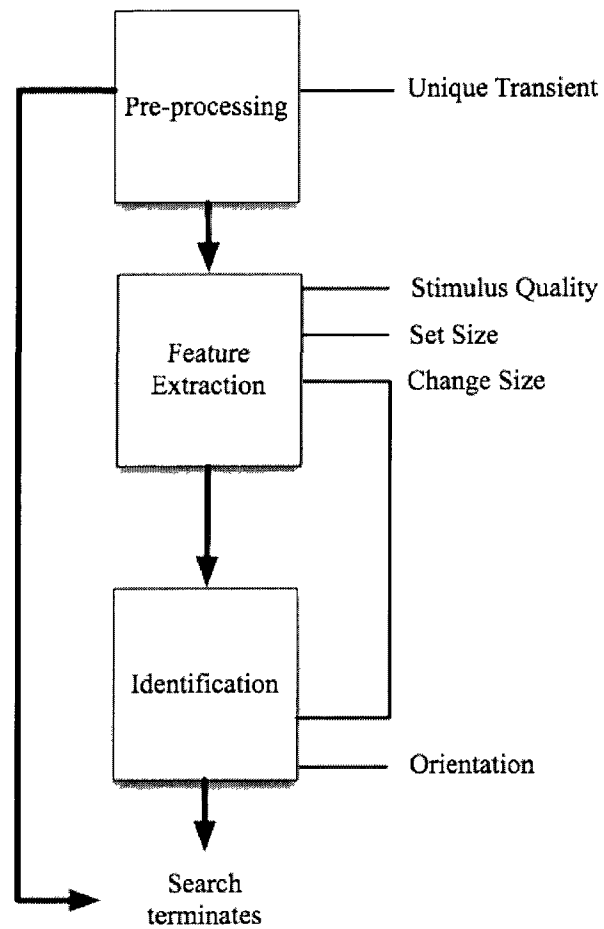


Figure 24. Stage model showing the impact of Stimulus Quality, Set Size, and Change Size on Feature Extraction, and the effect of Change Size and Orientation on Identification.

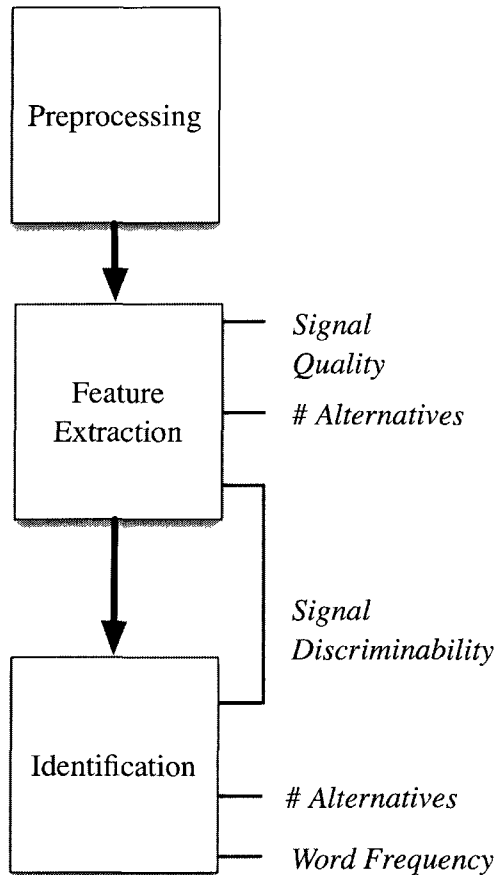
Figure 25 shows a comparison between the current model and the perceptual stages of Sanders (1990). As we had seen in Figure 5, Sanders' stage model includes factors which correspond to three factors in this experiment: Stimulus Quality (Signal Quality), Set Size (Number of Stimulus Alternatives), and Change Size (Signal Discriminability). Figure 25 shows that the current model, as determined by the additive factors analysis, has a stage analogous to Sanders' Feature Extraction stage. This stage is affected by Stimulus Quality (Signal Quality) in both Sanders model and in the current model. The present experiments show this stage to also be affected by both Set Size and Change Size, which correspond to factors from Sanders (Number of Stimulus Alternatives, Signal Discriminability) which also have their effects at this stage.

The stage where Orientation was shown to have its effects corresponds well with Sanders' Identification stage. In Sanders' model, a factor with properties similar to Orientation also has its effects at the Identification stage (i.e., Word Frequency also relies on identifying the object). The current experiments also show evidence for an effect of Change Size on the same stage as Orientation, and Sanders, similarly, shows Stimulus Discriminability as having an effect on the Identification stage.

Gating Hypothesis. The model described above is consistent with the additive factors paradigm, as well as with Sanders' stage model for choice reaction. However, in considering the functions of the Identification stage, it is hard to find a plausible explanation for the effect that Change Size would have on the Identification stage. An alternative, and potentially superior, hypothesis for explaining the effects of Change Size

involves *gating*. On this hypothesis large changes are detected at the Feature Extraction stage, and once those changes are detected, the Identification stage is bypassed completely (see Figure 25). In contrast, when changes are small, the Identification stage is required to detect and/or verify the presence of a change. The gating hypothesis is a positive addition to the generic additive factors model, since it explains how Change Size could affect processing in the Identification stage to the extent that the Orientation effect disappears completely when large changes are present (see Figure 17). It also eliminates the need to explain why Change Size interacts with Orientation when Stimulus Quality and Set Size (which both interact with Change Size) do not. Finally, it offers an account of the flow of information processing which integrates well with Rensink's (2000, 2002c, 2005) framework, as will be discussed in the following section.

Sanders (1990) model



Current stage model

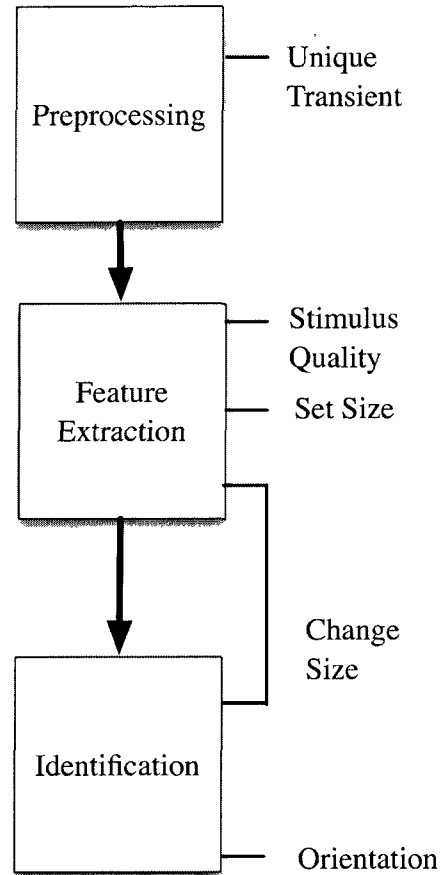


Figure 25. Comparison between Sanders' (1990) stage model and current stage model.

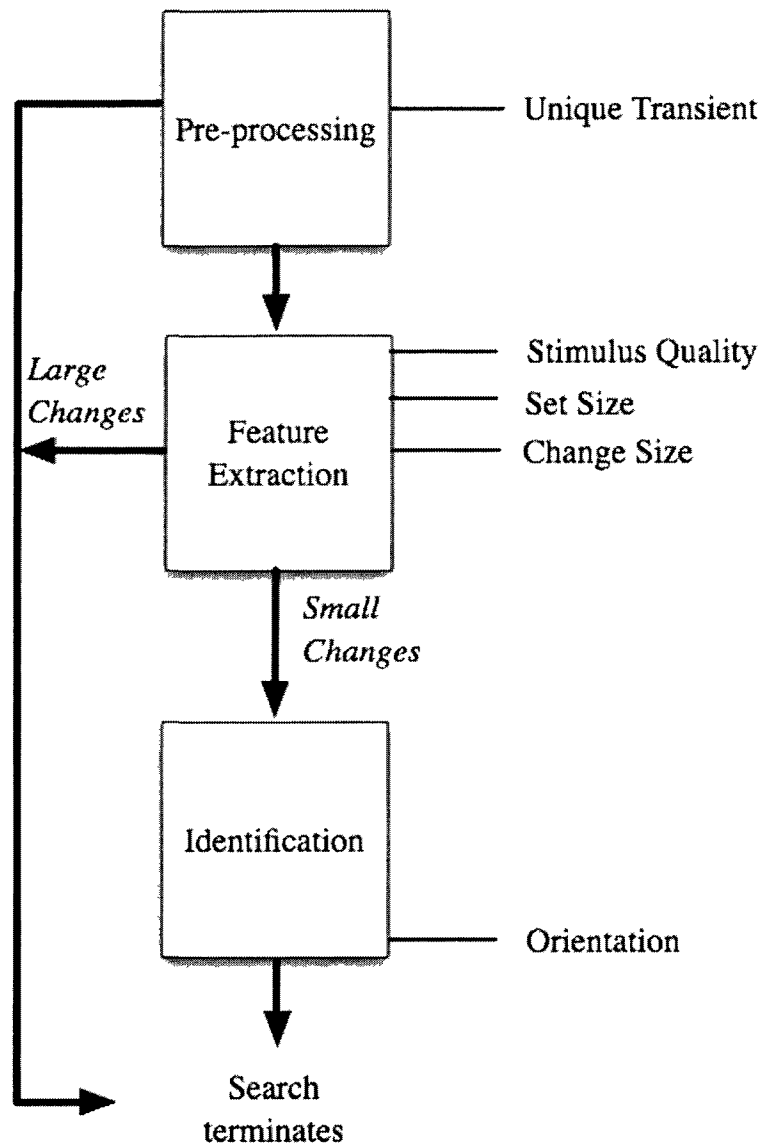


Figure 26. Stage model with *gating hypothesis*. Change Size acts as a gate at the Feature Extraction stage. When large changes are present the Identification stage can be bypassed. When small changes are present, processing must continue into the Identification stage.

Augmenting the Stage Model

Selective Integration of Constructs from Rensink's Triadic Architecture

The current stage model provides evidence for an order of processing proceeding through three stages: Pre-processing, Feature Extraction, and Identification. The only previous framework describing change blindness, Rensink's (2000, 2002c, 2005) triadic architecture, posits the existence of three interconnected systems and several sub-systems. Rensink's triadic architecture should be viewed as a framework as it does not include clear assumptions regarding the order in which processing occurs as would be expected in an information processing model. Nevertheless, it would be desirable to take advantage of the level of constructs offered by Rensink, while at the same time, via the current experiments, provide an empirically grounded ordering for the stages of processing involved.

There are three main systems in Rensink's triadic architecture (see Figure 27): The Proto-objects system, the Setting system, and the Object system.

Proto-objects System. The *Proto-objects* system contains a featural representation of the entire scene, a representation which decays within 300 ms. The Proto-objects system is an early system which represents the contents of the visual scene as features in a loosely bound, or *incoherent*, state. It derives the information needed for this featural representation from very early processing of points and lines.

Setting System. The *Setting* system does a rapid analysis of the scene, and helps to select which pieces of the scene (i.e., which *proto-objects*) should next be bound by the

Object system. The Setting system is held (Rensink, 2000c, 2002, 2005) to contain two separate modules which Rensink called the *layout module*, and the *gist module*. For consistency and explanatory purposes the layout module will here be renamed the location module. The location module is able to quickly identify the locations of objects in a scene, without processing their identity (Rensink, 2000c, 2002, 2005). Operating in parallel with the location module, the gist module is able to rapidly assess the overall content of the scene (“I see a forest”, “I see a classroom”), without reference to the locations of particular objects in the scene (Rensink, 2000c, 2002, 2005).

Object system. The *Object* system allows the features of the selected proto-objects to be bound into *coherent* objects, and maintained in that bound state until another set of objects is selected for attention by the Setting system. This activity is performed by two modules, the *focussed attention module* and the *attentional nexus*. The focussed attention module receives information from the Setting system on where attention should be directed. The focussed attention module then directs the attentional nexus to bind the features of the relevant objects, storing them in vSTM. The focussed attention module then maintains the bound representation in vSTM for as long as the object is attended.

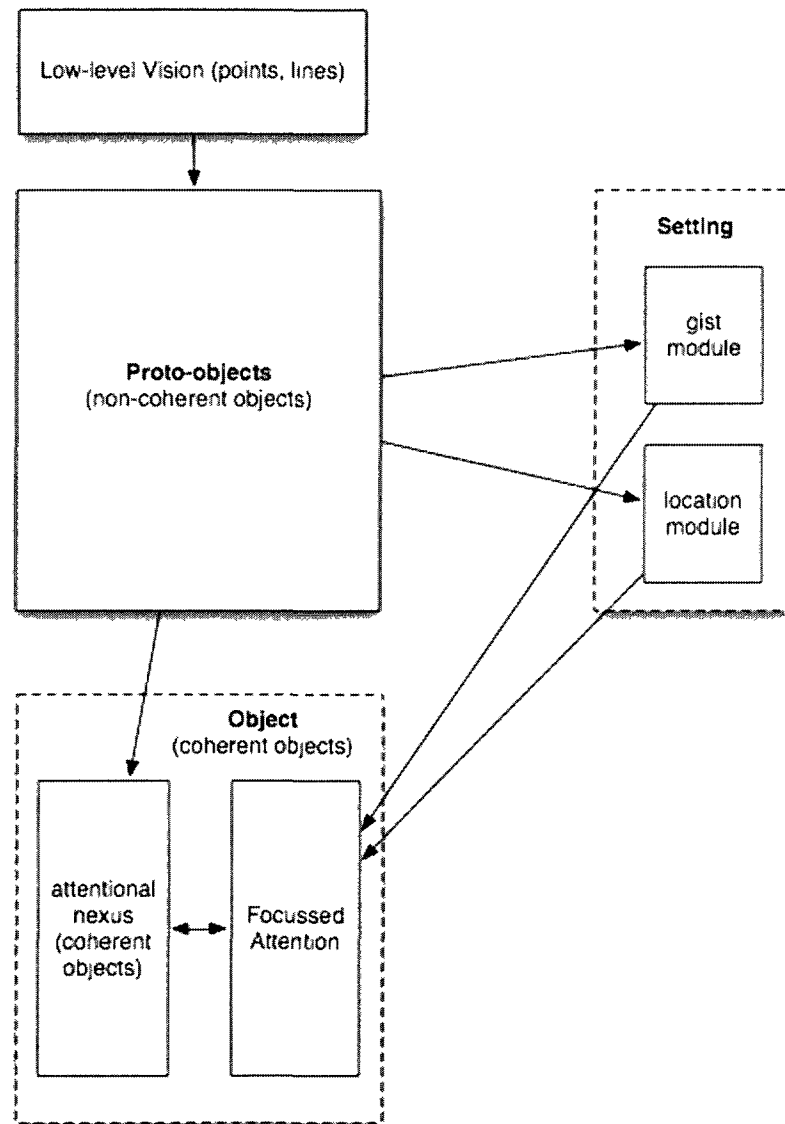


Figure 27. Rensink's triadic architecture (2000c, 2002, 2005), re-drawn, simplified, and adapted, and presented in a way that suggests an ordering of modules similar to the current stage model. This diagram shows the three main parts of Rensink's triadic architecture: the Proto-objects, the Setting, and Object modules.

Rensink's (2000c, 2002, 2005) triadic architecture is designed as a framework through which to think about change blindness. It is not as empirically grounded as the current modelling work, and does not intend to be. As such, it is a different kind of effort from the current stage modelling. With a few liberties, however, key constructs from the triadic architecture can be selected and integrated into the current stage model. To this end, Rensink's triadic architecture is shown along with the current model in Figure 28. In both approaches, as I have diagrammed in Figure 29, an initial stage represents very early processes which detect transients, a second stage involves an decomposition of the scene (or information displayed) into features, and a third stage resolves collections of features into objects.

Pre-processing stage. Both Rensink's framework and the current model identify a preprocessing stage. For Rensink, this stage is associated with the decomposition of the scene into points (Transduction stage) and then lines (Primary Processing stage) (Rensink, 2000c, 2002, 2005). These correspond to the retinotopically coded primary visual cortex (points) and the orientation selectivity of the complex cells (lines). At this very early stage, the scene (display) still has not been represented as features. Transients are detected very early (Sanders, 1990), and automatically, but only when there are unique visual onsets. If there is no unique onset (as when, for instance, there are many simultaneous onsets), then change, if it is to be detected, must be detected at a later stage.

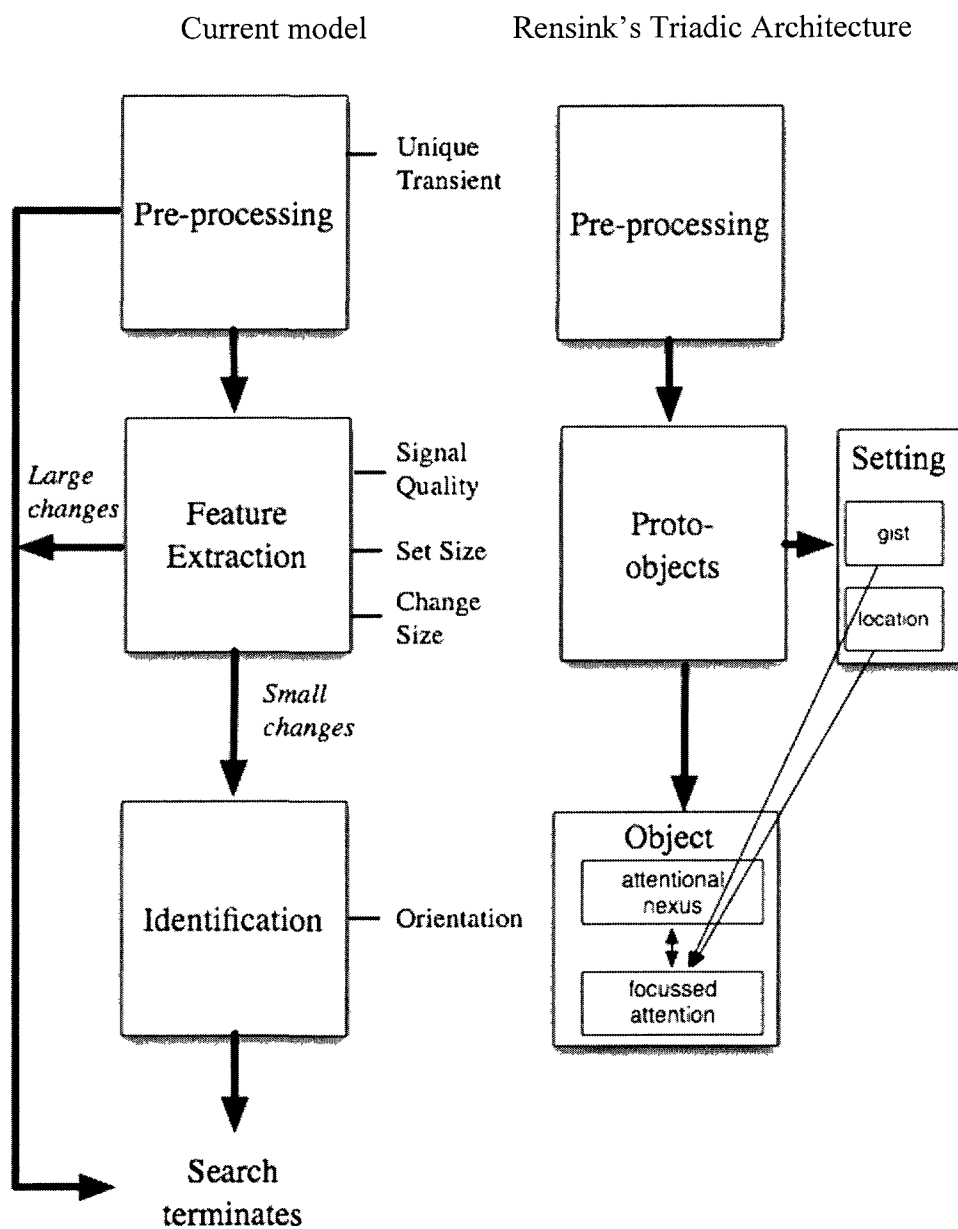


Figure 28. Comparison of Current model with Rensink's (2000c, 2002, 2005) triadic architecture.

Feature Extraction stage. Rensink's Proto-object system corresponds to the Feature Extraction stage in the current model (see also Sanders, 1990). In both approaches, a scene is represented as a collection of features. The scene is thus coarsely resolved, but nevertheless sufficiently detailed for separate early modules to identify the locations of objects in a scene and to extract a gist of their contents (Rensink, 2000c, 2002, 2005).

Rensink assumes that it is possible for changes to be detected in early processing (at the proto-objects stage), but that this detection requires later conscious attention for the change to be experienced. Since proto-object representations can persist for up to 300ms after a stimulus has disappeared (Rensink, 2000c, 2002, 2005), it can be assumed that the storage of proto-objects persists over the 80ms interstimulus interval in the current experiments—long enough to provide a basis for comparison with the incoming stimulus. This is supported in the present research by evidence that Set Size has its effects on the feature extraction stage. Rensink's location module could assist the change detection process by identifying all of the objects which might be changing. According to the gating hypothesis discussed above, the coarse resolution of the proto-objects stage will permit the detection of large changes: If the change is large, the Feature Extraction stage is able to detect the change without the object needing to be fully coherent. Stimulus Quality, in reducing the effective available resolution should make it harder for

large changes to be detected at this stage, as is indeed suggested by the interaction between Stimulus Quality and Change Size found in the present research.

While the location and gist modules provide a mechanism for selecting which object should be attended, these modules would be equally useful to the Feature Extraction stage in detecting large visual changes in a scene. The layout module specifies the objects which could be changing, so a rough comparison could be made without fully bound versions of the objects being available. The gist module could emphasize more important regions of a scene for more rapid comparison of salient objects, without the necessity for those objects to be explicitly identified.

Identification stage. If a change is less certain, the object is passed on to the Identification stage to verify the change. Both Rensink's Object system and Sanders' (1990) Identification stage function to resolve collections of features as objects. At this stage, it is possible to resolve objects well enough to detect small changes. Although Rensink does not state explicitly, presumably the Object system must be able to maintain representations of the past version of an object as well as the present version, in order to compare them. Parenthetically, when the representations of previously displayed objects are being maintained for comparison, this might reduce the amount of storage capacity available for objects currently being displayed, reducing the number of objects that can be compared at once. This narrowing of attention when looking for changes might exacerbate the change blindness effect.

The present research, by demonstrating an effect of familiarity, suggests that information on the identities of the objects are also activated (i.e., an object is identified as an “L” rather than an “F”). This information is available in addition to the visual characteristics of bound objects. Identity information can thereby be used to determine whether a change has occurred and presumably this can happen more rapidly than a comparison of visual representations.

To summarize, the structure provided by the current stage model can be enriched by selective introduction of constructs from Rensink’s triadic architecture. Specifically, the layout and gist modules are helpful not simply in understanding which objects are selected for Identification, but in understanding the mechanism by which large changes could be detected at the Feature Extraction stage without a detailed analysis of the scene. Rensink’s attentional nexus and focussed attention systems provide a locus for the binding of visual objects, but also for their identification, and if changes are being sought, for their comparison. The identification of objects allows for their more rapid comparison. The resources required for a full visual comparison of a present object with a past object is only used as a last resort.

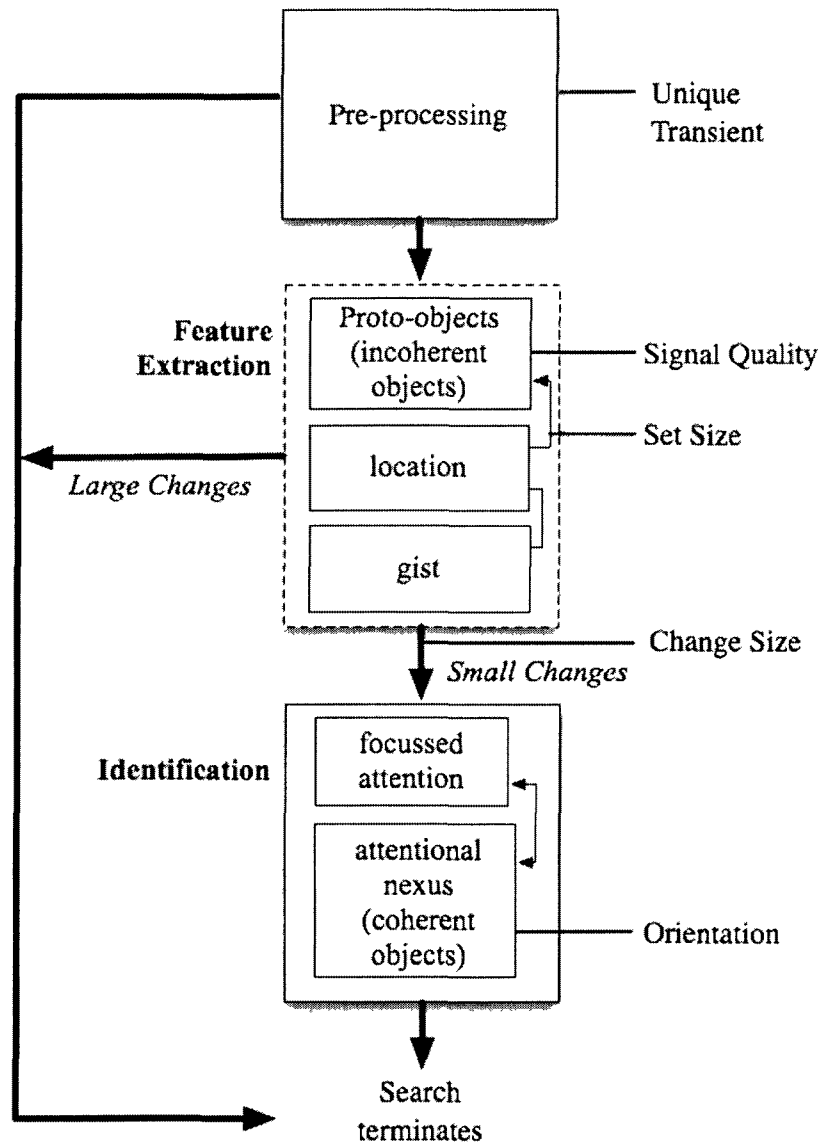


Figure 29. Stage model, elaborated using constructs from Rensink (2000c, 2002, 2005).

Converging Evidence For Familiarity Effects

In the present dissertation, the role of familiarity on change detection was examined using upright versus inverted letters. Insofar as the stage model of change detection describes a general process, a similar role of familiarity should extend beyond letter stimuli. If it does not, it would call into question both the familiarity effect as well as the stage model account of familiarity on change detection. Faces are an apt candidate to investigate orientation (and thus familiarity) effects. There are assumed to be separate, implicit mechanisms for identifying faces (Kanwisher, McDermott, & Chun, 1997; LaBar, Crupain, Voyvodic, & McCarthy, 2003) and experiments on the special status of faces have shown that inverting faces impairs their recognizability (Valentine, 1988).

There is some evidence that familiarity of faces has an impact on change detection. This evidence, however, has not been conclusive. Ro, Russell and Lavie (2001) used a flicker paradigm in which a single face was presented within an array of non-facial stimuli. Changes to the face stimulus were detected more quickly than changes to the non-facial stimuli, suggesting an effect of familiarity on change detection. However, Palermo and Rhodes (2003) showed that Ro et al.'s results could be explained by the fact that the face stimulus was the only face in an array of other objects and as such, the face was the unusual object in the array (the "odd-one-out", as they put it). In other words, the only face stimulus in the display was also unusual, or unique, with respect to the other stimuli in the array. When Palermo and Rhodes put a single non-face object in a sea of faces, it was found that the non-face object now had the advantage. They concluded that

the effect of familiarity reported by Ro et al. could be entirely accounted for by the fact that the face was the unique stimulus in the array, and not because it was a facial stimulus.

A more direct examination of the impact of familiarity on change detection was recently reported by Tovey, Brown, Theus, Runnels, and Herdman (2010). Tovey et al. used the same design as Experiment 1 of the present research, but substituted faces in place of letters. Faces were presented in upright versus inverted format. Tovey et al. observed the same effect of Orientation on change detection as in the present research. That is, changes to familiar (upright) stimuli were detected more quickly than changes to inverted stimuli. Moreover, an additivity between Orientation and Set Size was observed, as seen in the current experiments, providing additional evidence that these two factors affect different processing stages as described in the current stage model. An interaction between Change Size and Orientation was also seen, where the effect of Orientation disappeared for large changes, additional evidence for the gating hypothesis. This finding suggests that the effects demonstrated in the current experiments for letters extend to stimuli other than letters.

Conclusions

The core contributions of this dissertation are in (a) demonstrating an effect of object familiarity on change blindness, replicated clearly across three experiments and (b) the development of a stage model of change blindness. The stage model was based on the three perceptual stages from Sanders (1990): Preprocessing, Feature Extraction, and

Identification. The stage model was extended using constructs from Rensink's (2000c, 2002, 2005) triadic architecture. The current stage model was developed, in part, in order to localize familiarity in the processing sequence. Familiarity was shown to have its effects at the Identification stage. The modeling was done using an additive factors approach (Sternberg, 1969; see also Johnson & Proctor, 2004; Pachella, 1974; Sanders, 1990). Additivity and interactions between familiarity (operationalized as Orientation) and three other factors were analysed, as follows. First, an additivity between Orientation and Set Size showed that familiarity had its effects at a distinct stage (Experiment 1). Second, an additivity between Orientation and Stimulus Quality showed that familiarity had its effects at a later stage than Stimulus Quality (Experiment 2), in this case, at the Identification stage. A final experiment confirmed these results with increased power, and also showed, via an interaction between Change Size and Orientation, that Change Size effectively acts as a gate (Experiment 3). Accordingly, a *gating hypothesis* was proposed wherein large changes are detectable at the Feature Extraction Stage, whereas small changes can only be detected when two coherent objects are compared in the Identification stage.

The current stage model, elaborated using Rensink's constructs, provides guidance regarding the ways in which changes are detected. The Preprocessing stage detects unique visual transients. The Feature Extraction stage uses the layout and gist modules (after Rensink 2002c) to guide the detection of large changes by comparing Proto-objects. The Identification stage detects change first by comparing the identity of

the previous object with the current object, or, if the objects cannot be identified, by comparing the visual representation of the current object with the visual representation of the previous object.

In summary, this dissertation makes a number of contributions to the literature. It offers clear evidence for an effect of object familiarity on change blindness. It develops a model of change blindness, and localizes familiarity in the Identification stage of that model. The dissertation also shows that Sanders' (1990) model of choice reaction can be extended to fit the current model, and that a mapping can be made between this model and Rensink's triadic architecture, enabling constructs from Rensink (2000c) to be brought into the model. Finally, the dissertation proposes a gating hypothesis, which suggests that large changes in incoherent objects can be detected at the Feature Extraction stage, while small changes require a comparison of coherent objects at the Identification stage.

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