An Adaptive Transparency Algorithm for Visual Search Using an Eye-Tracker

by
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Abstract

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Visual search is an important element of human-computer interaction. Whether one is playing games, analyzing medical images, or browsing the Web, they are performing many visual searches; they are looking for things. As computer interfaces become more complex, and eye-tracking input devices become more integrated into everyday lives, there is an increasing opportunity to develop appropriate support for efficient visual searches. Efficient visual searches are quicker, more successful, arguably less stressful, and may result in a more pleasurable interaction compared to inefficient visual searches. Considering that the number of items an average person can attend to at once is quite small, this research seeks to reduce and remove distractors in a conjunctive visual search task by utilizing gaze-contingent, attentional, fade functions. It is demonstrated that a real-time reduction in distractors leads to an increase in search efficiency.

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Chapter 1

Introduction

1.1 Overview

Visual search is an important element of daily activities, including many human-computer interactions. Whether one is playing games, analyzing medical images, or browsing the Web, they are performing many visual searches; they are looking for things which may or may not be present.

As computer interfaces become more complex, and eye-tracking input devices become more integrated into everyday lives, there is an increasing opportunity to develop appropriate support for efficient visual searches. Efficient visual searches are quicker, more successful, possibly less stressful, and may result in a more pleasurable interaction compared to inefficient visual searches.

James [58] stated that "when …things are apprehended by the senses, the number of them that can be attended to at once is small" [p. 406]. If the average person were to consider the environment around them, the sights, the smells, and the sounds, they would quickly discover that human capacity for processing all that information is quite limited; one simply cannot attend to everything at the same time (see [72] and [8]). This is a fundamental concept in the human visual system, which to this day is not completely understood.

What is it that drives attention to areas of interest? Why does one look at one thing before another? How does one get the complete picture? Is it possible to make the difficult searches easier? Questions like this, and the desire to further the understanding of the human visual system, are the motivation for this research.

The research presented herein explores the notion that inherently inefficient visual searches can still be optimized. That is to say, such searches, through adaptive techniques, can be made at least somewhat more efficient. The application of such research can have direct and measurable real-world benefits.

Eye tracking, not unlike human-computer interaction, is an interdisciplinary study. It lies at the cross-section of neurology, physiology, psychology, and computer science. Because of this, one must first form a basic understanding through these various lenses (Section 1.3).

With a broadened understanding of the domain, one can more easily understand the Tools for Visual Search (Chapter 2). Our Methods and Results are presented in Chapter 3. Before presenting conclusions (Chapter 5), a Case Study (Chapter 4) is first presented.

1.2 Nomenclature

This research spans multiple academic disciplines and, as such, the nomenclature is not always consistent. We have normalized across the disciplines to present the nomenclature described in Figure 1.1.

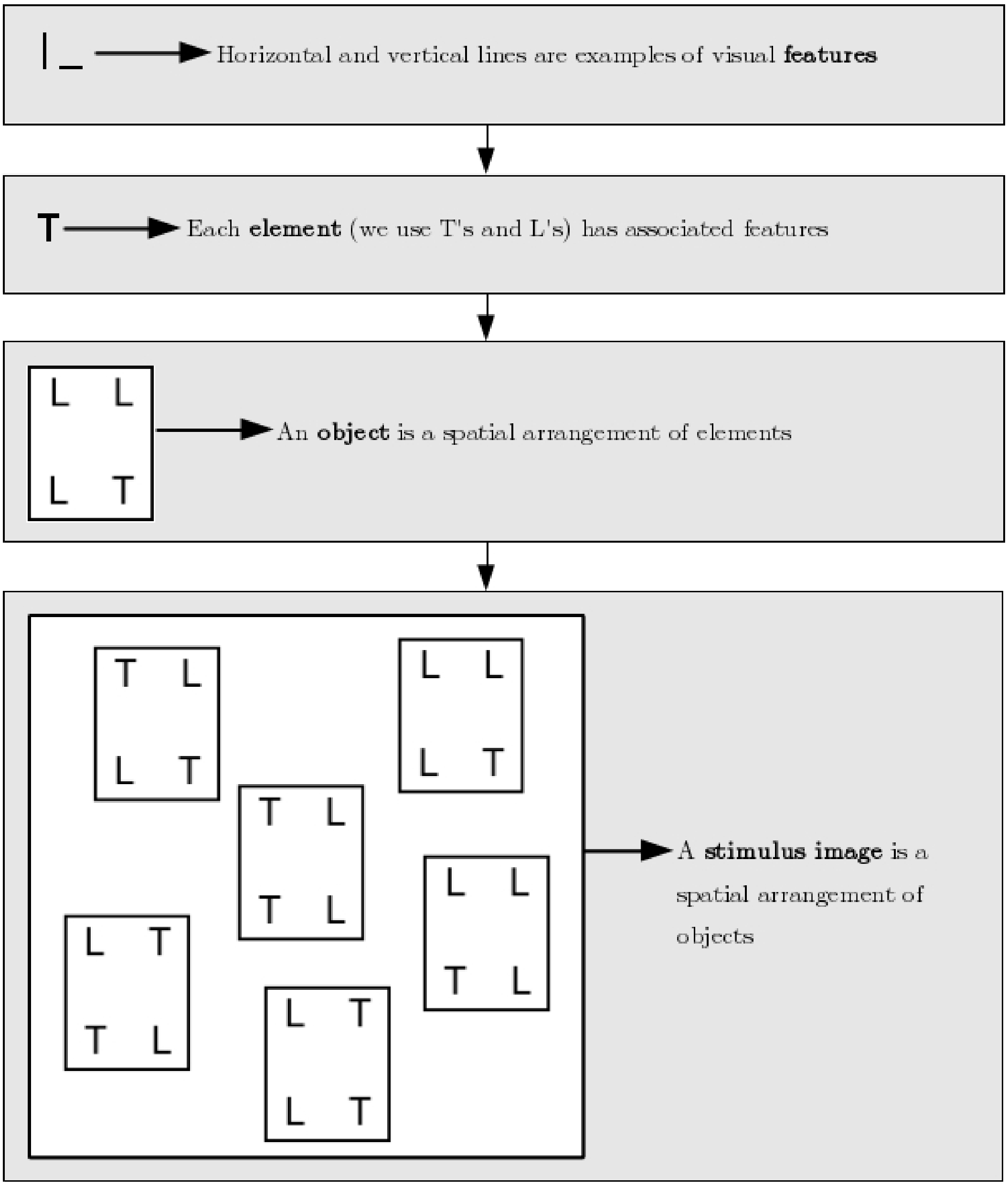


Figure 1.1: Nomenclature. The primary nomenclature of this research is broken into four main components - features, elements, objects, and visual stimulus. In a visual search task, an object may be known as a target (the object you are looking for) or a distractor (not the object you are looking for)

1.3 Background Information

1.3.1 Visual Attention

> Everyone knows what attention is. It is the taking possession by the mind, in clear and vivid form, of one out of what seem several simultaneously possible objects or trains of thought. Focalization, concentration, of consciousness are of its essence. It implies withdrawal from some things in order to deal effectively with others . . . [58, p. 403].

A complete discussion of the modern history of visual attention is recounted by Duchowski [25] as originally provided by Heijden [50]. The discussion below is a summary of those accounts.

1.3.1.1 Attention

Helmholtz [51] argued that attention is a non-voluntary mechanism, stating that the "natural tendency of attention . . . is to wander to ever new things" (in [50, p. 34]). However, Helmholtz conceded that one can "look" out of the corner of their eye, and he further argued that "[ones] attention is quite independent of the position and accommodation of the eyes . . . and [is] free to direct itself by a conscious and voluntary effort . . . " (in [58, p. 438]).

According to Duchowski [25], this is interpreted to mean that "although visual attention can be consciously directed to peripheral objects, eye movements reflect the will to inspect these objects in detail" [p. 5]. That is to say, eye movements may provide evidence of attention, but we must concede that evidence of attention does not guarantee that attention has actually occurred.

While there is some ambiguity as to whether Helmholtz actually believed that attention forces eye-movement, it is conservatively safe to interpret that, somewhere in there, there is evidence of correlation between attention and eye movement. That is to say, they are related at least some of the time.

1.3.1.2 Expectation

James [58] argued that "the things to which we attend are said to interest us and this interest is the cause of our attending" [p. 416]. In this sense, James considered attention to be a covert mechanism much like imagination or thought, stating that "the object has the initiative, not the mind" [p. 449]. Although James recognized certain overt aspects of attention, he argued that "there is no such thing as voluntary attention sustained for more than a few seconds at a time" [p. 420]. As such, James also, admittedly, recognized attention to be a non-voluntary and effortless mechanism defined by the area of focus.

Heijden [50] classified the two views as attention (Helmholtz) and expectation (James). Although radically different, these two views are not considered to be mutually exclusive. If we describe attention in terms of a low-level, bottom-up, or feature-driven mechanism, then we can consider these views to form the foveal (James) and parafoveal (Helmholtz) components [25]. For example, considering an image stimulus, certain areas of the image may draw attention. These areas may first be attended in the periphery, or parafoveally, requiring further inspection through foveal gaze (by looking directly at the areas).

Posner [91] also provided a similar classification and discussed attention along two dimensions: control (endogenous vs. exogenous) and the involvement of the oculomotor system (so-called "covert" attention vs. "overt" attention).

1.3.1.3 Intention

However, as simplistic and elegant as this explanation of visual attention may be, there must be some high-level visual and cognitive functions involved. Indeed, Gibson [46] was able to demonstrate a third component of visual attention - intention. Gibson demonstrated that it is possible to vary the intention to react while keeping the expectation of the stimulus objects fixed and vice versa, it is possible to vary the expectation of the stimulus objects while keeping the intention to react fixed. Duchowski [25] offers the following analogy. If a viewer is made to expect words describing animals, then the misprint "sael" may be read as "seal". However, if the expectation is of words describing watercraft, then the misprint "sael" may be read as "sail". Heijden [50] points out that it is possible that Helmholtz and James overlooked this important factor in their experiments.

1.3.1.4 Selective Filter

Broadbent [8] presented the filter theory of attention after performing an auditory split memory-span experiment. In the experiment, participants were given a pair of head-phones and asked to recall spoken numerals. In one ear, the participants would hear {7,2,3} and, simultaneously, in the other ear they would hear {9,4,5}. Participants always reported the sequence as {7,2,3,9,4,5} or {9,4,5,7,2,3}, and never with interwoven responses. This lead Broadbent to conclude that information may enter in parallel, but then it is selectively filtered to sensory channels.

1.3.1.5 Selection Model

However, Deutsch and Deutsch [20] rejected Broadbent's claims stating that the information processing capabilities required from the filter were so complex that the filter had to be as complicated as the limited capacity channel it had to protect [50]. Instead, Deutsch and Deutsch proposed a system with a large number of central structures, or classifying mechanisms, suggesting that a message will reach the same perceptual and classifying mechanisms whether or not attention is paid to it [50]. They argued that each central structure had a preset importance weighting and this weighting is what decides when something is selected.

Interestingly, we can draw a connection between Broadbent's filter theory and Helmholtz's theory and Deutsch and Deutsch's selection model and James' theory although, as Heijden [50] points out, Deutsch and Deutsch never even refer to James' work.

Again, these seemingly different ideas were not considered to be mutually exclusive and in 1971 (although developed almost a decade earlier) a unified theory of attention, developed by Anne Treisman [112, 113], was recognized.

Treisman's [112] theory was a combination of the work of Broadbent and Deutsch and Deutsch. It presented an attenuation filter followed by central structures referred to as dictionary units. Selection in Treisman's theory was similar to that of Broadbent with the exception that messages were not blocked by the filter, but just attenuated. After attenuation, messages would pass on to the dictionary units. The dictionary units have variable weightings applied to importance, relevance, and context. As such, Treisman brought together the "expectation" and "selective filter" views of attention.

Although Treisman's theory, along with Broadbent and Deutsch and Deutsch, were quite convincing at the time, they all failed to recognize the third factor of attention as put forth by Gibson [46] - intention. Duchowski [25] also points out that Treisman's theory was unable to explain the scene integration problem. That is, even though we view the visual scene through a selective filter, limited in scope, how is it that we can piece together a coherent scene of the entire visual field? As an example of scene integration, consider the Kanizsa illusion [60] (Figure 1.2).

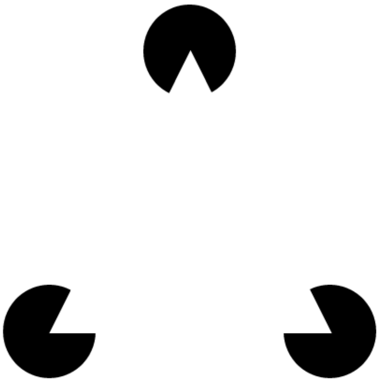


Figure 1.2: Kanizsa Illusion. The shape of a triangle is clearly visible even though it is not part of the scene.

1.3.1.6 Scanpaths

Although the Kanizsa [60] (Figure 1.2) illusion appears to support a Gestalt theory of recognition, that is a parallel, one-step, process; early recordings of eye movements helped cast doubt.

Yarbus [132] presented participants with a stimulus image and asked a range of questions specific to the scene. The eye movements recorded suggested sequential viewing patterns suggesting that visual recognition may be, at least somewhat, serial in nature.

Later, Noton and Stark [82, 83] extended the work of Yarbus by showing that even without the leading questions, the sequential patterns, coined scanpaths, were still observed. Furthermore, they noted that subjects tended to fixate on regions of interest, or “informative details”, and the movements over these regions were variable from one participant to the next. The work of Yarbus and Noton and Stark led to the belief that visual scenes were constructed piecewise.

1.3.1.7 Spotlight

Posner et al. [91] argued that there is an attentional mechanism, dissociated from foveal vision (and independent of eye movements), that moves covertly about a visual scene - much like a spotlight. That is to say, one can attend to an object while their gaze is actually maintained elsewhere - a concept eluded to, many years earlier, by Helmholtz [51] (see 1.3.1.1). In this sense, the orientation of attention is a parallel process that precedes detection. This concept of a spotlight, in terms of the orienting of attention, also draws a strong connection to the areas of interest, or “informative details”, proposed by Noton and Stark [82, 83].

1.3.1.8 Feature Integration

As pointed out by Duchowski [25], Posner et al. and Noton and Stark advanced the theory of visual attention along the same lines as Helmholtz and James, and then later by Broadbent and Deutsch and Deutsch. Once again, Treisman [109] (and Gelade [110]) brought these concepts together and created what is known as the Feature Integration Theory (FIT) of attention.

FIT suggests that attention is the mechanism which integrates the spatially separated features of a particular region of a stimulus so that an object can be viewed as a whole [25]. The underlying foundation of FIT is an internal map of locations that contains feature boundaries and simple properties of the features (e.g., color, orientation, size, etc.), but not what the features are. In essence, attention selects features from this master map of locations [25].

1.3.1.9 Window

Erikson and Yeh [35] (as described by [50]) proposed a model that addressed the limited spatial distribution of attention. They describe three important properties in a zoom lens analogy:

1. Attention can vary its spatial distribution much like a zoom lens can zoom in and out to vary its field of view.

2. The processing capacity of attention is inversely related to the size of area attended. E.g., a zoomed in, or narrow, field of view has higher potential processing capacity compared to a zoomed out, or wide, field of view.

3. It takes time for attention to transition from one state to another much like attempting to focus a zoom lens.

Kosslyn [66], later proposed a more refined model of visual attention (similar to that of Eriksen and Yeh) that describes attention as a selective aspect of perceptual processing, incorporating a “window” for selecting patterns in the visual buffer. Although the window concept is similiar in nature to Broadbent’s selective filter and Treisman’s attenuation filter, the novelty presented by Kosslyn is that the window size can be adjusted and a key hypothesis in Kosslyn’s model is that of a redundant stimulus-based attention-shifting subsystem (a context-sensitive spotlight) [25].

1.3.1.10 Bottom-up Model

Duchowski [25] describes visual attention, in terms of eye-movements, as a cyclic, bottom-up (or feature-driven) process. First, a visual scene, or stimulus, is viewed mostly in peripheral vision (and, therefore, at low resolution). At this stage, interesting features draw attention to their location for more-refined visual inspection. Second, attention is terminated at the current foveal location and redirected to the first, or most-prominent, feature that attracted attention. Lastly, once the eyes are repositioned (that is, the fovea, and attention, is directed at the feature of interest), the feature is inspected at high resolution.

However, Duchowski [25] points out that although the bottom-up model of visual attention forms a basis for the computational models of visual search (see Section 1.3.2), it is incomplete and there are several questions that must be considered:

> 1. If attention is truly driven by the features of the stimulus, then exactly what are the types of features that do this, and in what ways do they drive the attention?

2. Is visual attention solely driven by features? E.g., would we ever need the capability of making voluntary eye movements?
3. What is the link between attention and eye movements? Is attention always associated with the foveally viewed portion of the visual scene?

To attempt to answer the first question would require a "measure of the perceptive power of the human visual system" [25, p. 12]. That is to say, "we would expect to find regions in the brain that engage and disengage attention as well as those responsible for controlling . . . the movements of the eyes" [25, p. 12]. There has been much research into the concept of features and it is further described in Section 1.3.2.2.

To adequately answer the second question would require a complete model of visual attention (including higher-level cognitive functions) and is beyond the scope of this research, however, Section 1.3.2 does elaborate on the subject.

It is well known that astronomers are trained to observe constellations out of the "corner" of their eye (e.g., in the peripheral vision) [91]. However, eye-tracking devices can only track overt eye-movements, and therefore, the third question presents a well-known problem in eye-tracking research - that is, "we assume that attention is linked to foveal gaze direction, but we acknowledge that it may not always be so" [25, p. 12]. The relationship between overt and covert attention is not completely understood. While some argue that these are actually the same process (e.g., [96]) there are others that argue for some degree of independence (e.g., [65]).

1.3.2 Visual Search

> Loosely following William James, we can assert that everyone knows what visual search tasks are because everyone does them all the time. Visual search tasks are those tasks where one looks for something [123, p. 13].

In a visual search task, the item that the observer is searching for is known as the target, while non-target items are known as distractors; collectively the set of items or objects is known as the stimulus. The ability to efficiently locate a visually distinctive target in a given stimulus is crucial for performing many everyday tasks [87]. Such tasks may be as simple as locating a mouse pointer on a computer screen, getting a bottle of beer from the refrigerator, or locating a car in a parking lot [87]. On the other hand, visual search tasks can be quite complex and may include tasks like airport security screening, medical image analysis, examination of bridges for metal fatigue, or air traffic control [124]. Historically, the literature has placed special emphasis on the analysis of medical images (e.g., [2, 31, 59, 67, 68, 69]).

There are two basic types of visual searches - feature search and conjunction search [110, 127] (see Figure 1.3). In a feature search task, the presence of a unique feature (e.g. color, red among green) generates a strong signal that quickly exceeds the background noise[127] and the target is identified quickly and efficiently. In a conjunction search task, the target cannot be identified by a unique feature and focal attention is necessary for the detection of targets [110]. According to Rensink [95], conjunctions can either be weak (at the level of sets) or strong (at the level of items). For example, a weak conjunction could be a search for a red vertical line among green vertical lines and red horizontal lines - that is, the set of distractors contains all of the features of the target set but at the level of items the target is unique. In a strong conjunction, each target contains the same features as a distractor item, for example, a search for an 'L' among 'T's.

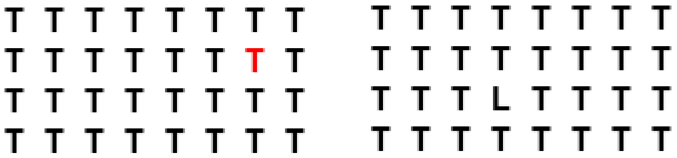


Figure 1.3: Feature Search (left) vs. Conjunction Search (right). The red T is efficiently identified amongst a group of black T's (feature search, left), while a black L, containing the same features as black T's, is less efficient to locate (conjunction search, right).

1.3.2.1 Guided Search Theory

The most undoubted and influential theory of visual search is the Guided Search Theory [14, 125, 126, 127]. Pomplun [87] summarized the Guided Search Theory as a visual search that proceeds in two consecutive stages: an initial stage of pre-attentive processing that guides a subsequent stage of serial search. After stimulus onset, a parallel analysis is carried out across the display, and pre-attentive information is extracted from it to generate an "activation map" that indicates likely target positions. The activation for each search item consists of a top-down and a bottom-up component. The top-down (task-driven) activation of an item increases with greater similarity of that item to the target, whereas its bottom-up (stimulus-driven) activation increases with lower similarity to other items in its neighbourhood. This activation map guides shifts of attention during the subsequent serial search process so that the most promising items are checked first. The Guided Search Theory has received support from many scientific studies, e.g., [40, 52, 79, 88, 97, 121].

1.3.2.2 Features

It is generally accepted that the difficulty of a search task can be explained by the similarity relationships between targets and distractors and between different types of distractors [27], although, it is important to note that Plaisted et al. [86] have demonstrated that this is not entirely true for conjunction search among children with autism. This study, however, is primarily concerned with normally developed persons and, therefore, it is important to look at the details of different features. There is reasonable consensus about a small number of properties that can be considered basic features for visual search; and much debate over others [123]. Wolfe [123] suggests that a basic feature supports both efficient search and effortless texture segmentation. According to these guidelines the following properties are considered to be basic features of visual search - color, orientation, motion, size, curvature, depth, vernier offset, and gloss. Wolfe's [123] account of basic visual search features is summarized below.

1.3.2.2.1 Color

Color is the most basic feature. Several scientific studies show that color supports efficient search and effortless texture segmentation, e.g., [11, 12, 30, 39, 48, 77, 100, 115]. Even with up to nine distractor colors, that are well separated in color space, search can still be efficient [26, 99, 131].

1.3.2.2.2 Orientation

According to Wolfe [123], subjects can discriminate between lines that differ by 1 or 2 degrees in orientation but require a difference of about 15 degrees to support efficient visual search. Foster et al. [43, 44, 120] argue that orientation tasks can be accounted for by two channels, one near vertical and one near horizontal but Wolfe et al. [130] argue for channels roughly corresponding to the categorical terms "steep", "shallow", "left" and "right". For example, Wolfe [125] explains that it is harder to find a vertical target among distractors tilted 20 degrees off vertical than it is to find a target tilted 20 degrees off vertical among vertical distractors. Wolfe attributes this finding to the fact that the tilted target is easy to find because it is uniquely "tilted right" while the vertical target is merely the "steepest" item and is not categorically unique.

1.3.2.2.3 Motion

Motion is an uncontroversial basic feature of visual search [123]. Moving targets can be found efficiently among stationary distractors [22, 73, 81], although [21] has shown that search is less efficient for a stationary target among moving distractors. Ivry [55] has shown that it is more efficient to find a fast moving target among slow distractors than a slow moving target among fast moving distractors. Wolfe [123] points out that the feature space for motion includes axes of motion speed and direction - leading to a complicated interaction. For example, heterogeneity in motion direction impairs search for an item of unique speed but heterogeneity in speed does not impair search for a unique direction [24].

1.3.2.2.4 Size

A target of one size will be found efficiently among distractors of another size when a sufficient size difference exists [4, 28, 80, 92, 106, 110]. Size has been shown to behave like a feature orthogonal to other features such as orientation and color [19, 28, 29]. Treisman and Gormican [111] have shown that it is harder to find small among big than big among small, but given one size of distractors, it was no easier to find a bigger target than a smaller one. Search for targets of different sizes can be efficient even if the targets are defined by chromatic change, texture, motion, illusory contours, etc. [13].

1.3.2.2.5 Curvature

A significant amount of research supports the efficient search of curved lines among straight distractors [9, 49, 111], however, if the target is straight and the distractors are curved the search is less efficient. Early research suggested that curvature as a feature may in fact just be a point of high variance in orientation. Wolfe et al. [130] tested this theory by having subjects search for curved targets among uncurved distractors that were roughly equated for local change in orientation and efficient search for curvature remained possible.

1.3.2.2.6 Depth

Enns and Rensink [34] have demonstrated that efficient search is possible on 3-D stimuli by showing that subjects can find an apparently 3-D line (target) presented among flat distractors composed of similar lines in similar relationships. Subjects can also efficiently search line drawings of targets that appear to differ only in 3-D orientation from the distractors [32, 33]. Efficient search is also possible on a target item that lies at one depth when the distractors lie at another even when there is no difference in average depth between the target and distractors [81].

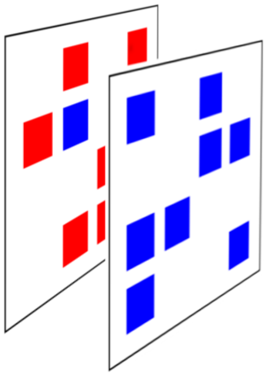


Figure 1.4: Depth Feature Search. The target (blue square in back plane) is efficiently located when target-like distractors (blue squares) are located in the front plane.

1.3.2.2.7 Vernier Offset

Vernier offsets, small departures from the colinearity of two line segments, have been found to support efficient visual search [36, 37, 38, 70, 119] (see Figure 1.5). Although some have argued that vernier offsets can actually be described as a special case of orientation, experiments conducted by Fahle (see [36, 37, 38]) make this an unlikely explanation. Fahle [36] has also shown that subjects can learn a left-vernier among right-vernier search, but only on the basis of an orientation cue and the efficiency of vernier search increases with the difference between the target and the distractors.

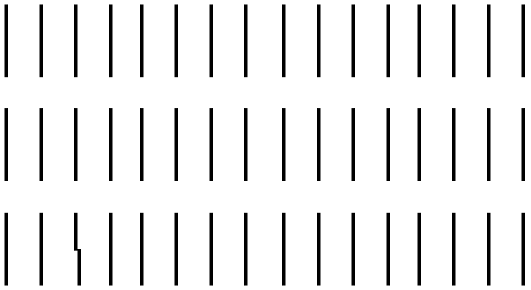


Figure 1.5: Vernier Offset Feature Search. The vernier offset line (third from left, bottom) is efficiently located amongst distractor lines containing no departure in colinearity.

1.3.2.2.8 Gloss

Gloss is the resulting perception of a spot that is darker than the background in the image presented to one eye and brighter in the other eye [10, 51, 114]. A glossy item can be found efficiently among matte distractors and a matte target can be found efficiently amongst glossy distractors [128]. Glossy surfaces are also directly connected to highlights and Rensink and Cavanagh [94] have shown pre-attentive sensitivity to the location of highlights.

1.3.2.3 Eye Movements

According to Duchowski [25], although most eye movements used to reposition the fovea can be explained by several basic types, only three types of movements need to be modelled to gain insight into overt visual tasks; these are saccades, fixations, and smooth pursuits.

1.3.2.3.1 Saccades

Saccades are fast (10 ms to 100 ms; see [25]), ballistic eye movements used to rapidly change gaze position from one region in the visual field to another [3] and, therefore, are especially important in performing visual search tasks [3]. Saccadic eye movements are guided by top-down (see Chen and Zelinsky [15] and Pomplun [87]) and bottom-up (see Sobel and Cave [102]) mechanisms.

1.3.2.3.2 Fixations

Fixations occur when the fovea is fixated on a point, or region, of interest. Typically, eye movements consist of alternating saccades and fixations, with smooth pursuits being the exception [25]. Fixations typically occur over the range of 150 ms to 600 ms and are known to fluctuate approximately 5° about the area of interest [25].

1.3.2.3.3 Smooth Pursuits

Smooth pursuit movements follow the motion of an object [124] and have been studied much less (however, see [62, 78]). Although we recognize that smooth pursuits are an important type of eye movement, the research presented in this thesis does not elicit such events and therefore the subject matter has not been elaborated.

1.3.2.4 The Real World

Most searches in the real world are not searches for targets defined by a single attribute, but rather searches for targets defined by conjunctions of two or more features [123].

Guided Search mechanisms cannot be used in a strong conjunction task because targets differ only in the way their features are arranged; and as such search for strong conjunctions usually degenerates to selective integration [95]. Selective integration is a function of visual attention that combines selected parts or properties into structures that forms a basis for further processing [95]. For example, one may combine three adjacent lines into a single complete figure. As of 2003, Rensink [95] reports that there are still many unresolved issues with strong conjunctions.

Many traits, however, are known. For example, conjunction searches are constrained by stimulus density and become less efficient when the set is very dense [17, 84]. Conjunction search has also been shown to be less efficient in relationship to increasing age; Zacks and Zacks [133] have shown that younger adults aged 18-21 respond quicker than older adults aged 60-72. Searches for conjunctions of two instances of one type of feature are generally very inefficient [131, 125]. However, efficient search seems possible for any pairwise combination of basic features [123] and triple conjunctions even seem to be more efficient than standard conjunctions [19, 92, 127].

1.3.2.5 Search Termination

Simply put, successful searches end when the target is found. However, not all searches are successful. As Wolfe and Horowitz [124] point out, if an unsuccessful search is truly serial, than it is quite easy to imagine when it will be terminated; when all items have been examined and the target was not found.

Chun and Wolfe [16] proposed that efficient search termination can be explained in terms of the Guided Search model. According to this theory, an activation map is created and items are ranked according to likeliness to be the target. Chun and Wolfe argue that search proceeds through this ordered list until the target is found or some adaptively set activation threshold is reached. Chun and Wolfe also propose that some trials are terminated by guesses and that the statistical probability of guessing increases as search time increases.

Wolfe and Pokorny [129] suggest that "once a distractor has been visited by attention and rejected as a candidate target, it would seem reasonable to prevent attention from paying a return visit" [p. 357]. This prevention of re-inspection (for a limited time), according to Posner et al. [90], is known as inhibition of return (IOR).

Although the effect of IOR is robust and replicable (e.g., see [45, 71, 89, 107]), the role of IOR in visual search has been debated. For example, Klein [63, 64] found evidence for inhibition of return to facilitate foraging in visual search tasks but Wolfe and Pokorny [129] failed to replicate the finding. More recently, Smith and Henderson [101] have also found some supporting evidence of IOR in visual search tasks, but were unable to statistically satisfy the view that IOR supports foraging tasks. Klein and MacInnes [64] suggested that the display context is critical in order to observe IOR in search tasks - IOR is absent when the display disappears.

1.3.3 Human Computer Interaction

> Another promising area is the use of eye-tracking techniques to support interface and product design. Continual improvements in ... eye-tracking systems ... have increased the usefulness of this technique for studying a variety of interface issues [75, p. 39].

Visual search is truly an interdisciplinary topic. It's embedded in our everyday lives, in everything we do. Indeed, it is only natural for eye-tracking to find a home in human-computer interaction - the intersection of computer science, psychology, design, and many other fields of study. Although eye-tracking has historically been used to study the interactions between humans and computers, research has recognized the utility of using eye movements, or eye gaze, for interacting with a graphical interface [98], as an input device.

Jacob [56] argues that it is helpful to utilize the natural skills humans have developed through evolution and experience when interacting with computers. Direct manipulation interfaces have been largely successful because of the fact they relate so closely to natural human behaviours (e.g., point, grab, move, etc.). However, eye movements are different from other inputs, so we must proceed carefully, especially with eye movement input devices.

Bolt [5, 6], and later Fono and Vertegaal [41], demonstrated that eye movements could be used to deal with the complexity of a multi-window software environment by making the behaviour and reactivity of the windows contingent on user gaze.

Drawing on the foveal and parafoveal aspects of vision, another common use of eye-movements as input is to create the illusion of higher resolution images than what is technically possible [108]. Tong and Fisher demonstrated this effect for a head-mounted flight simulator by rendering the portion of the display that is currently being gazed upon at a higher resolution than the peripheral display.

Glenn et al. [47] demonstrated the use of eye-movements for simple target acquisition tasks and note the validity of such interfaces. Ware and Mikaelian [118] further validated the use of eye-movements as input by demonstrating that simple target selection and cursor positioning operations could be performed approximately twice as fast when compared to conventional mouse movements.

Starker and Bolt [105] created a system that "analyzes the user's patterns of eye movements and fixations in real-time to make inferences about what item or collection of items shown holds most relative interest for the user. Material thus identified is zoomed-in for a closer look and described in more detail via synthesized speech" [p. 3].

One area of promise for eye-tracking, or eye movements, as input is with disabled users, such as quadriplegics [54, 53], or users whose hands are occupied, such as airline pilots [56].

More recently, there has been an interest in attentive displays that use eye-gaze to find opportune times to interrupt or adapt the display [117, 116] or jump the mouse pointer to the currently gazed region [134]. There is also a growing interest in mobile applications (e.g., [23]).

Applications of visual search for health and medical purposes is an active area of research given that many medical imaging applications utilize image segmentation [85] and that 10-30% of all cancers in the breast are not reported (even though they are visible retrospectively) [74]. Although, Mello-Thomas et al. [74] have demonstrated that visual search is not entirely to blame for false negative search results in radiology mammogram type searches; rather, scan path analysis shows that eye position often dwells on locations of cancers, suggesting that some higher level decision making process is also to blame. Forlines and Balakrishnan [42] (also see [85]) have demonstrated improved search performance in cell slide pathology tasks when using hybrid segmentation techniques.

Jacob and Karn [57] point out that success in using eye movements as input has been rather limited because it is technically challenging and labor-intensive, and because eye movement data is typically noisy and difficult to interpret.

The research presented in this thesis is primarily interested in attentive and adaptive applications of eye tracking as an input device to a graphical user interface for a very specific domain of visual search applications. First, we must understand the most closely related research, presented in Secion 2.

Chapter 2

Tools for Visual Search

2.1 Rapid Serial Visual Presentation

According to Coltheart [18] the human visual system is entirely capable of processing visual images at a rapid rate. Wittenburg et al. [122] demonstrated that a Rapid Serial Visual Presentation (RSVP) interface, for viewing scenes when fast-forwarding or rewinding video, provided faster, more accurate, search compared to traditional methods used for VCRs and DVDs [42]. However, RSVP has known limitations when searching for more than one target at a time (e.g., see [93]. Spence [103] describes RSVP in terms of its use within HCI. Although other modes of RSVP are possible, the conventional ones recounted by Spence are summarized below.

2.1.1 Carousel-mode RSVP

The earliest instantiation of RSVP is the carousel mode. Typically in this mode, a mouse click on a folder would present a flow of images, representing the contents of the folder, in a self-enclosing circular trajectory from one side of the folder to the next. Each image would only be visible for 200 to 400 milliseconds, and as many as 50 images could be viewed in as little as 3 to 4 seconds.

2.1.2 Collage-mode RSVP

Collage-mode RSVP is not unlike the common understanding of a collage, a group of images, spread out before oneself - except, images are continuously introduced to the collage at a rapid rate eventually covering previously introduced images. Typically, the user can control the rate of presentation, or even reverse it.

2.1.3 Floating-mode RSVP

In floating-mode, each image is initially presented in the center of the screen at a smaller than normal resolution and size. After a brief moment, the image moves toward a display boundary, expanding in size.

2.1.4 Shelf-mode RSVP

In shelf-mode RSVP, an image is initially presented at full resolution in the bottom right hand corner of the display. At a constant rate, after approximately 500 ms, the image will move to the top left corner of the display, while decreasing in size; and a new image is presented in the bottom right.

2.2 Image Segmentation

Many techniques are known to exist for segmenting images. These include, but are not limited to, k-means clustering, histogram-based techniques, edge detection, and region growing [42] (also see [85]). Forlines and Balakrishnan [42] conducted three visual search experiments using image segmentation.

Experiment one took a set of images of a given size and target prevalence and segmented them into a collection of individual pieces. The pieces were then randomly composited into larger images with higher target prevalence. This technique was shown to have a significant reduction in error rate for low-prevalence conditions, however there was a trade-off between accuracy and speed.

Experiment two took an original image with a scattered, seemingly random, layout of distractors and re-arranged them into a grid layout. The motivation was to shorten the search gaze path. Forlines and Balakrishnan [42] showed that "an ordered layout is beneficial for low-prevalence tasks, but may incur a penalty for high-prevalence tasks". This technique didn't show any significant effects or interactions related to search time.

Experiment three was a hybrid approach using image segmentation and RSVP. An original image was segmented into individual distractors, and then rapidly presented to the user not requiring the user to move their eyes to different locations. Participants were shown to commit fewer errors using this technique, however, again there was a trade off between accuracy and speed.

2.3 Fish-Eye

Ashmore et al. [1] conducted a study to test the hypothesis that applying a Fitts' law model (see [134]) to eye pointing would reduce selection time through a reduction in target distance caused by the fish-eye. The experiment revealed the type of lens is important, some lenses were shown to lead to significant improvements in search time and accuracy while others showed negative results.

2.4 Attentional Fade Functions

Although RSVP and image segmentation, and even combinations of the two, have been shown to improve visual search, stimulus context may be inherently lost. That is, some targets may be more easily identified when viewed as part of a scene as a whole (i.e., any scene where the relative displacement of items is important could influence the search strategy). For example, consider you are examining a photograph of a baseball game and are looking for the ball. If you identify a person in a throwing position, that may influence where you look next - most likely in the direction the person appears to be throwing. If the image is segmented, this type of context-based strategy is not possible. Additionally, RSVP is known to suffer from some drawbacks such as repetition blindness [61].

We propose an attentional fade function technique (Figure 2.1) that is not mutually exclusive from the related works and can potentially maintain context over a greater time span. It is believed that maintaining context will lead to more efficient, more practical, real-world, applications of visual search. Attentional fade functions are a gaze-contingent technique that modify the opacity of items that have been visually inspected; typically, lowering opacity as gaze-time increases. The term attentional is derived from the underlying concept that attention and gaze are interwoven (see Section 1.3).

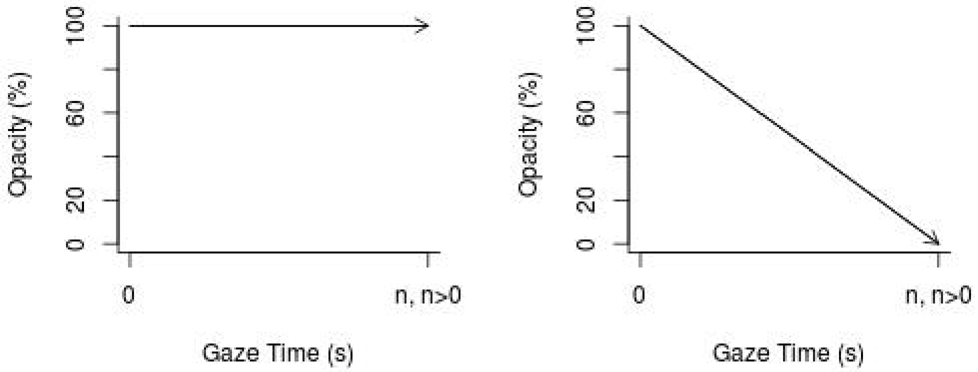


Figure 2.1: Attentional Fade Functions. Left, a function that remains constant as gaze time increases (the equivalent of not using attentional fade functions). Right, as gaze time increases, the opacity of gazed items decreases, fading the item from the scene, according to a linear function.

2.4.1 Benefits

Consider a serial search task. A scene with 2 items is more efficient to search than a scene of 20 items, a scene of 20 items is more efficient to search than a scene of 200 items, and so forth. The fewer the items one has to search through, theoretically, the faster you respond and therefore the more efficient (or more appropriately, the less inefficient) the search task is.

It is known that the number of items a person can attend to at once is quite small (generally 5 to 9 [76]), and therefore, one can make the argument that during an unordered, large, visual search task, at least some portion of time is spent trying to remember where one has been; that is, what items have already been inspected. Repeat inspections may be performed unknowingly.

By utilizing attentional fade functions, it is hypothesized that as the scene changes (e.g., distractors are faded and/or removed) it is constantly re-evaluated (mostly in the periphery) and the search strategy is potentially, adaptively, adjusted. Items that have not been gazed upon remain unfaded (higher resolution) and are therefore more-prominent candidates for closer inspection. Items that have been gazed upon are faded (lower resolution) and serve as a visual memory queue that they have been inspected. That is to say, the attentional fade functions may operate on two distinct levels:

1. Conscious search decision; i.e, “knowing” that faded areas represent regions that have been searched; and
2. Lower level, more covert, internal visual search decision; i.e., by exploiting areas such as pre-attentive visual search and inhibitory tagging.

2.4.2 Parameters

There are several questions with respect to the parameters of attentional fade functions, such as:

1. Should the function fade immediately?
2. Should the function fade to 0% opacity?

3. How does one define the rate of fading?

The first question is interesting in that according to Coltheart [18] humans are able to quickly process visual images within a time frame as small as a 200 ms glimpse. This gives a fairly well defined lower bound for an initial constant, but does not provide an upper bound. The length of this initial parameter could also be object (or even stimulus image) dependent, adding more complexity to the problem.

The second question comes back to the root of the need for such techniques in visual search. We know fading to 0% ultimately changes the context of the visual search scene. However, it remains to be seen whether it is beneficial or harmful.

The third question is the most difficult to answer. Without a doubt, the rate of fading, and the total fade time, of an attentional fade function is certainly related, to some degree, to the objects and stimulus image. If the objects are small and do not require the fovea to be repositioned then fade time may be shorter. However larger objects, requiring many shifts in fovea position, may require longer, slower, or even more rigid, fade intervals.

To answer all these questions in their entirety would require many studies and cannot be completed in a single thesis. This research is intended to provide the foundation for future research and therefore will seek to answer the broader question of whether or not attentional fade functions are beneficial at all. Once this is accomplished, future research can focus on optimizing the parameters of such functions.

After developing a visual search stimulus image (Section 3.2) a pilot study (Section 3.3) is conducted to attempt to somewhat narrow the bounds of the parameters and develop a set of attentional fade functions (Section 3.4.1). Next, a broad study (Section 3.4) is initially conducted, followed by a more in-depth, focused, study (Section 3.5).

Chapter 3

Methods and Results

3.1 Technical Design

The technical design (Figure 3.1) is a typical, two-computer, eye-tracking experiment configuration. One computer runs the eye-tracking and calibration software while the other runs the experimental software, with the two communicating over a local Ethernet connection.

The eye tracker is a SensoMotoric Instruments Inc. (SMI) iView X RED, 50Hz, factory configured eye-tracking system. The system employs non-invasive, binocular, dark-pupil, infrared technology with a tracking resolution $< 0.1°$ and a gaze position accuracy $< 0.5°$. The RED tracking unit is mounted to the monitor, a 17 inch display with an optimal screen resolution of 1280 x 1024.

The experimental software is written in C++ and uses the OpenGL graphics API. The software uses TCP/IP User Datagram Protocol (UDP) sockets to communicate with the eye-tracking system through the SMI Remote Command Language. The software is executed on a MacBook Pro running Mac OS X version 10.6.8 with 4GB 1067 MHz DDR3 RAM and a 2.66 GHz Intel Core i7 processor.

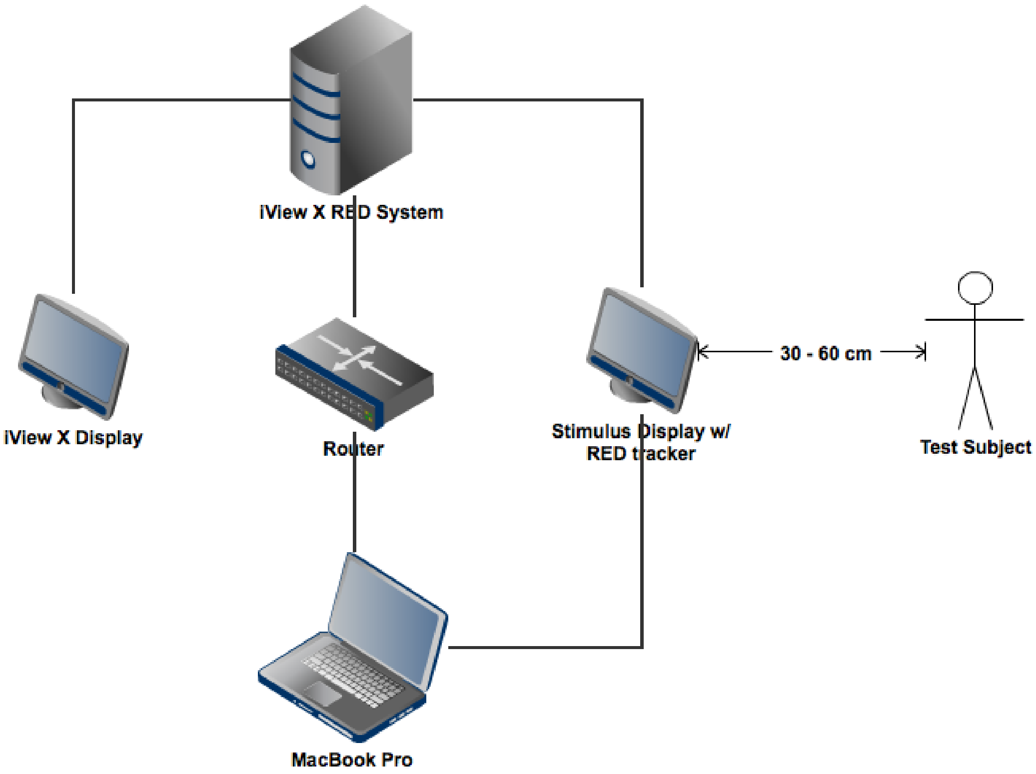


Figure 3.1: Technical Architecture and Design.

3.2 Stimulus Image

Stimulus images were developed with the following requirements in mind:

1. The stimulus image shall elicit a serial search strategy, through strong conjunction, to be more indicative of real life scenarios [123].
2. The recognition of each object shall be slow enough to actually engage the attentional fade functions.
3. The overall search shall take multiple seconds in order for participants to experience some level of stress and provide opportunity to use the functions to their advantage as part of their search strategy (if an overt strategy is possible).

To generate a standard strong conjunction search task, the target and the distractors were given the same elements; a combination of T's and L's. That is, a combination or horizontal and vertical lines. Instead of making each object a single T or L, a combination of four T's and L's were used (Figure 3.2). This is intended to satisfy the desire for slower recognition. When the stimulus image is generated, the objects are randomly displaced spatially about the screen adding an extra level of complexity to the search task.

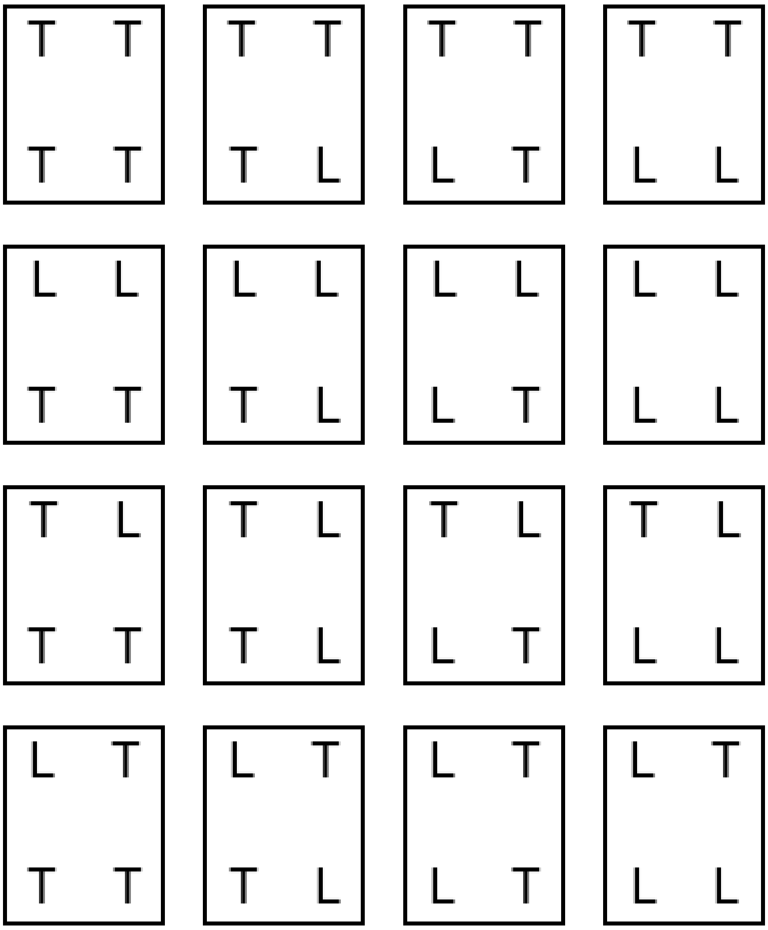


Figure 3.2: Set of Objects. We use a combination of 4 T's an L's per object, resulting in a total possible set of 16 unique objects.

In terms of colors, the stimulus image, and objects, were restricted to black and white. We felt that by doing this it would not exclude participants with common types of color blindness (in any circumstance that may require more relaxed recruiting restrictions) and also not introduce any additional confounding effects. The objects would be presented on a black background.

3.3 Study 0: Pilot Study

An informal pilot study was conducted with 4 participants. The purpose of the pilot study was threefold:

1. Confirm that the technical design is sound and the software is functioning correctly.
2. Gain a basic understanding of the bounds of the parameters for the attentional fade functions.
3. Gain a basic understanding of fatigue rates.

Each participant performed a series of several visual searches and were encouraged to speak freely on their overall feelings of the various conditions. For example, when presented with a very quick linear fade function, a participant may respond, without being asked, that the fade was too quick and that they were unable to find the target because object recognition could not be made. Adjustments were made, immediately, based on feedback in an attempt to determine the bounds of parameters. Participants were also continuously asked about whether or not they were beginning to fatigue.

The study only looked into linear and step-linear functions due to the fact that they are easier to manipulate (within the source code) quickly based on immediate feedback.

Technically, the design was deemed to be operational. The experimental software was communicating with the eye-tracking system and there was no noticeable latency over the expected visual search times.

Accuracy was observed to be an issue. Often times, a participant would report looking at one object, but the the software would pick up the object beside it (that is, an object not being attended to was fading). After some investigation it was determined that the issue was a combination of the eye-tracking system calibration and limitations, and participant head movements.

A strategy was developed to cope with the accuracy issues. A chin rest was purchased to restrict participants from moving their head during a search task. We discovered we were able to fine-tune some settings within the calibration software to get more accurate calibrations. We also modified the experimental software to use larger objects and added a buffer around objects that when gazed upon was considered to be part of the object (Figure 3.3).

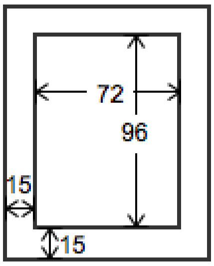


Figure 3.3: Object Dimensions (pixels) with Buffer. Given a 15px buffer, the stimulus image, when generated, would not place any two objects within 30px of each other.

A short while after this strategy was deployed, we received a software upgrade from SMI which included noticeable improvements to the system calibration and overall system accuracy and performance.

In terms of function parameters it was observed that functions with lifetimes less than 0.5 seconds resulted in very high error rates and unsuccessful search terminations. Lifetimes around 1 second seemed to be most desirable, while lifetimes greater than 2 seconds were simply too long (e.g., target being found without fully engaging attentional fade function).

All participants reported some level of discomfort with functions that faded immediately compared to functions that initially remained constant, for a short period of time, before fading. All participants appeared to prefer step-linear fade functions compared to a linear equivalent with the same lifetime.

As expected, response times were observed to increase with the number of objects. We determined that approximately 24 objects would yield response times around 10 seconds (for target-present searches). This also gave some confirmation that the search was in fact a strong conjunction.

In terms of search volume, participants generally reported to be fatiguing around the the 10th consecutive search.

3.4 Study 1: Broad Study

Upon completion of the pilot study it was decided that a further, more systematic, study of a larger set of attentional fade functions was warranted.

3.4.1 Functions

The fade functions presented in this research have 4 distinct characteristics:

1. Initial constant opacity to allow object recognition.
2. Linear, or step linear, fading curves.
3. Fade to black or fade to defined minimum opacity.
4. Maximum total fade interval of 1 second (including initial constant).

and have been divided into three distinct categories:

1. Constant, C (Figure 3.4)
2. Linear, L (Figure 3.5)
3. Step-Linear, S (Figure 3.6)

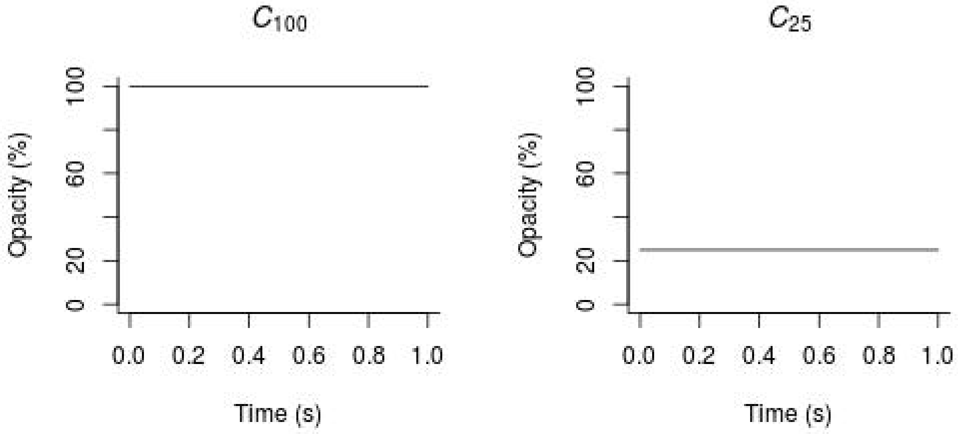


Figure 3.4: Constant Functions.

The two constant functions, C_{100} and C_{25}, form the basis for comparison against the fading functions. C_{100} is considered to be the baseline test, the stimulus image is viewed as it is. C_{25} is a corollary to the baseline in the sense that it represents the stimulus image viewed at the defined minimum opacity, 25%.

The initial constant for all attentional fade functions is to allow object recognition and reduce overall frustration (as originally discussed in Section 2.4.2 and confirmed in the pilot study). However, we decided to also test functions with a slightly longer initial constant of 300 milliseconds, as we recognize that this parameter is highly participant-dependent.

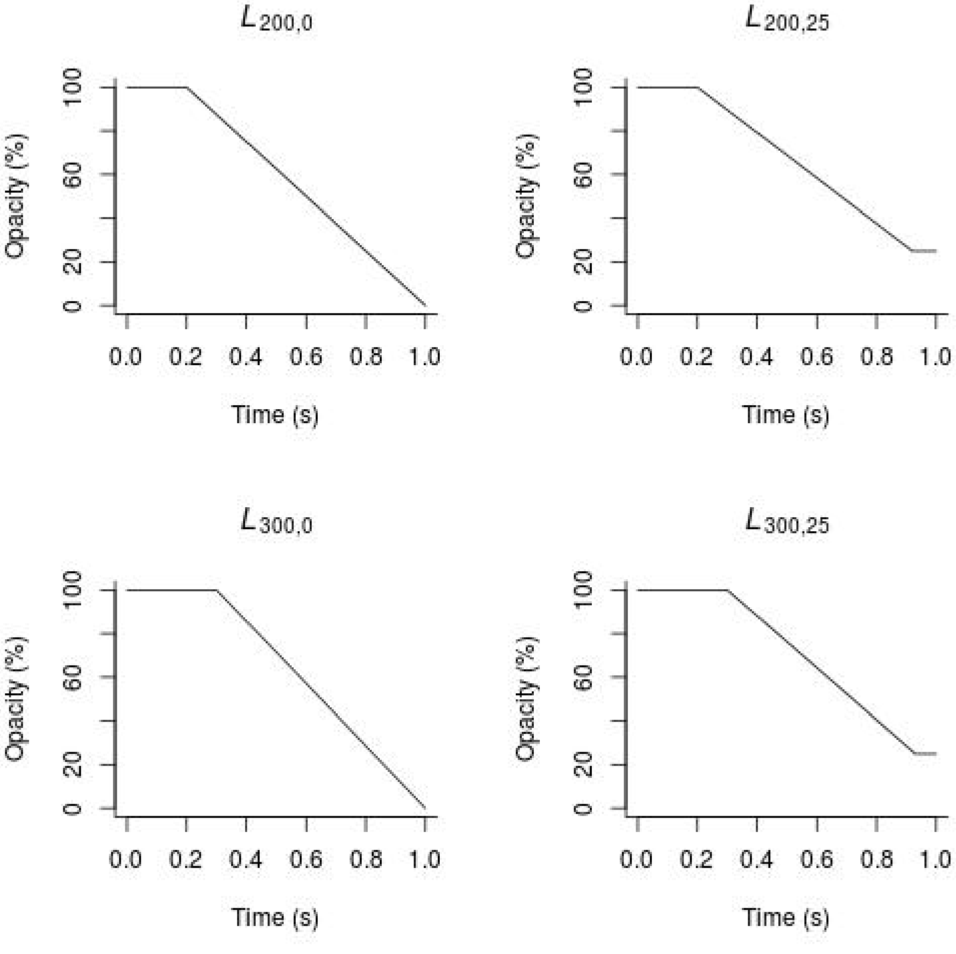


Figure 3.5: Linear attentional fade functions with different parameters. Note, the subscript labelling indicates initial constant length, in ms, and final opacity, in percent.

The idea with the step-linear functions (Figure 3.6) is that the visual search task is complicated enough to elicit returning to the same object more than once (for re-inspection) and the additional constant allows for easier object recognition during this re-inspection. Additionally, linear and step-linear functions will provide different overall stimulus uniformity (in terms of opacity) during a visual search task; that is, with a step function, there is more likelihood that many of the gazed objects will be at an equivalent opacity when compared to a linear function.

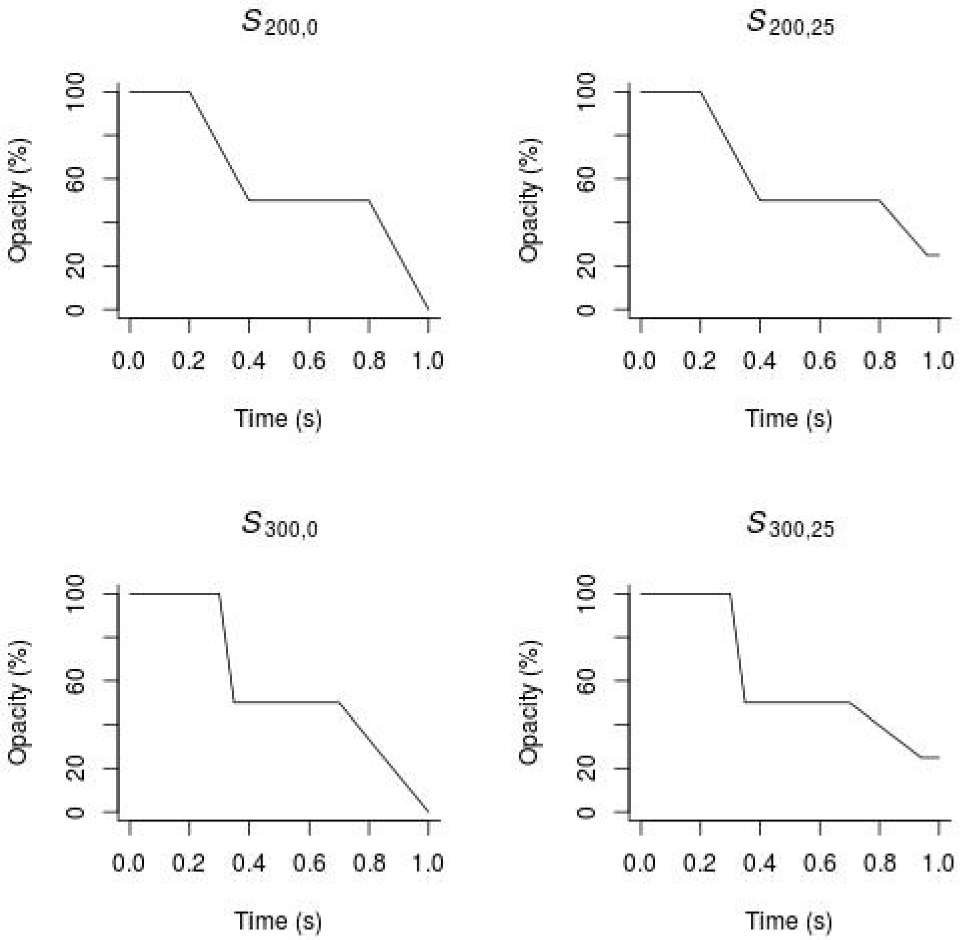


Figure 3.6: Step-linear attentional fade functions with different parameters. Note, the subscript labelling indicates initial constant length, in ms, and final opacity, in percent. All step-linear functions include a single step to 50% opacity.

We recognize that the set of attentional fade functions developed for this research is not exhaustive or representative of all parameters, but it is a good foundation for developing a basic understanding of this type of interaction. Unfortunately, we were unable to test different total fade intervals given the increased complexity of the analysis and the number of participants (or participant time) required. Therefore, only the maximum fade interval of 1 second is considered.

3.4.2 Experimental Design

We use a within-subjects, repeated measures, design with function and target-presence as independent variables. This design allows us to reduce the number of participants required. We decided to use a 10 x 10 balanced Latin square [7] to generate the participant-function order. Consider Table 3.1, where each row indicates the function order, from left to right, for a single participant. Mapping the numbers to functions yields the following function sequence for the first trial: $\{1{:}C_{100}$, $2{:}C_{25}$, $10{:}S_{300,25}$, $3{:}L_{200,0}$, $9{:}S_{300,0}$, $4{:}L_{200,25}$, $8{:}S_{200,25}$, $5{:}L_{300,0}$, $7{:}S_{200,0}$, $6{:}L_{300,25}\}$.

The benefits of a balanced Latin square is that the order is completely counter-balanced. For example, C_{25} would only ever appear directly after C_{100}, once; and C_{25} would only ever appear second in the order, once. That is to say, all functions would appear after every other function only once and in each sequential position only once, for 10 participants.

Although the function order was completely counter-balanced, we knew that the experimental design, as a whole, would not be truly balanced because there were other factors that needed to be considered, such as target order and target presence. Additionally, target prevalence rate and object spatial distribution also add complexity to the experimental design.

A target prevalence rate of 50% was selected for this experiment. That means that in 50% of the searches the target would be present and in the other 50% the target would be absent. Although, in many real-world cases the prevalence rate may be as low as 10%, or even 1% [42], 50% typically yields a low error rate and reduces the expectancy confounds. For the purpose of this stage of the study, we were more concerned with honest error rates (e.g., we did not want the participant to assume the target was always present).

Participant	**Function**									
1	1	2	10	3	9	4	8	5	7	6
2	2	3	1	4	10	5	9	6	8	7
3	3	4	2	5	1	6	10	7	9	8
4	4	5	3	6	2	7	1	8	10	9
5	5	6	4	7	3	8	2	9	1	10
6	6	7	5	8	4	9	3	10	2	1
7	7	8	6	9	5	10	4	1	3	2
8	8	9	7	10	6	1	5	2	4	3
9	9	10	8	1	7	2	6	3	5	4
10	10	1	9	2	8	3	7	4	6	5

Table 3.1: Participant-Function Balanced Latin Square. A 10 x 10 balanced Latin square. Each row represents a unique sequence of items, in our case, functions.

Given the assumed fatigue rate of 10 consecutive searches (derived from the pilot study, Section 3.3), it was decided to simply perform 10 searches per function, using 10 unique targets. Therefore, only 10 objects were used as targets. The objects containing 4 T's and 4 L's were excluded outright and out of the remaining 14 objects, 10 were randomly chosen. Although 6 objects were removed from the list of potential targets, they still remained in the stimulus image as distractors. This yields a total of 100 searches per participant.

Target order was not of great concern in terms of counter-balancing because the object spatial distribution would be randomly generated at run-time and the target would not always be present; and, additionally, the search task was a strong conjunction. However, we decided to again use a 10 x 10 balanced Latin square to also define this sequence so that it would at least be (somewhat, considering target prevalence) counter-balanced per participant. That is to say, each row of the participant-function balanced Latin square (Table 3.1) corresponds to an additional 10 x 10 balanced Latin square (e.g., see Table 3.2 or Table 3.3) where each cell of the participant-function balance Latin square points to a corresponding row in this new target order balanced Latin square.

Participant 1										
Func.	Target and Presence									
C_{100}	▨ 1	▨ 2	10	3	9	4	8	▨ 5	▨ 7	▨ 6
C_{25}	2	3	1	▨ 4	▨ 10	▨ 5	9	6	▨ 8	▨ 7
$S_{300,25}$	▨ 3	4	▨ 2	▨ 5	1	▨ 6	10	▨ 7	9	8
$L_{200,0}$	▨ 4	▨ 5	3	6	2	7	▨ 1	▨ 8	▨ 10	9
$S_{300,0}$	5	6	▨ 4	▨ 7	▨ 3	8	2	▨ 9	▨ 1	10
$L_{200,25}$	▨ 6	7	▨ 5	▨ 8	4	▨ 9	▨ 3	10	2	1
$S_{200,25}$	7	8	▨ 6	9	5	10	▨ 4	▨ 1	▨ 3	▨ 2
$L_{300,0}$	8	▨ 9	7	10	▨ 6	▨ 1	▨ 5	2	4	▨ 3
$S_{200,0}$	9	10	▨ 8	1	7	▨ 2	▨ 6	▨ 3	5	▨ 4
$L_{300,25}$	10	1	9	▨ 2	8	▨ 3	▨ 7	▨ 4	▨ 6	5

Participant 2										
Func.	Target and Presence									
C_{25}	1	2	▨ 10	3	9	▨ 4	▨ 8	▨ 5	▨ 7	6
$L_{200,0}$	2	3	▨ 1	▨ 4	▨ 10	▨ 5	9	6	▨ 8	7
C_{100}	3	4	▨ 2	▨ 5	▨ 1	▨ 6	10	▨ 7	9	8
$L_{200,25}$	▨ 4	5	3	6	▨ 2	▨ 7	▨ 1	8	▨ 10	9
$S_{300,25}$	▨ 5	▨ 6	4	▨ 7	▨ 3	8	▨ 2	9	1	10
$L_{300,0}$	▨ 6	7	▨ 5	8	4	▨ 9	▨ 3	10	2	▨ 1
$S_{300,0}$	7	▨ 8	▨ 6	9	▨ 5	▨ 10	4	1	3	▨ 2
$L_{300,25}$	8	9	▨ 7	10	▨ 6	1	5	▨ 2	▨ 4	▨ 3
$S_{200,25}$	9	10	8	▨ 1	7	▨ 2	▨ 6	▨ 3	5	▨ 4
$S_{200,0}$	10	1	9	▨ 2	▨ 8	▨ 3	7	▨ 4	▨ 6	5

Table 3.2: Left, Participant 1 Function-Target Order and Presence. A 10 x 10 balanced latin square indicating the target sequence, with target-presence highlighted. The shaded cells indicate a target-present search, while the unshaded cells indicate target-absent searches. E.g., Participant 1 would search first with function C_{100} for target 1 (present), followed by target 2 (present), followed by target 10 (absent), and so on; finishing with target 6 (present). Participant 1 would then search with function C_{25} for target 2 (absent), target 3 (absent), target 1 (absent), and so on; finishing with target 7 (present).

Table 3.3: Right, Participant 2 Function-Target Order and Presence. Participant 2 searches in similar fashion to participant 1, but notice that the function-order and target presence conditions are different while the target order remains the same.

The distribution of the target prevalence was simply split per function. For each block of 10 searches, for each function, the target prevalence rate would be 50%. However, the target presence order was randomly chosen while the distribution among target was 50%. For example, for the total 100 searches that a participant would perform, target 1 would be present 5 times and absent 5 times, target 2 would be present 5 times and absent 5 times, and so on.

3.4.3 Hypotheses

H1. Participants will respond quicker, committing more errors, with target present than with target absent.

Rationale: Successful searches are terminated when the target is found and more often than not a present target will be located (e.g., see [42]). Literature review suggests target-absent cases require underlying threshold activation, conscious decision, or, in our case, complete fading of all objects in order to terminate. The implicit user decision to trade-off speed for accuracy is particularly present in target-absent trials [42].

H2. Participants will respond quicker, committing fewer errors, with function C_{100} than with function C_{25}.

Rationale: The objects are uniformly less salient with function C_{25} and we suspect that this may require a higher level of visual attention requiring longer fixation times. Additionally, this increase in visual attention may also increase stress levels resulting in poor target detection.

H3. Participants will respond quicker, committing fewer errors, with at least one fade function than with function C_{100}.

Rationale: Objects that have been gazed upon, or attended to, will fade to a decreased opacity, however, novel objects shall remain much more salient. We suspect this may provide a guide for searching (at a conscious level) but also positively affect the underlying visual search processes (e.g., pre-attentive processing). In essence, we suspect that a search utilizing a fading function may provide incremental improvements to efficiency as the search time increases and objects that have not been inspected become more salient, while the baseline C_{100} provides a uniform level of inefficiency. The combination of conscious and unconscious improvements may lead to more confident responses, resulting in less errors in the fading condition.

H4. Participants will respond quicker, committing fewer errors, with at least one step-linear function than with linear functions.
Rationale: Linear fading functions do not offer a distinct opportunity for object re-inspection and may force a higher level of visual attention requiring longer fixation times. Additionally, this increase in visual attention may also increase stress levels resulting in poor target detection. In the case of step-linear functions there is a distinct opportunity for re-inspection which should not require the same levels of visual attention as linear functions since the fading is constant during this time and therefore should require a shorter fixation.

3.4.4 Results and Discussion

10 participants volunteered for the study. Ages ranged between 18 and 35 and all had normal, or corrected-normal, vision as reported by the participant. There were 3 females and 7 males. The study was approved by the Saint Mary's University Research Ethics Board and a monetary incentive was provided to encourage participation.

Each participant was given the same instructions - to determine as quickly, and accurately, as possible whether the target was present or absent. The participant would be shown a target centered on the screen (Figure 3.7), and given as long as needed to study it. When the participant was ready to begin the search, they would press the space key. Upon pressing the space key, the stimulus image would appear (Figure 3.8) and the visual search task would begin. As soon as the participant was confident in their response they would press the space key again to end the search, causing the stimulus to also disappear and the initial screen to re-appear (Figure 3.9). The participant would then verbally indicate their response to the examiner; "yes" if the target was found, "no" if the target was not found. The participant was also encouraged to state if he/she was unsure about a response by responding with "not sure" - such occasions may arise when the participant prematurely presses the space bar to terminate a search.

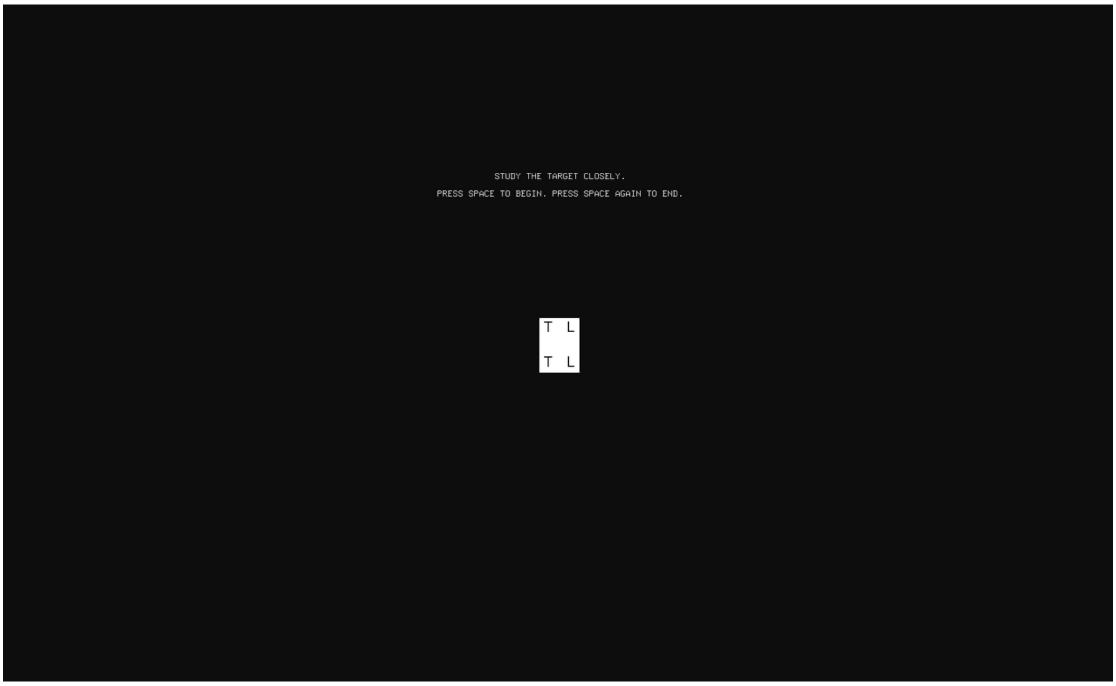


Figure 3.7: Visual Search Task: Screen 1. The participant is presented with the actual target in the center of the screen. The prompt states "STUDY THE TARGET CLOSELY. PRESS SPACE TO BEGIN. PRESS SPACE AGAIN TO END.".

After each function (i.e., block of 10 searches), the participant was asked to relax, remove their head from the chin rest, and complete a short survey (see Appendix B). These rests were typically short in duration, as many participants were eager to continue the task. There was no set time for rest, however, after 50 searches there was a specific rest period of 3-5 minutes. At the end of the entire session, the participant was asked to complete a general survey (see Appendix A). Although we recognize that this type of self-report may lead to fleeting responses, from an HCI perspective, depending on the application, some self-reported criteria (such as overall comfort, for example) may be a lot more, or a lot less, important than performance.

Participants were not informed of the target prevalence rate, nor were they given accurate feedback on whether their responses were correct or incorrect. Positive feedback was given in any case where the participant enquired about their performance.

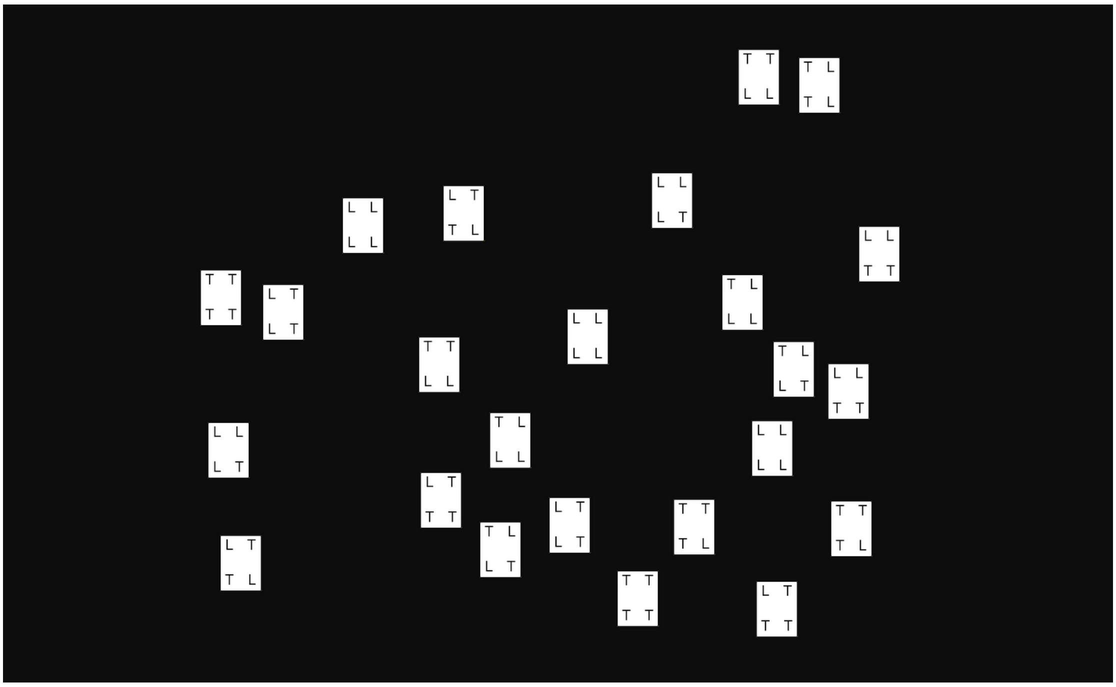
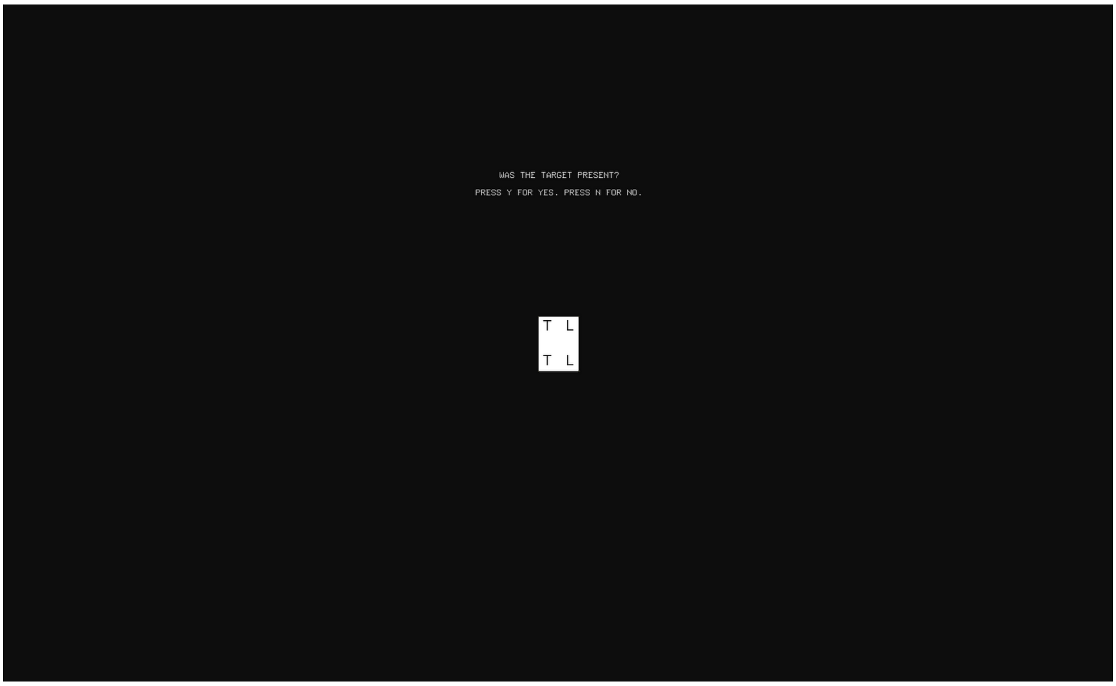


Figure 3.8: Visual Search Task: Screen 2. The participant begins the visual search. Stimuli are randomly positioned about the screen.


WAS THE TARGET PRESENT?

PRESS Y FOR YES. PRESS N FOR NO.

Figure 3.9: Visual Search Task: Screen 3. The participant has indicated that they are ready to respond. The prompt states “WAS THE TARGET PRESENT? PRESS Y FOR YES. PRESS N FOR NO.” However, participants verbally provided their answers to the researcher.

3.4.4.0.1 Response Time Analysis

4 individual searches in which the response time was greater than three standard deviations from the mean were considered as outliers and removed from the data set. We speculate that these were cases where the participant was not fully focused on the visual search task and/or may have forgotten the target. This accounts for less than 1% of our data.

As expected, a quick visual analysis of the response times (Figure 3.10) appears to show that a significant difference between target-present and target-absent median response times may exist. This is indicated by the notches of the boxes not overlapping. We verify this below, using a repeated measures ANOVA with Function and Target Presence as within-subjects factors.

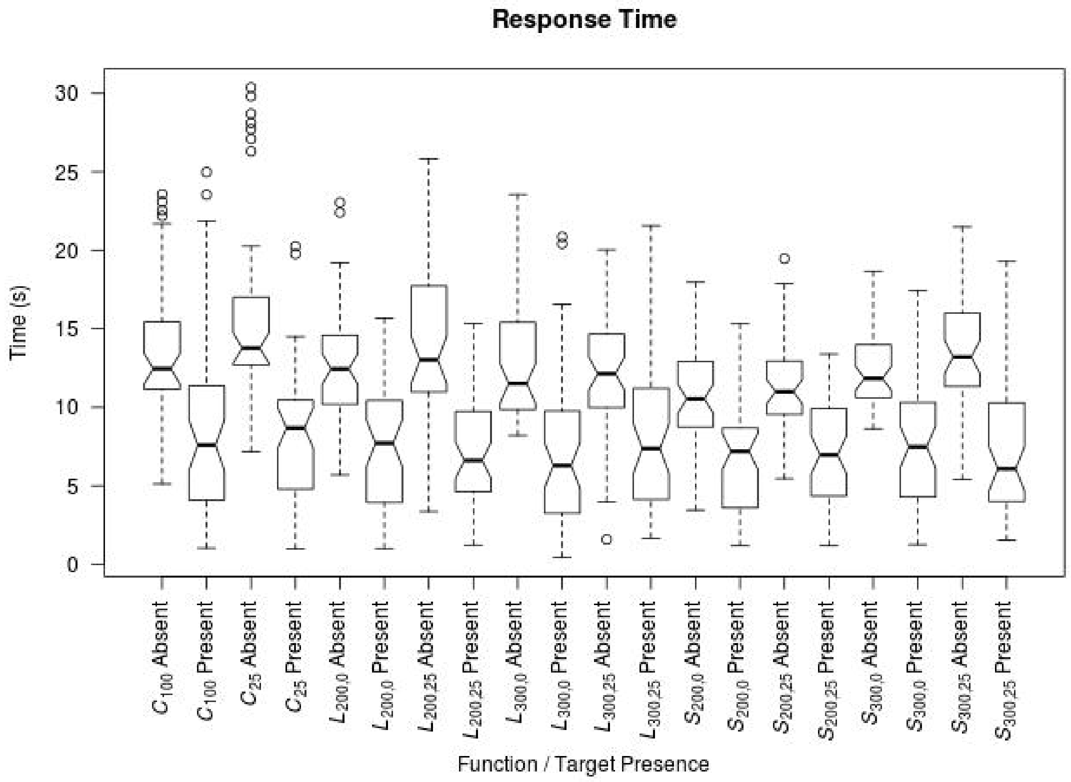


Figure 3.10: Broad Study Response Time Box Plots. A standard box and whisker plot generated by R. Outliers are noted as hollow circles, while the whiskers extend to the minimum and maximum values (excluding outliers). The box shows the lower quartile, median, and upper quartile. Noticeably different than a standard box plot is the notches in the box; these demonstrate a, roughly, 95% confidence interval around the median (within the IQR, 25 to 75 percentile) that allows for a quick visual inspection for possible statistical difference. That is, if the notches of two boxes do not overlap, it is an indication that a statistically significant difference amongst the medians may exist.

Mauchly's test of sphericity shows that the sphericity assumption is violated for function ($p = 0.035$, $\epsilon = 0.359$) and the interaction of function and target presence ($p = 0.007$, $\epsilon = 0.314$). However, target presence only has two levels and therefore it is assumed that it meets the sphericity assumption. Therefore, we report the results below, with modified degrees of freedom, using a Greenhouse-Geisser adjustment.

Tests of within-subjects effects confirms that both function ($F_{3.231,29.080} = 3.554$, $p = 0.024$) and target presence ($F_{1,9} = 115.324$, $p < 0.001$) have a significant main effect on response time. However, there is no significant interaction between the two ($F_{2.826,25.432} = 1.746$, $p = 0.185$).

Function	**Target-Present**		**Target-Absent**	
	Mean	SE	Mean	SE
C_{100}	8.389	1.241	13.844	0.986
C_{25}	8.397	0.673	15.782	1.665
$L_{200,0}$	7.411	0.672	12.956	0.707
$L_{200,25}$	7.627	0.604	14.283	1.424
$L_{300,0}$	7.231	0.838	12.880	1.101
$L_{300,25}$	8.257	1.027	12.120	0.483
$S_{200,0}$	6.539	0.663	10.842	0.726
$S_{200,25}$	6.916	0.497	11.223	0.635
$S_{300,0}$	7.517	0.489	12.465	0.528
$S_{300,25}$	7.319	0.557	13.714	0.939

Table 3.4: Broad Study Mean Response Times.

A post-hoc pair-wise comparison, using a Bonferroni adjustment, does not show any significant difference among any function pairs. An attempt to employ an a priori approach to the Bonferroni adjustment (e.g., re-distributing the Bonferroni weights to the function pairs of greatest interest) also reveals no significant interactions. However, as expected, with only two options for target presence (present and absent) all pairs differ significantly ($p < 0.001$) and this supports *H1* as all functions mean response times are quicker under the target-present condition.

Mean response times (seconds) and standard error are reported in Table 3.4. Although the mean response times are lower for function C_{100} than function C_{25}, we cannot support *H2* as there is no indication the difference is significant. Likewise for *H3* and *H4*; although there are mean values to support these hypotheses, there is no indication that the differences are significant and, therefore, we cannot support *H3* or *H4*.

3.4.4.0.2 Error Analysis

An error was considered to be any case whereby the user responded incorrectly (including unsure). Mean error rates are reported in Table 3.5. In total (over 10 participants each performing 100 visual searches with the same 4 outliers as above removed) there were 424 true-positives (TP), 14 false-positives (FP), 475 true-negatives (TN), 70 false-negatives (FN), and 13 unsure responses.

Function	**Target-Present**		**Target-Absent**	
	Mean	SE	Mean	SE
C_{100}	0.180	0.081	0.040	0.027
C_{25}	0.100	0.045	0.040	0.027
$L_{200,0}$	0.160	0.050	0.040	0.027
$L_{200,25}$	0.140	0.060	0.040	0.027
$L_{300,0}$	0.200	0.079	0.000	0.000
$L_{300,25}$	0.160	0.065	0.080	0.044
$S_{200,0}$	0.220	0.055	0.140	0.067
$S_{200,25}$	0.160	0.050	0.070	0.052
$S_{300,0}$	0.120	0.033	0.000	0.000
$S_{300,25}$	0.040	0.027	0.020	0.020

Table 3.5: Broad Study Mean Error Rates.

Tests of within-subjects effects (repeated measures ANOVA) shows that target presence has a significant effect ($F_{1,9} = 11.023$, $p = 0.009$) on error rate, but function does not ($F_{9,81} = 1.677$, $p = 0.108$). There is also no significant interaction between the two ($F_{9,81} = 0.660$, $p = 0.743$).

A post-hoc pair-wise comparison, using a Bonferroni adjustment, for target presence conditions shows that all pairs (present and absent) differ significantly ($p = 0.009$). Since Table 3.5 shows that all functions have a higher error rate for target-present cases compared to target-absent cases, *H1* is supported.

Since there is no significant effect of function on error rate, we cannot support *H2*, *H3*, or *H4*.

It is also useful to examine the error rates from the classical perspective of accuracy, sensitivity, and specificity as well as a more modern approaches such as signal detection theory [104]. Since we did not find significant effects amongst error rates given function, we only speak to these metrics and do not provide in-depth analysis.

Sensitivity (3.2) is a measure of the ability of the function to identify positive results, while specificity (3.3) is a measure of the ability of the function to identify negative results. That is to say, a high sensitivity value indicates that the function identified all true-positives (e.g., few false-negatives), while a high specificity value indicates that the function identified all true-negatives (e.g., few false-positives). Accuracy (3.1) is a combination of sensitivity and specificity and identifies the proportion of correct responses in the experiment.

$$\text{accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}} \tag{3.1}$$

$$\text{sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3.2}$$

$$\text{specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{3.3}$$

In signal detection theory (see [104]), d' (3.4) represents the separation, or spread, between the means of the hit (responding yes when target is present) and false-alarm (responding yes when target is absent) distributions (also referred to as the signal and noise distributions). That is to say, d' is a true measure of sensitivity. A value of 0 indicates an inability to distinguish between signal and noise, wheres larger values indicate a greater ability to distinguish signals from noise (see [104]). d' is calculated by subtracting the z-score of the false-alarm rate (F) from the z-score of the hit rate (H).

$$d' = \phi^{-1}(H) - \phi^{-1}(F) \tag{3.4}$$

According to [104], problems may arise when hit or false-alarm rates equal 0 or 1. An approach to avoid this situation is to use a loglinear adjustment. E.g., add 0.5 to both the number of hits and the number of false alarms and add 1 to the number of signal trials and the number of noise trials, before calculating the hit (H) and false-alarm (F) rates.

The bias of the response can be measured by c (3.5). A negative value indicates a bias toward the yes response, while a positive value indicates a bias toward the no response.

$$c = -\frac{\phi^{-1}(H) + \phi^{-1}(F)}{2} \tag{3.5}$$

The accuracy, sensitivity, and specificity (including d' and c with loglinear adjustments) are reported in Table 3.6 and visualized in Figure 3.11. For these performance metrics, cases where a participant responded with unsure were excluded.

As indicated by the high specificity values, the rate of false positives was very low across all functions. However, the same cannot be said for sensitivity. The sensitivity values are not as high as specificity indicating a higher rate of false negatives. This is further confirmed by the positive C values, indicating a bias toward the no response.

Function	**Accuracy**	**Sensitivity**	**Specificity**	d'	c
C_{100}	0.890	0.820	0.960	2.546	0.381
C_{25}	0.939	0.918	0.960	2.995	0.156
$L_{200,0}$	0.908	0.836	0.970	2.834	0.463
$L_{200,25}$	0.927	0.857	1.000	3.355	0.641
$L_{300,0}$	0.900	0.800	1.000	3.154	0.756
$L_{300,25}$	0.897	0.840	0.958	2.602	0.333
$S_{200,0}$	0.863	0.812	0.914	2.181	0.227
$S_{200,25}$	0.888	0.840	0.938	2.443	0.254
$S_{300,0}$	0.940	0.880	1.000	3.472	0.597
$S_{300,25}$	0.989	0.979	1.000	4.199	0.218

Table 3.6: Broad Study Function Performance Metrics.

Surprisingly, function C_{25}, produced very few false negatives. It is speculated that this may be a direct result of the higher visual attention required by this function, but participants were very focused on the task.

The performance of function $S_{300,25}$ is notably better than that of the baseline, and in fact, the entire set of functions. This function also scores the highest d' value indicating a greater ability to distinguish between signal and noise.

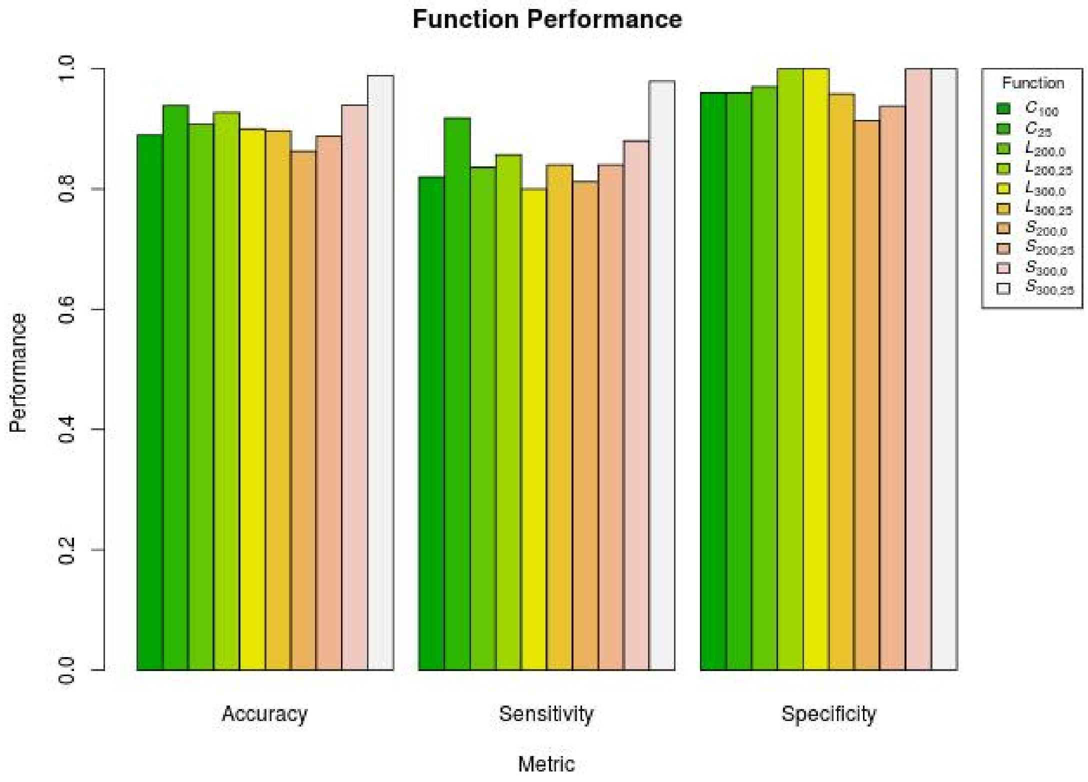


Figure 3.11: Broad Study Performance. Accuracy, Sensitivity and Specificity is plotted for each function. $S_{300,25}$ is notably above the rest.

3.4.4.0.3 Survey Analysis

The mean results of the function specific survey are reported in Table 3.7. Participants were asked the following questions and provided responses on a Likert scale from 1 to 5 (see Appendix B):

1. How **helpful** did you find the fading to be, in this case? [1]

2. How **distracting** did you find the fading to be, in this case? [1]

3. How **stressful** was this search task?

4. How did you find the **speed** of the fading, in this case?

---

[1] For functions that did not fade, this question was ignored

One participant did not provide helpful, distracting, or speed responses for functions $L_{200,0}$, $L_{200,25}$, or $L_{300,0}$. These cases have been ignored in the calculations.

Function	**Helpful**		**Distracting**		**Stressful**		**Speed**	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
C_{100}	-	-	-	-	1.80	0.32	-	-
C_{25}	-	-	-	-	2.20	0.41	-	-
$L_{200,0}$	2.55	0.44	2.22	0.32	1.70	0.33	3.44	0.24
$L_{200,25}$	3.22	0.43	1.77	0.32	1.40	0.16	2.55	0.24
$L_{300,0}$	2.66	0.37	2.44	0.37	1.80	0.41	3.00	0.33
$L_{300,25}$	2.60	0.22	2.20	0.38	1.70	0.26	2.40	0.31
$S_{200,0}$	2.80	0.38	2.30	0.42	1.40	0.22	2.70	0.30
$S_{200,25}$	2.80	0.44	1.90	0.45	1.40	0.31	2.40	0.31
$S_{300,0}$	3.10	0.31	2.10	0.27	1.40	0.22	2.90	0.27
$S_{300,25}$	2.40	0.40	2.10	0.37	1.60	0.26	2.80	0.20

Table 3.7: Broad Study Function Survey Mean Results.

Helpful (Figure 3.12) and distracting (Figure 3.13) results are somewhat complimentary but seem to be highly variable and dependent upon the preference of the participant. The majority of participants report all functions, except $L_{200,0}$, to be at least somewhat helpful while the majority of participants report all functions to be less than somewhat distracting. It's important to note, however, that sometimes a participant would report a function to be helpful but also distracting, while others were not as helpful but also not as distracting. Sometimes this was consistent with their relative performance (i.e., a function that "felt" helpful performed better) and sometimes it was not (i.e. a function that "felt" distracting actually performed better).

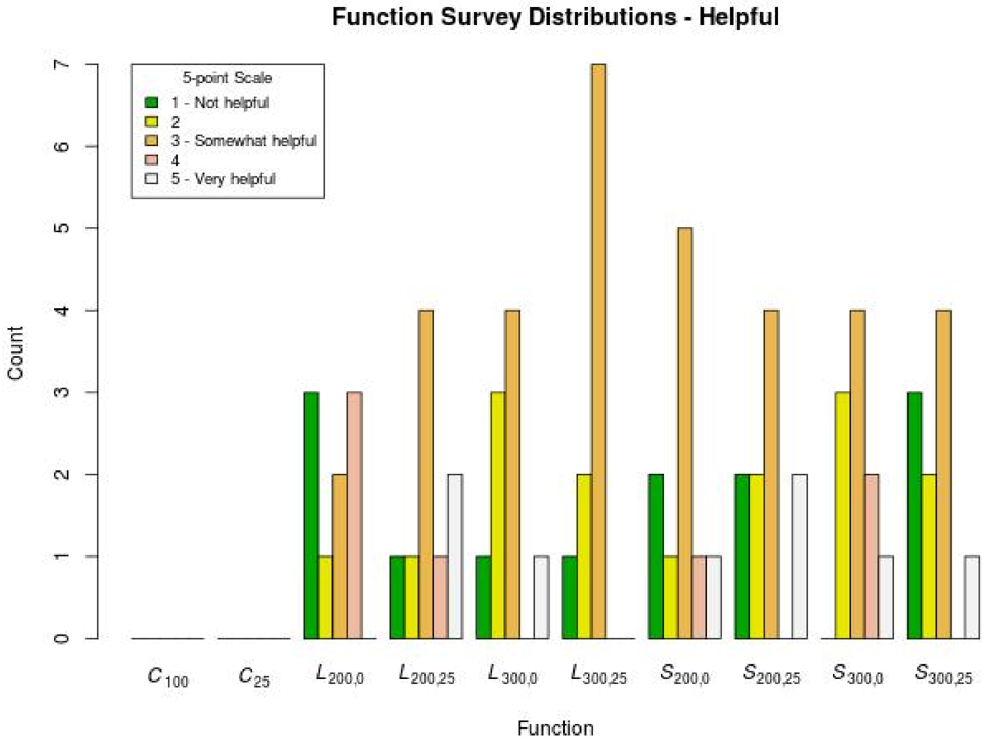


Figure 3.12: Broad Study Function Survey Distributions - Helpful.

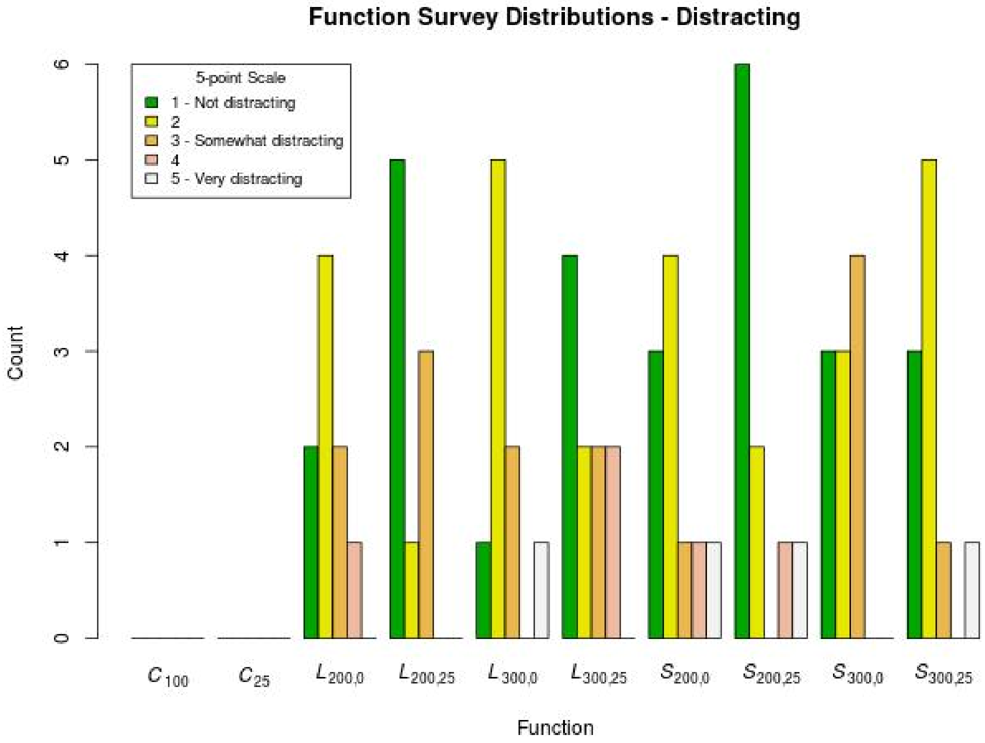


Figure 3.13: Broad Study Function Survey Distributions - Distracting

Function C_{25} was one of only two functions (the other being $L_{300,0}$) that received a maximum stress level score (see Figure 3.14) although we note that the count for each of these is only 1. Interestingly, there is a slight pattern in that step-linear functions were on average equal to or less stressful than the linear functions, which were equal to or less stressful than the constant functions. However, overall, the majority of participants reported all functions to be less than somewhat stressful. It's important to note though, that many functions did not receive a single score above somewhat stressful, while the baseline, C_{100}, and its compliment, C_{25}, both did.

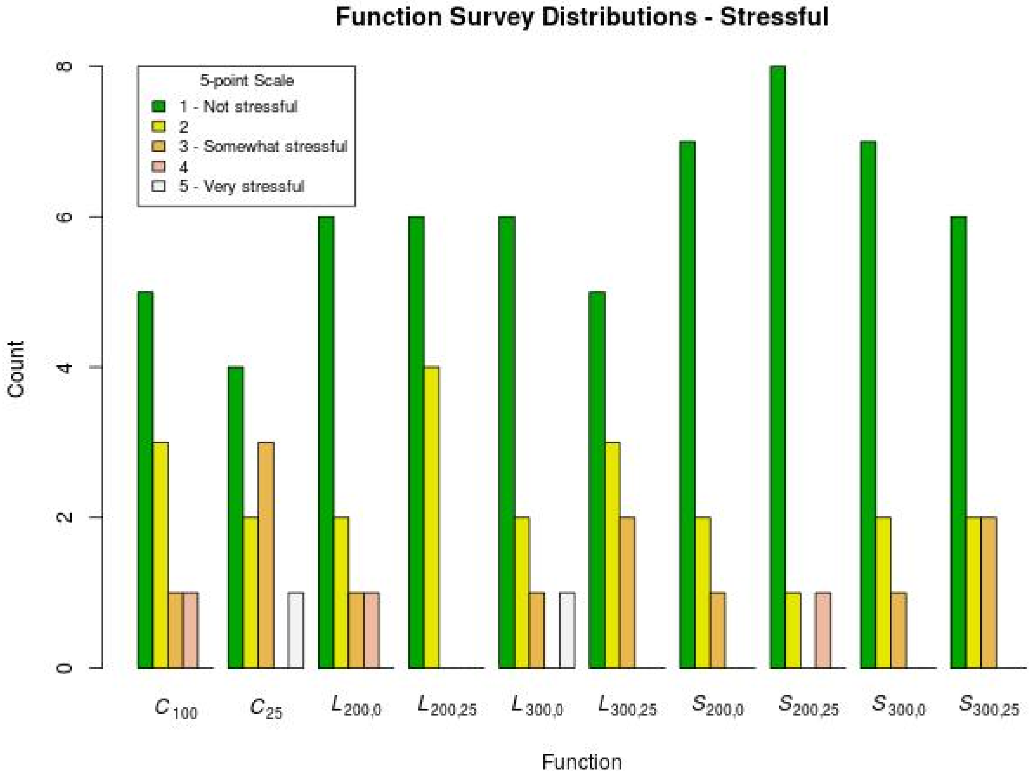


Figure 3.14: Broad Study Function Survey Distributions - Stressful

Speed results are difficult to interpret. For the most part, the exception being $L_{200,0}$ and $S_{300,0}$, the majority of participants reported the speed of the fade functions to be just right; however, again this seemed to be highly dependent upon the participant - but, this is not unexpected (see Figure 3.15). Function $S_{300,0}$

and $S_{300,25}$ had notably tighter groupings of responses about the response of "just right", compared to the other functions.

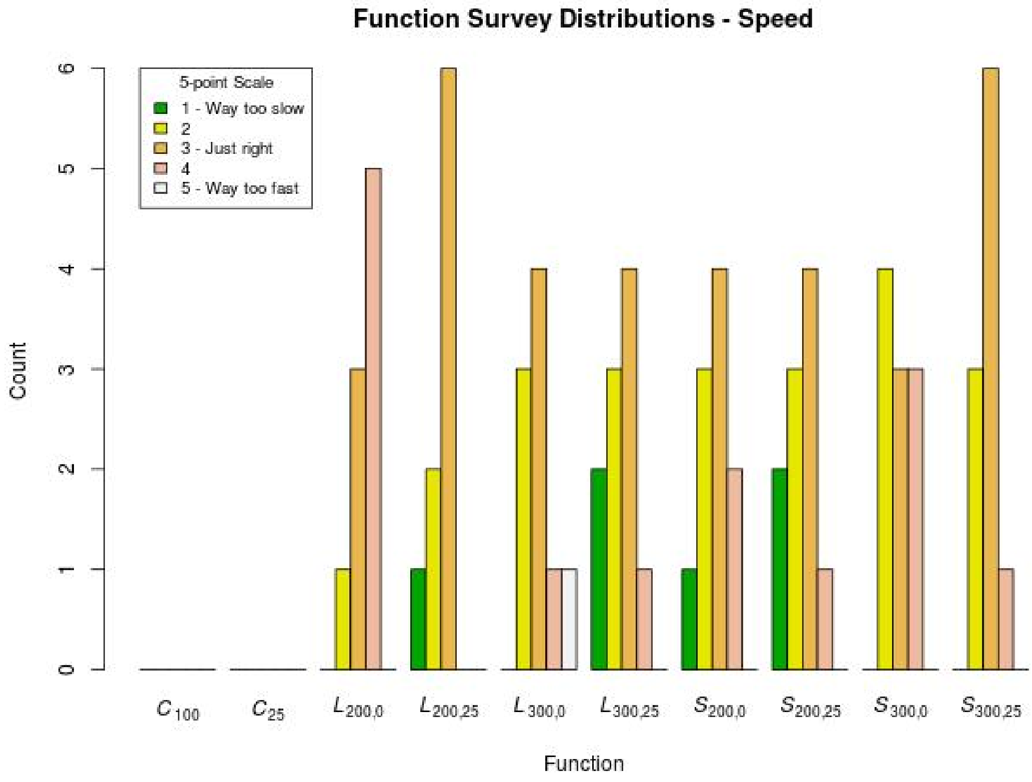


Figure 3.15: Broad Study Function Survey Distributions - Speed

The general survey (see A) results, summarized below, are also difficult to interpret. Reports of helpfulness were mixed. 5 participants reported that the fading of items was helpful, overall, while 1 reported that it was distracting. 3 participants noted that in some cases the fading was helpful and in other cases it was distracting. The remaining participant reported that it didn't make any difference. As with the function specific survey results above, these results do not always correlate with the performance of the participant.

6 participants reported that the thing they liked about fading was that it helped them remember what they had already seen or it helped them find the next target.

2 participants reported that they disliked the total disappearance of an object, while 4 reported disliking the speed at times (either too slow, or too fast).

8 participants (1, 3, 4, 5, 6, 7, 8, and 9; see Appendix C) reported that they felt they performed better when items faded away, while 1 participant (2) reported worse, and 1 participant (10) reported unsure. All 8 of the participants that felt they performed better, scored an equal or higher accuracy with at least 1 fade function compared to the baseline C_{100} (although 3 of these participants also scored a perfect accuracy with the baseline constant). Interestingly, the remaining 2 participants (2 and 10) also performed equally or better with at least 1 fade function, in terms of accuracy.

Based on the remaining results from the general survey the participants were segmented into the following groups (counts are in parenthesis):

1. Age Group
    - A. 18 - 22 (3)
    - B. 23 - 27 (5)
    - C. 28 - 32 (1)
    - D. $>$ 32 (1)
2. Gender
    - M. Male (7)
    - F. Female (3)
3. Student
    - Y. Full-time Student (4)
    - N. Not a Student (6)
4. Computer Group (daily usage)
    - A. $<$ 1 hour (1)
    - B. 1 - 5 hours (2)
    - C. 6 - 10 hours (2)
    - D. $>$ 10 hours (5)
5. Gamer
    - Y. Gamer (6)
    - N. Not a Gamer (4)

A mixed effects repeated measures ANOVA analysis was conducted for each segmented group listed above.

With age group as a between-subject factor and function and target presence as independent variables, there is no significant differences between the means of each group for neither response time ($F_{3,6} = 0.877$, $p = 0.504$) nor error rate ($F_{3,6} = 0.193$, $p = 0.898$).

With gender as a between-subject factor and function and target presence as independent variables, there is no significant differences between the means of each group for neither response time ($F_{1,8} = 0.222$, $p = 0.650$) nor error rate ($F_{1,8} = 0.134$, $p = 0.724$).

With student as a between-subject factor and function and target presence as independent variables, there is no significant differences between the means of each group for neither response time ($F_{1,8} = 0.149$, $p = 0.710$) nor error rate ($F_{1,8} = 0.179$, $p = 0.683$).

With computer group as a between-subject factor and function and target presence as independent variables, there is no significant differences between the means of each group for response time ($F_{3,6} = 0.411$, $p = 0.751$), however there is a significant difference between the means for error rate ($F_{3,6} = 5.019$, $p = 0.045$). However, a post-hoc pair-wise comparison, using an a priori Bonferroni adjustment (i.e., we give 0 weight to group A comparisons as there is only a single participant in that group, and redistributed the weight evenly) shows no significant difference amongst the groups. We note that group A only consists of a single participant, while B and C each only have 2. With this sampling size, and the results of the Bonferroni pair-wise comparisons, it's difficult to put much weight on the results.

With gamer as a between-subject factor and function and target presence as independent variables, there is no significant differences between the means of each group for neither response Time ($F_{1,8} = 0.002$, $p = 0.968$) nor error rate ($F_{1,8} = 2.174$, $p = 0.179$).

3.5 Study 2: Focused Study

In the broad study (Section 3.4) we created a grid of constant, linear, and step-linear functions, each with different properties (initial constant, fade pattern/rates, and minimum opacity). The purpose of this study was to systematically explore the space of possible fading functions in order to estimate candidates for the "best combination" of these parameters.

There were many questions left unanswered after completing the broad study. We only had 10 participants and each participant was spending upwards of 1 hour performing 100 visual searches raising concern over fatigue, attention, and overall insufficient amounts of collected data to answer the hypotheses.

Therefore, we decided that the focused study would concentrate on a smaller group of functions in order to ensure that the participants were fully engaged and that participation was more enticing (i.e., people were less willing to participate, even with monetary compensation, in longer sessions compared to shorter sessions). Additionally, with more interest in participation, we could collect more data.

Although using the same target prevalence rate would allow for easier comparison between the studies, 50% target-prevalence is not indicative of many real world situations. Therefore, it was decided to use a lower target prevalence rate in this study.

3.5.1 Experimental Design

Given the considerations above, it was decided that a within-subjects, repeated measures, design with function and target-presence as independent variables would once again be used.

The function set was reduced to the primary baseline (C_{100}), one linear function ($L_{300,0}$), and one step-linear function ($S_{300,25}$).

The selection of these functions was based on the objectives of this research, as pointed out in Section 2.4.2, to understand the broader question of whether or not attentional fade functions are beneficial at all. Function $S_{300,25}$ was too intriguing to not study further; it provided faster response times than the baseline in both, target-present and target-absent, searches, while at the same time yielding the lowest errors for target-present searches and the overall highest accuracy. Yet, half of participants reported the function to be less than somewhat helpful. Out of the linear functions, function $L_{300,0}$ provided the fastest response times for target-present searches and the second fastest response times for target-absent searches. Interestingly, $L_{300,0}$ was the only linear function to receive at least one survey response for very helpful, very distracting, very stressful, and way too fast. $L_{300,0}$ also produced no errors for target-absent searches. Again, these results were too conflicting and intriguing to not study further.

The target prevalence rate was cut in half and reduced to 25%. Given this rate, and the fact that we knew 100 searches was probably not ideal (given the length of time required to perform that many searches), it was determined that 16 searches per function, per participant, would be conducted, yielding a total search count of 48 - approximately half of the broad study.

Unlike the broad study, we did not have a set amount of expected participants and therefore, elected for a random design; the function order and target order was completely randomly generated. Target presence was randomly assigned within each function block and not globally balanced per target, as in the broad study.

3.5.2 Hypotheses

H5. Participants will respond quicker, committing more errors, with target present than with target absent.

Rationale: Successful searches are terminated when the target is found and more often than not a present target will be located (e.g., see [42]). Literature review suggests target-absent cases require underlying threshold activation, conscious decision, or, in our case, complete fading of all objects in order to terminate. The implicit user decision to trade-off speed for accuracy is particularly present in target-absent trials [42].

H6. Participants will respond quicker, committing fewer errors, with at least one fade function than with function C_{100}.
Rationale: Objects that have been gazed upon, or attended to, will fade to a decreased opacity, however, novel objects shall remain much more salient. We suspect this may provide a guide for searching (at a conscious level) but also positively affect the underlying visual search processes (e.g., pre-attentive processing). In essence, we suspect that a search utilizing a fading function may provide incremental improvements to efficiency as the search time increases and objects that have not been inspected become more salient, while the baseline C_{100} provides a uniform level of inefficiency. The combination of conscious and unconscious improvements may lead to more confident responses, resulting in less errors in the fading condition.

H7. Participants will respond quicker, committing fewer errors, with $S_{300,25}$ than with $L_{300,0}$.
Rationale: Linear fading functions do not offer a distinct opportunity for object re-inspection and may force a higher level of visual attention requiring longer fixation times. Additionally, this increase in visual attention may also increase stress levels resulting in poor target detection. In the case of step-linear functions there is a distinct opportunity for re-inspection which should not require the same levels of visual attention as linear functions since the fading is constant during this time and therefore should require a shorter fixation.

3.5.3 Results and Discussion

25 participants volunteered for the study. Ages ranged between 18 and 27 and all had normal, or corrected-normal, vision as reported by the participant. There were 18 females and 7 males. The study was approved by the Saint Mary's University Research Ethics Board and a monetary incentive was provided to encourage participation.

Each participant was given the same instructions as in the broad study - to determine as quickly, and accurately, as possible whether the target was present or absent. The participant would be shown a target centered on the screen (Figure 3.7), and given as long as needed to study it. When the participant was ready to begin the search, they would press the space key. Upon pressing the space key, the stimulus would appear (Figure 3.8) and the visual search would begin. As soon as the participant was confident in their response they would press the space key again to end the search, causing the stimulus to also disappear and the initial screen to re-appear (Figure 3.9). The participant would then verbally indicate their response to the examiner; "yes" if the target was found, "no" if the target was not found. The participant was also encouraged to state if he/she was unsure about a response by responding with "not sure" - such occasions may arise when the participant prematurely presses the space bar to terminate a search.

After each function (i.e., block of 16 searches), the participant was asked to relax, remove their head from the chin rest, and complete a short survey (Appendix B). These rests were typically short in duration, as many participants were eager to continue the task. There was no set time for rest. At the end of the entire session, the participant was asked to complete a general survey (Appendix A). Again, we recognize that this type of self-report may lead to fleeting responses, however from and HCI perspective, depending on the application, some self-reported criteria may be a lot more or a lot less important that performance.

Participants were not informed of the target prevalence rate, nor were they given accurate feedback on whether their responses were correct or incorrect; rather, positive feedback was given in any case where the participant enquired about their performance.

This study used the same 10 targets used in the broad study.

3.5.3.0.4 Response Time Analysis

15 searches in which the response time was greater than three standard deviations from the mean were considered as outliers and removed from the data set. We speculate that these were cases where the participant was not fully focused on the visual search task, and/or may have forgotten the target. This accounts for less than 2% of our data.

As expected, a visual analysis of the response times (Figure 3.16) appears to indicate that a significant difference between target-present and target-absent median response times. We verify this below, using a repeated measures ANOVA with Function and Target Presence as within-subjects factors.

Mauchly's test of sphericity shows that, unlike the broad study (Section 3.4), the sphericity assumption is not violated for function ($p = 0.353$) nor the interaction of function and target presence ($p = 0.530$). Target presence only has two levels and therefore it is assumed that it meets the sphericity assumption.

Tests of within-subjects effects confirms that both function ($F_{2,48} = 7.360$, $p = 0.002$) and target presence ($F_{1,24} = 126.174$, $p < 0.001$) have a significant main affect on response time. However, there is no significant interaction between the two ($F_{2,48} = 3.190$, $p = 0.050$) at the 95% confidence level.

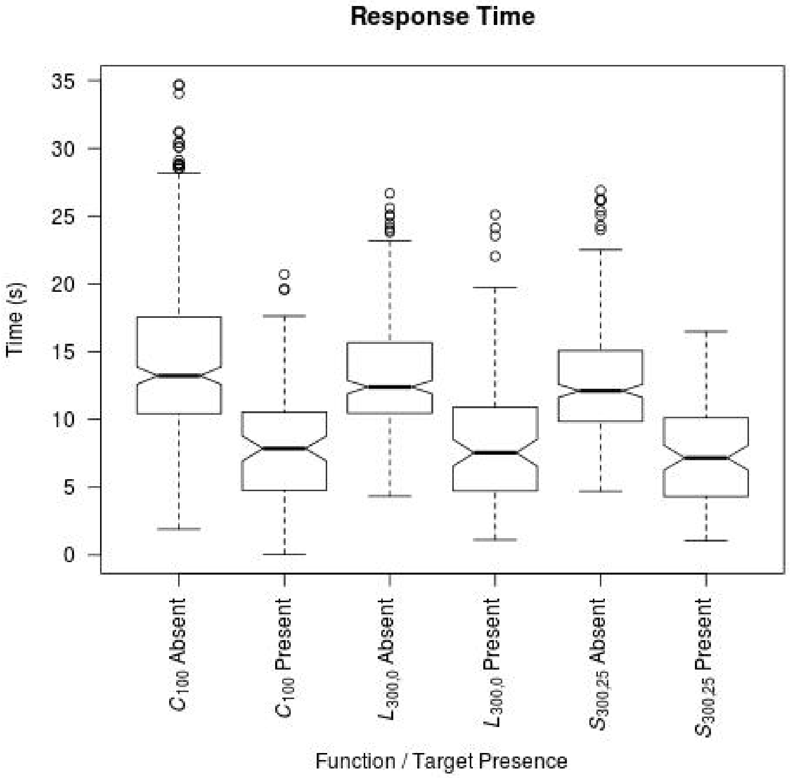


Figure 3.16: Focused Study Response Time Box Plots. A standard box and whisker plot generated by R. Outliers are noted as hollow circles, while the whiskers extend to the minimum and maximum values (excluding outliers). The box shows the lower quartile, median, and upper quartile. Noticeably different than a standard box plot is the notches in the box; these demonstrate a, roughly, 95% confidence interval around the median (within the IQR, 25 to 75 percentile) that allows for a quick visual inspection for possible statistical difference. That is, if the notches of two boxes do not overlap, it is an indication that a statistically significant difference amongst the medians may exist.

A post-hoc pair-wise comparison, using a Bonferroni adjustment, shows a significant difference among function pair $\{C_{100}, S_{300,25}\}$ ($p = 0.008$, $C_{100} = 11.578$, $S_{300,25} = 10.021$) but no significant difference amongst $\{L_{300,0}, S_{300,25}\}$ ($p = 0.073$) or $\{C_{100}, L_{300,0}\}$ ($p = 0.294$). These findings support *H6* but not *H7*. As expected, with only two options for target presence (present and absent), all pairs differ significantly ($p < 0.001$) and this supports *H5* as target-present mean response times for all functions are lower than target-absent.

Although we recognize that the interaction of function and target presence is not significant (at the 95% confidence interval), it is generally accepted that an analysis of simple effects are warranted when you have specific predictions.

Tests of within-subjects effects, for target-absent cases only, confirms that function ($F_{2,48} = 8.202$, $p = 0.001$) has a significant affect on response time. A pair-wise comparison, using a Bonferroni adjustment, shows a significant difference among the pairs $\{C_{100}, L_{300,0}\}$ ($p = 0.045$, $C_{100} = 14.945$, $L_{300,0} = 13.149$) and $\{C_{100}, S_{300,25}\}$ ($p = 0.006$, $C_{100} = 14.945$, $S_{300,25} = 12.883$).

Tests of within-subjects effects, for target-present cases only, does not show any significant difference among the means ($F_{2,48} = 2.855$, $p = 0.067$).

Function	**Target-Present**		**Target-Absent**	
	Mean	SE	Mean	SE
C_{100}	8.212	0.535	14.945	1.094
$L_{300,0}$	8.723	0.705	13.149	0.732
$S_{300,25}$	7.159	0.396	12.883	0.709

Table 3.8: Focused Study Mean Response Times.

Mean response times are reported in Table 3.8. Surprisingly different from the broad study is that function $L_{300,0}$ was, on average, slower than function C_{100} and function $S_{300,25}$ for target-present searches. Function $S_{300,25}$ is also observed to be almost 1 second faster, on average, for target-absent searches when compared to the broad study. It is difficult to say what may attribute to these changes - the target prevalence rate was reduced, the amount of searches was modified, the gender and age distributions are different (majority male in broad study vs. majority female in focused study), and the number of participants is much larger in this study.

Function C_{100} and function $S_{300,25}$ were significantly different according to the post-hoc pair-wise comparison. The mean response times of function $S_{300,25}$, for target-present and target-absent conditions, are quicker than that of Function C_{100} and this supports *H6*. Although there are mean values to support *H7*, there is no indication that the differences are significant and, therefore, we cannot support *H7*.

3.5.3.0.5 Error Analysis

An error was considered to be any case whereby the user responded incorrectly (including unsure). Mean error rates are reported in Table 3.9. In total (over 25 participants each performing 48 visual searches with the same 15 outliers as above removed), there were 245 true-positives (TP), 16 false-positives (FP), 870 true-negatives (TN), 51 false-negatives (FN), and 3 unsure responses.

Function	**Target-Present**		**Target-Absent**	
	Mean	SE	Mean	SE
C_{100}	0.153	0.039	0.027	0.012
$L_{300,0}$	0.227	0.053	0.030	0.014
$S_{300,25}$	0.160	0.043	0.011	0.009

Table 3.9: Focused Study Mean Error Rates.

Tests of within-subjects effects (repeated measures ANOVA) shows that target presence has a significant effect ($F_{1,24} = 18.430$, $p < 0.001$) on error rate, but function does not ($F_{2,48} = 2.037$, $p = 0.142$). There is also no significant interaction between the two ($F_{2,48} = 1.563$, $p = 0.220$).

A post-hoc pair-wise comparison, using a Bonferroni adjustment, for target presence conditions shows that all pairs (present and absent) differ significantly ($p < 0.001$). Since Table 3.5 shows that all functions have a higher error rate for target-present cases compared to target-absent cases, *H5* is supported.

Since there is no significant effect of function on error rate, we cannot support

H6 or *H7*.

It is also useful to examine the error rates from the perspective of accuracy, sensitivity, and specificity as defined in section 3.4.4.0.2. Since we did not find significant effects amongst error rates given function, we only speak to these metrics and do not provide in-depth analysis.

The accuracy, sensitivity, and specificity (including d' and c with loglinear adjustments) are reported in Table 3.10 and visualized in Figure 3.17. For these performance metrics, cases where a participant responded with unsure were excluded.

Function	**Accuracy**	**Sensitivity**	**Specificity**	d'	c
C_{100}	0.951	0.867	0.979	3.113	0.459
$L_{300,0}$	0.923	0.777	0.972	2.655	0.572
$S_{300,25}$	0.954	0.838	0.993	3.363	0.707

Table 3.10: Focused Study Function Performance Metrics.

As indicated by the high specificity values, the rate of false positives was very low across all functions. However, the same cannot be said for sensitivity. The sensitivity values were not as high as specificity indicating a much higher rate of false negatives; not to be unexpected. This is further confirmed by the positive C values, indicating a bias toward the no response.

Compared to the broad study, the accuracy is a much tighter grouping, and nearly indistinguishable; it is speculated that this is possibly just the result of testing a larger sample, but again, we cannot rule out the impact of any one of the changes in this study compared to the broad study (see Section 3.5.3.0.4). We do, however, notice a difference amongst the d' values indicating function $S_{300,25}$ was the most distinguishable when comparing signal and noise distributions.

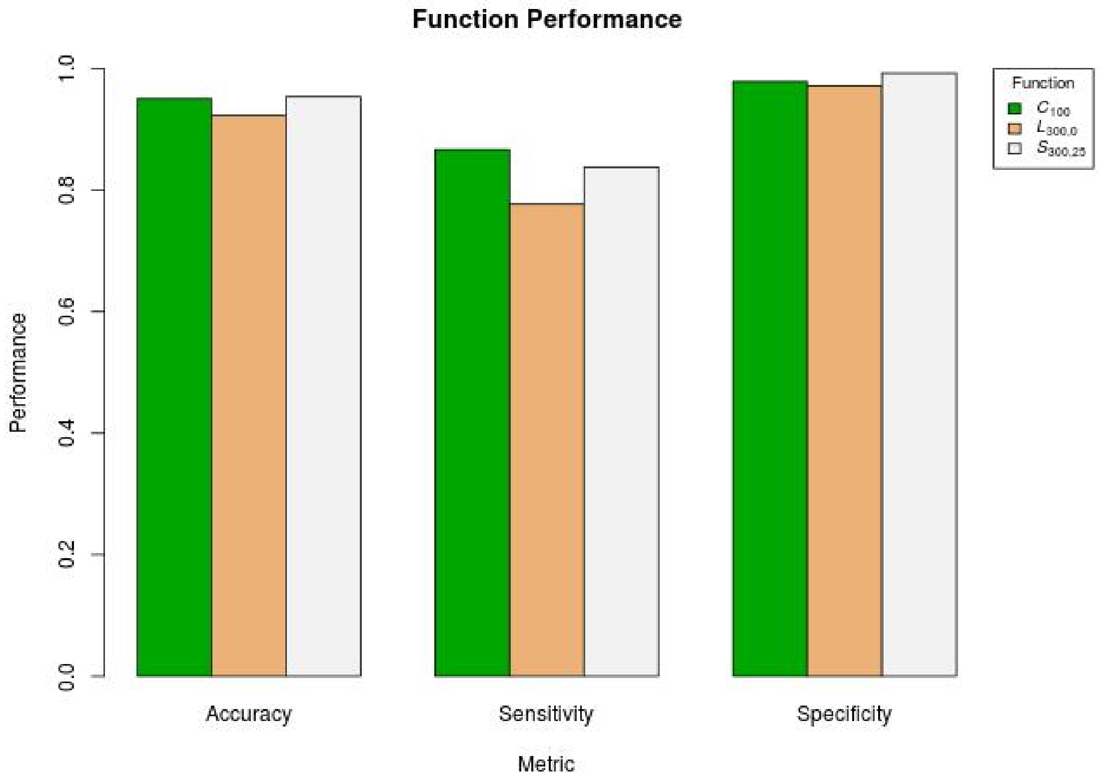


Figure 3.17: Focused Study Performance. Accuracy, Sensitivity and Specificity is plotted for each function.

Although function $S_{300,25}$ maintains the highest overall accuracy (also observed in the broad study), we see a noticeable difference amongst the sensitivity metrics, with function C_{100} producing less false negatives than function $S_{300,25}$, but only marginally less.

3.5.3.0.6 Survey Analysis

The mean results of the function specific survey are reported in Table 3.11. Participants were asked the following questions and provided responses on a Likert scale from 1 to 5 (see Appendix B):

1. How **helpful** did you find the fading to be, in this case? [2]
2. How **distracting** did you find the fading to be, in this case? [2]
3. How **stressful** was this search task?
4. How did you find the **speed** of the fading, in this case?

Function	**Helpful**		**Distracting**		**Stressful**		**Speed**	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
C_{100}	-	-	-	-	1.80	0.20	-	-
$L_{300,0}$	2.56	0.21	2.72	0.20	1.96	0.17	3.16	0.21
$S_{300,25}$	3.00	0.19	2.52	0.20	2.00	0.22	3.00	0.18

Table 3.11: Focused Study Function Survey Mean Results.

Helpful (Figure 3.18) and distracting (Figure 3.19) results are much more conflicting when compared to the broad study. The majority of participants reported that both fading functions were somewhat helpful, but at the same time the majority of participants also reported that both fading functions were somewhat distracting, with function $S_{300,25}$ receiving the most credit in both cases.

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[2] For functions that did not fade, this question was ignored

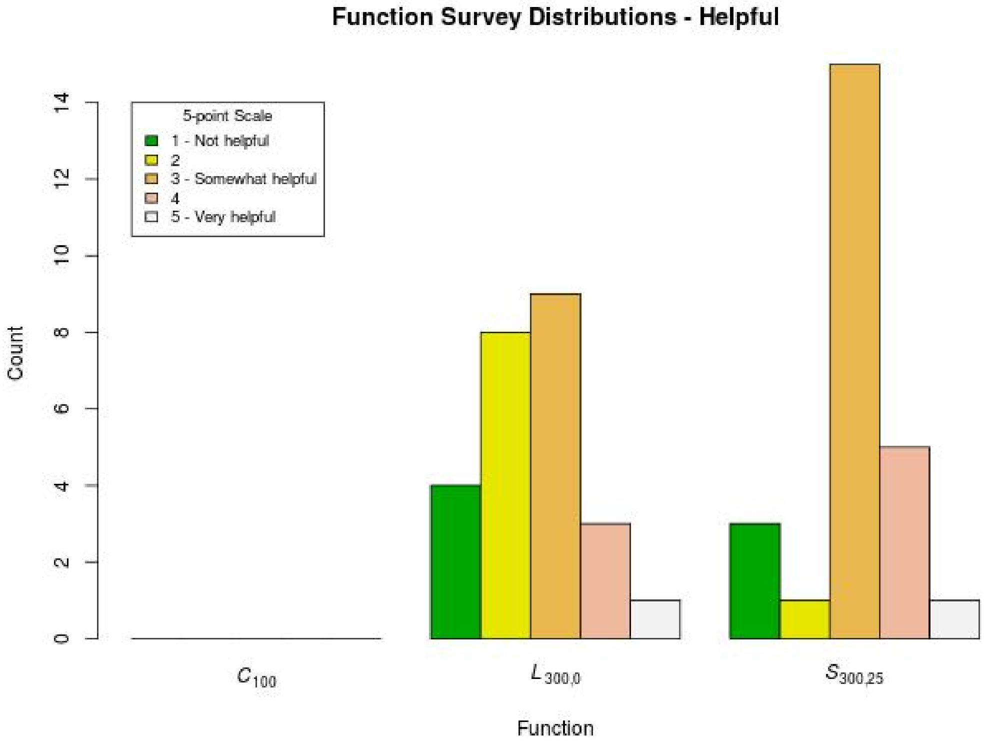

Figure 3.18: Focused Study Function Survey Distributions - Helpful.

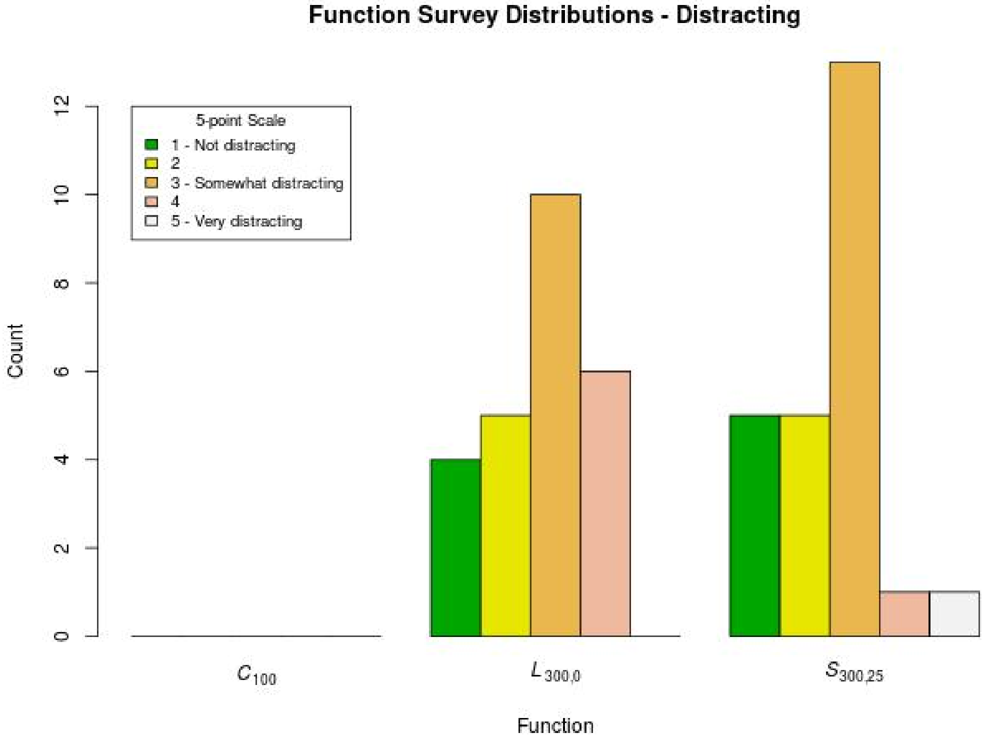

Figure 3.19: Focused Study Function Survey Distributions - Distracting

None of the functions received a maximum stress level score (see Figure 3.20). The stress pattern observed in the broad study is not observed in this study; in fact, the opposite is true - the step-linear function ($S_{300,25}$) was, on average, more stressful than the linear function ($L_{300,0}$), which was, on average, more stressful than the constant function (C_{100}). Additionally, function $S_{300,25}$ received the most scores above somewhat stressful.

In terms of speed (Figure 3.21), unlike the broad study, the majority of participants felt that function $L_{300,0}$ was somewhere between just right and way too fast. However, we do observe the majority of participants reporting function $S_{300,25}$ to be just right (although, with a broader distribution than observed in the broad study).

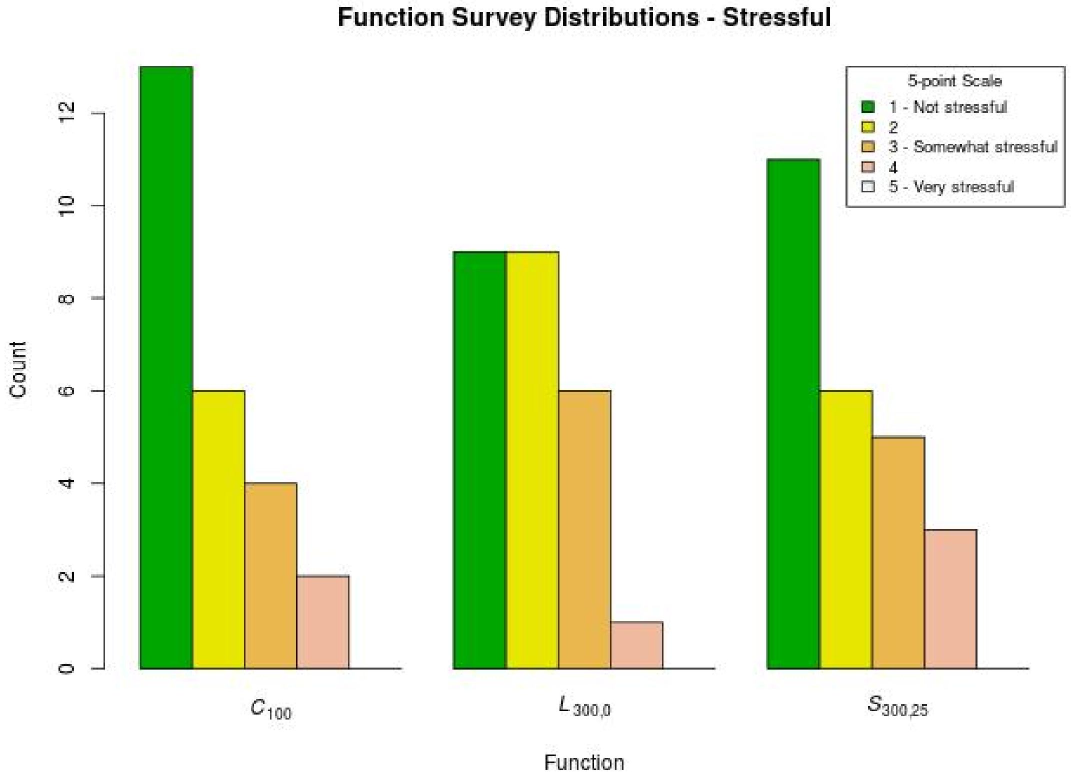

Figure 3.20: Focused Study Function Survey Distributions - Stressful

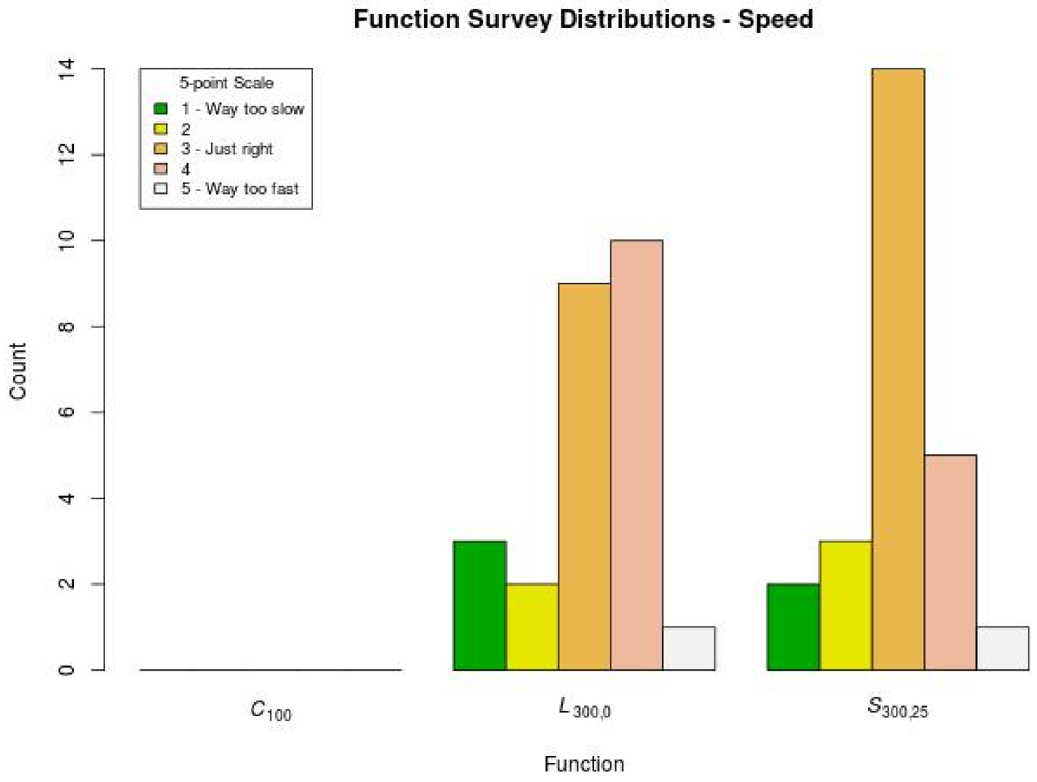

Figure 3.21: Focused Study Function Survey Distributions - Speed

The general survey (see A) results are summarized below. 12 participants reported that the fading of items was helpful while 9 reported that it was distracting. The remaining 4 participants noted that fading was helpful with Function $S_{300,25}$ but distracting with Function $L_{300,0}$ and this seems to support the results of the response time and performance metrics.

12 participants reported that the thing they liked about fading was that it helped them remember what they had already seen or it helped them find the next target. 2 participants noted they specifically liked the step-linear type of fade.

8 participants reported that they felt the fading was distracting, while 5 participants specifically disliked the speed of function $L_{300,0}$. 3 participants reported they did not like total disappearance of an object.

Only 8 participants (9, 10, 12, 15, 18, 20, 21, 22; see Appendix D) reported that they felt they performed better with fading, while 10 (3, 7, 8, 11, 16, 17, 19, 23, 24, 25) reported they felt they performed worse. The remaining participants reported they felt there was no difference in performance. 7 of the participants who felt that they performed better when items faded away, scored an equal or higher accuracy with at least 1 fade function; where 4 of these participants scored a perfect accuracy with the baseline constant C_{100}. Of the 10 participants that felt they performed worse when items faded away, 7 scored an equal or lower accuracy with at least 1 fade function; where 6 of the participants scored a perfect accuracy with the baseline. Of the remaining participants, 6 scored an equal or higher accuracy when items faded away; where 4 of these participants scored a perfect accuracy with the baseline.

Based on the remaining results from the general survey the participants were segmented into the following groups (counts are in parenthesis):

1. Age Group
    - A. 18 - 22 (21)
    - B. 23 - 27 (4)
    - C. 28 - 32 (0)
    - D. > 32 (0)
2. Gender
    - M. Male (7)
    - F. Female (18)
3. Student
    - Y. Full-time Student (22)
    - N. Not a Student (3)
4. Computer Group (daily usage)
    - A. < 1 hour (2)
    - B. 1 - 5 hours (15)
    - C. 6 - 10 hours (8)

   - D. > 10 hours (0)
5. Gamer
   - Y. Gamer (13)
   - N. Not a Gamer (12)

A mixed effects repeated measures ANOVA analysis was conducted for each segmented group listed above.

With age group as a between-subject factor and function and target presence as independent variables, there is no significant difference between the means of each group for neither Response Time ($F_{1,23} = 3.538$, $p = 0.073$) nor error rate ($F_{1,23} = 0.650$, $p = 0.428$).

With gender as a between-subject factor and function and target presence as independent variables, there is no significant difference between the means of each group for neither response time ($F_{1,23} = 0.894$, $p = 0.354$) nor error rate ($F_{1,23} = 0.204$, $p = 0.655$).

With student as a between-subject factor and function and target presence as independent variables, there is no significant difference between the means of each group for neither response time ($F_{1,23} = 2.669$, $p = 0.116$) nor error rate ($F_{1,23} = 2.966$, $p = 0.098$).

With computer group as a between-subject factor and function and target presence as independent variables, there is no significant difference between the means of each group for response time ($F_{2,22} = 1.240$, $p = 0.309$), however there is a significant difference between the means for error rate ($F_{2,22} = 5.123$, $p = 0.015$). A post-hoc pair-wise comparison, using a Bonferroni adjustment, shows groups {A,B} ($p = 0.014$) and {A,C} ($p = 0.023$) are significantly different. The mean error rates for the groups are displayed in Table 3.12.

Although the results are significant, we note that Group A has only 2 participants. With this sample size, it's difficult to place much weight on the results. However, the two participants within Group A did perform poorly in regards to performance, but above average in terms of response time. This could suggest that the participants in question were not entirely focused, in terms of attention, on the task at hand. As an aside, a re-analysis of the focused study was performed without these specific participants but the results of the ANOVA analysis remain unchanged.

Computer Group	**Target-Present**		**Target-Absent**	
	Mean	SE	Mean	SE
A	0.542	0.102	0.000	0.028
B	0.144	0.037	0.017	0.010
C	0.135	0.051	0.036	0.014
D	-	-	-	-

Table 3.12: Focused Study Computer Group Error Rates.

With gamer as a between-subject factor and function and target presence as independent variables, there is no significant differences between the means of each group for neither response time ($F_{1,23} = 1.126$, $p = 0.300$) nor error rate ($F_{1,23} = 0.490$, $p = 0.491$).

3.6 Summary of Results

We presented 7 hypotheses over two studies. Below is a summary of the findings.

3.6.1 Supported Hypotheses

H1. Participants will respond quicker, committing more errors, with target present than with target absent.

Result: Supported. Target presence has a significant effect on response time ($p < 0.001$) and all pairs differ significantly ($p < 0.001$). Response times for all functions, for target present, are less than target absent. Target presence has a significant effect on error rate ($p = 0.009$) and all pairs differ significantly ($p = 0.009$). Error rates for all functions, for target present, are greater than target absent.

H5. Participants will respond quicker, committing more errors, with target present than with target absent.

Result: Supported. Target presence has a significant effect on response time ($p < 0.001$) and all pairs differ significantly ($p < 0.001$). Response times for all functions, for target present, are less than target absent. Target presence has a significant effect on error rate ($p < 0.001$) and all pairs differ significantly ($p < 0.001$). Error rates for all functions, for target present, are greater than target absent.

3.6.2 Rejected Hypotheses

H2. Participants will respond quicker, committing fewer errors, with function C_{100} than with function C_{25}.

Result: Rejected. Although C_{100} response times are quicker, there is no indication of significant differences amongst functions. There is also no indication that function has a significant affect on error rate.

H3. Participants will respond quicker, committing fewer errors, with at least one fade function than with function C_{100}.

Result: Rejected. There is no indication of significant differences amongst response time given functions. There is also no indication that function has a significant affect on error rate.

H4. Participants will respond quicker, committing fewer errors, with at least one step-linear function than with linear functions.

Result: Rejected. There is no indication of significant differences amongst response time given functions. There is also no indication that function has a significant affect on error rate.

H6. Participants will respond quicker, committing fewer errors, with at least one fade function than with function C_{100}.

Result: Rejected. Function has a significant affect on response time ($p = 0.002$) and functions C_{100} and $S_{300,25}$ differ significantly ($p = 0.006$), and mean response times of function $S_{300,25}$ are less than that of C_{100} for both target-absent and target-present conditions. However, There is no indication that function has a significant affect on error rate.

H7. Participants will respond quicker, committing fewer errors, with $S_{300,25}$ than with $L_{300,0}$.

Result: Rejected. Although function has a significant affect on response time ($p = 0.002$), there is no significant difference between $L_{300,0}$ and $S_{300,25}$ ($p = 0.073$). There is also no indication that function has a significant affect on error rate.

Chapter 4

Case Study

A potential application of such gaze-contingent techniques is within the security sector. Agencies in this sector receive massive amounts of data that requires significant manual labour to analyze. On top of the labour involved, there is a time-sensitive aspect to reviewing the data. We will show that a slight, but significant, difference in response time and error rates can translate into a significant effect on overall costs and gains.

4.1 ABC Security

Let's consider the hypothetical company ABC Security. They specialize in analyzing satellite images from around the world and assessing potential security threats. ABC Security receives massive amounts of satellite images daily, from numerous sources, and must analyze the images as quickly as possible to generate reports for customers.

ABC Security currently employs 100 Security Analysts. The Analysts are each compensated with a \$55,000/year salary, working 8 hours a day, 5 days a week. This works out to approximately \$26.44/hour. ABC Security is under a tight budget and cannot currently afford to hire any new Analysts, yet they are unable to meet the demand to analyze all the data they receive.

An Analyst is allotted a mandatory 30 minutes for lunch and two 15 minute breaks daily. The remainder of a typical day is approximately 5 hours analyzing images and 2 hours writing reports. However, recognizing normal interruptions may occur, it is safe to assume a conservative 4 hours is spent analyzing images. ABC Analysts currently take an average of 60 seconds to set up each image for analysis.

Approximately 25% of the images analyzed must be set aside for closer inspection and further processing, these are considered target-present cases. Let's assume the complexity of the search task is similar to that of the Focused Study. Although the study found a mean difference between response times for function C_{100} (baseline) and function $S_{300,25}$ (step-linear fade), it was not considered significant. Therefore, we will consider the average response time of a target-present search to be that of the baseline, 8.212 seconds.

The remainder of the cases are considered target absent. The Focused Study found a significant difference among function C_{100} and function $S_{300,25}$ in this case, and the respective response times will be considered; 14.945 seconds, and 12.883 seconds.

The total time in seconds (S_t) to search X images is given by Equation (4.1).

$$S_t = (P_p X (T + S_p)) + (P_a X (T + S_a)) \tag{4.1}$$

where T is the transition/setup time (seconds) per image, S_p is the average response time (seconds) for a target-present search, S_a is the average response time (seconds) for a target-absent search, P_p is the target-present rate, and P_a is the target-absent rate.

Under current conditions, in 4 hours, or 14400 seconds, the number of images an Analyst can process daily, on average, is given by:

$$14400 = \left(\frac{1}{4}X\,(60 + 8.212)\right) + \left(\frac{3}{4}X\,(60 + 14.945)\right)$$

$$14400 = 17.053X + 56.20875X$$

$$14400 = 73.23175X$$

$$196.63 = X$$

$$196 = X$$

Using the function $S_{300,25}$ technique, an analyst would be able to process this same number of images in S_t seconds, where:

$$S_t = \left(\frac{1}{4}196\,(60 + 8.212)\right) + \left(\frac{3}{4}196\,(60 + 12.883)\right)$$

$$S_t = (3342.388) + (10713.801)$$

$$S_t = 14056.189$$

$$S_t = 14057$$

Alternatively, in the same amount of time (14400 seconds), using the function $S_{300,25}$ technique would allow an Analyst to inspect X so many images, where:

$$14400 = \left(\frac{1}{4}X\,(60 + 8.212)\right) + \left(\frac{3}{4}X\,(60 + 12.883)\right)$$

$$14400 = 17.053X + 54.66225X$$

$$14400 = 71.71525X$$

$$200.79 = X$$

$$200 = X$$

Function $S_{300,25}$ would provide an average daily image increase of 4, per analyst, if it were adopted. This is an additional 1040 images yearly, per analyst. With 100 analysts, the total additional images analyzed yearly would be 104,000.

Utilizing the current technique, an analyst can process, on average, 50,960 images per year. With function $S_{300,25}$, this same analyst would process, 52,000 images.

An additional 104,000 images per year would not be possible even if 2 additional analysts were hired, using the current technique. With the function $S_{300,25}$ technique, ABC security can increase their productivity and remain within budget, without hiring additional analysts. This is a potential savings of more than $110,000.

4.2 Paying the Price

To this point we have yet to consider the cost of errors. It's reasonable to assume that the cost associated with errors is higher, in many cases, than the cost associated with doing things right the first time. Errors, especially unexpected errors, disrupt normal process, delay deliverables, inflict stress, and, ultimately, must be addressed; taking time and resources away from normal duties. Although many companies employ risk management programs, it is inevitable that mistakes happen, some much more costly than others.

Let's consider ABC Security once again. An error assessing a security threat can go one of two ways:

1. False Negative. No security threat is deemed to be present when, in fact, there is a threat.
2. False Positive. A security threat is deemed to be present when, in fact, there is no threat.

In the security sector, it is best to error on the side of caution. That is to say, false positives are desired over false negatives. False negatives can have serious consequences resulting not only in financial loss but, in extreme cases, loss of life.

In the focused study (Section 3.5), although there was no significant difference amongst the error rates of the functions, even slight, seemingly insignificant, differences can have a real financial impact in terms of errors.

As demonstrated in section 4.1, with no fading techniques, an analyst can process, on average, 50,960 images per year; where as, with fading technique $S_{300,25}$, an analyst can process, on average, 52,000 images.

Given the mean error rates as reported in Table 3.9, we can expect the following, approximate, number of errors to occur (based on the same 25% prevalence rate in section 4.1):

Function	**Total Images**	**Total Errors**	**False Negative**	**False Positive**
C_{100}	50,960	2981	1949	1032
$S_{300,25}$	52,000	2509	2080	429

Table 4.1: ABC Security Average Annual Errors.

If we consider X to be a single cost unit of a false negative and Y to be a single cost unit of a false positive, then we can assert that the error cost, or risk, R_C, of function C_{100} is:

$$R_C = 1949X + 1032Y \tag{4.2}$$

and the risk, R_S of function $S_{300,25}$ is:

$$R_S = 2080X + 429Y \tag{4.3}$$

Let's consider three different scenarios:

1. The cost of a false negative is equal to the cost of a false positive.

2. The cost of a false negative is less than the cost of a false positive.

3. The cost of a false negative is more than the cost of a false positive.

4.2.1 Scenario 1: False Negative = False Positive

In this scenario, we assume the cost associated with a false positive is equal to the cost associated with a false negative, e.g., 1:1.

$$R_C = 1949X + 1032Y \qquad R_S = 2080X + 429Y$$

$$R_C = 1949(1) + 1032(1) \qquad R_S = 2080(1) + 429(1)$$

$$R_C = 2981 \qquad R_S = 2509$$

Therefore, in this scenario, the risk is 472 cost units higher given function C_{100}. That is to say, the risk is higher with no fading technique given equal cost units for false positives and false negatives.

4.2.2 Scenario 2: False Negative < False Positive

In this scenario, we assume the cost associated with a false negative is less than the cost associated with a false positive. This could be one of any number of ratios, but let's examine a sample of 1:2, 1:10, and 1:100.

4.2.2.0.7 1:2

$$R_C = 1949X + 1032Y \qquad R_S = 2080X + 429Y$$

$$R_C = 1949(1) + 1032(2) \qquad R_S = 2080(1) + 429(2)$$

$$R_C = 4013 \qquad R_S = 2938$$

Therefore, in this scenario, the risk is 1075 cost units higher given function C_{100}. That is to say, the risk is higher with no fading technique given a cost ratio of 1:2.

4.2.2.0.8 1:10

$$R_C = 1949X + 1032Y \qquad R_S = 2080X + 429Y$$

$$R_C = 1949(1) + 1032(10) \qquad R_S = 2080(1) + 429(10)$$

$$R_C = 12269 \qquad R_S = 5899$$

Therefore, in this scenario, the risk is 5899 cost units higher given function C_{100}. That is to say, the risk is higher with no fading technique given a cost ratio of 1:10.

4.2.2.0.9 1:100

$$R_C = 1949X + 1032Y \qquad R_S = 2080X + 429Y$$

$$R_C = 1949(1) + 1032(100) \qquad R_S = 2080(1) + 429(100)$$

$$R_C = 105149 \qquad R_S = 60169$$

Therefore, in this scenario, the risk is 44980 cost units higher given function C_{100}. That is to say, the risk is higher with no fading technique given a cost ratio of 1:100.

4.2.3 Scenario 3: False Negative > False Positive

In this scenario, we assume the cost associated with a false negative is more than the cost associated with a false positive. This could be one of any number of ratios, but let's examine a sample of 2:1, 10:1, and 100:1.

4.2.3.0.10 2:1

$$R_C = 1949X + 1032Y \qquad R_S = 2080X + 429Y$$

$$R_C = 1949(2) + 1032(1) \qquad R_S = 2080(2) + 429(1)$$

$$R_C = 4930 \qquad R_S = 4589$$

Therefore, in this scenario, the risk is 341 cost units higher given function C_{100}. That is to say, the risk is higher with no fading technique given a cost ratio of 2:1.

4.2.3.0.11 10:1

$$R_C = 1949X + 1032Y \qquad R_S = 2080X + 429Y$$

$$R_C = 1949(10) + 1032(1) \qquad R_S = 2080(10) + 429(1)$$

$$R_C = 20522 \qquad R_S = 21229$$

Therefore, in this scenario, the risk is 707 cost units higher given function $S_{300,25}$. That is to say, the risk is higher with the fading technique given a cost ratio of 10:1.

4.2.3.0.12 100:1

$$R_C = 1949X + 1032Y \qquad R_S = 2080X + 429Y$$

$$R_C = 1949(100) + 1032(1) \qquad R_S = 2080(100) + 429(1)$$

$$R_C = 195932 \qquad R_S = 208429$$

Therefore, in this scenario, the risk is 12497 cost units higher given function $S_{300,25}$. That is to say, the risk is higher with the fading technique given a cost ratio of 100:1.

4.2.4 Summary

Although it is infinitely difficult to determine a uniform cost for a single error, or cost unit, the purpose of this analysis is to demonstrate that different techniques under different conditions can potentially yield much different risks. Depending on how ABC Security values false positives and false negatives, they can make an informed decision on which technique to employ.

As previously suggested, even slight, seemingly insignificant, differences can have a real financial impact in terms of errors. In the real world, one single mistake could have serious consequences on the bottom line.

Ultimately, this analysis is a driving force to create fading techniques that do provide significant reductions in errors. This would further justify the need for such techniques.

Chapter 5

Conclusions

5.1 Summary

We have presented a novel technique for reducing the number of distractors in a conjunctive visual search task, leading to an overall reduction in the inefficiency of the task; primarily the response time. This research progressed over three studies:

5.1.1 Study 0: Pilot Study

An informal pilot study with 4 participants was conducted. The purpose of the pilot study was to confirm the technical design, gain a basic understanding of the bounds of the parameters for the attentional fade functions, and gain a basic understanding of fatigue rates.

Technically, the design was deemed to be operational. In terms of function parameters it was observed that functions with lifetimes less than 0.5 seconds resulted in very high error rates and unsuccessful search terminations. Lifetimes around 1 second seemed to be most desirable, while lifetimes greater than 2 seconds were simply too long (e.g., target being found without fully engaging function).

All participants reported discomfort with functions that faded immediately compared to functions that initially remained constant, for a short period of time, before fading. All participants appeared to prefer step-linear fade functions compared to a linear equivalent with the same lifetime.

In terms of search volume, participants typically reported to be fatiguing around the the 10th consecutive search.

Upon completion of the pilot study, 10 attentional fade functions were developed: 2 constant, 4 linear, and 4 step-linear (see Section 3.4.1).

5.1.2 Study 1: Broad Study

A more systematic study of the 10 functions was conducted. We used a within-subjects, repeated measures, design with function and target presence as independent variables. A target prevalence rate of 50% was selected for this experiment. 10 participants volunteered for the study. The quantitative results of the study demonstrate that:

1. Participants will respond quicker with target present than with target absent
2. Participants will commit fewer errors with target absent than with target present.
3. Function does not have a significant effect on error rate.

Qualitatively, the results are mixed:

1. The majority of participants reported fade functions to be somewhat helpful, but at the same time, somewhat distracting.
2. Approximately 50% of participants reported fade functions to be helpful, overall, stating it helped them remember what they have already searched.
3. Step-linear functions were, on average, reported to be equal to, or less, stressful than linear functions, which were reported to be equal to, or less, stressful than the constant functions.

5.1.3 Study 2: Focused Study

A further, more focused, study of 3 functions was conducted. We used a within-subjects, repeated measures, design with function and target presence as independent variables. A target prevalence rate of 25% was selected for this experiment. 25 participants volunteered for the study. The quantitative results of the study demonstrate that:

1. Participants will respond quicker with target present than with target absent.
2. Participants will respond quicker with at least one fade function than with function C_{100}.
3. Participants will commit fewer errors with target absent than with target present.
4. Function does not have a significant effect on error rate.

Qualitatively, the results are mixed:

1. The majority of participants reported fade functions to be somewhat helpful, but at the same time, somewhat distracting.
2. Approximately 50% of participants reported fade functions to be helpful, overall - stating it helped them remember what they have already searched.
3. Step-linear functions were, on average, reported to be more stressful than linear functions, which were reported to be more stressful than the constant functions. The opposite pattern of the broad study.

5.2 Remarks

Visual search is an important part of everyday life and reducing inefficiencies in difficult visual search tasks is directly related to several key performance metrics, including, but not limited to quality of life and financial bottom line.

Our technique can provide significant reductions in response time of over 2 seconds for target-absent searches, while showing no significant difference in response time for target-present searches, all while having no significant effect on error rates. Although the pinnacle result would be an improvement in both response time and error rates, we believe this is a step in the right direction.

An exciting aspect of our novel approach is that it maintains the context of the visual stimulus (one gets to view objects in their natural positions) over a longer period of time when compared to related works. We also do not require any distortion or reconfiguration of the visual stimulus (other than fading in-place). Although our technique is novel, it is not mutually exclusive from related works and could potentially work in conjunction with such techniques.

The quantitative analysis is encouraging, but from a qualitative perspective, this research must be further refined. Many participants reported that the fading was distracting, yet, on average, their performance was better. There is room for improvement here, and we must make an effort to reduce the distractive nature of the technique. However, we also recognize that self-reports may lead to fleeting responses, and although a function may "feel" distracting, it could be inadvertently activating other processes by which one is kept more attentive and more engaged in the visual search.

5.2.1 Future Research

It would be very interesting to analyze the fade functions over many different target prevalence conditions. This is typically an important part of visual search analysis and must be conducted before any applicability of such techniques to real world problems.

There are many exciting avenues this research could take. If this research ever were to be integrated with real-world tasks, there would need to be complete object recognition support.

The ultimate goal of this research would be to provide a product that is highly adaptive and personalized. Much like one calibrates the eye tracker itself, one should be able to calibrate the adaptive visual search interface. One would be able to fine-tune the application to their search style and physiological capabilities. The technology could be completely non-intrusive and possibly worn as a pair of glasses. Fade parameters such as the initial constant, fade rate, and fade type could adapt to each specific user at a physchophysical level.

Long-term applications of such technology could be applied to 3-dimensional spaces, emersive virtual environments, and video-based application. Video gaming is also an interesting area of applicability.

Appendix A

General Survey

Question	**Available Answers**
What is your age?	1. 18 - 22 2. 23 - 27 3. 28 - 32 4. > 32
What is your gender?	1. Male 2. Female
Are you a full-time student?	1. Yes 2. No
How often, on average, do you use a computer each day?	1. < 1 hour 2. 1 - 5 hours 3. 6 - 10 hours 4. > 10 hours
Which operating systems do you use regularly?	1. Microsoft Windows 2. Mac OS X 3. Linux 4. Other
Do you play computer/video games?	1. Yes 2. No
How often do you play computer/video games, on average, each day?	1. < 1 hour 2. 1 - 5 hours 3. 6 - 10 hours 4. > 10 hours
What genre of computer/video games do you play?	1. Action 2. Shooter 3. Action-Adventure 4. Role-Playing 5. Simulation 6. Strategy 7. Sports 8. Other

What console/system do you use regularly?	1. Computer 2. Microsoft Xbox 3. Sony Playstation 4. Nintendo Wii 5. Apple iPhone/iPad 6. Other
Overall, did you find the fading of items to be helpful or distracting?	N/A
Overall, what did you like, if anything, about the fading of items?	N/A
Overall, what did you dislike, if anything, about the fading of items?	N/A
Overall, do you think you performed better or worse when items faded away?	N/A

Table A.1: General Survey.

Appendix B

Function Survey

Question	**Available Answers**
How helpful did you find the fading to be, in this case? [1]	1. Not helpful 2. 3. Somewhat helpful 4. 5. Very helpful
How distracting did you find the fading to be, in this case? [1]	1. Not distracting 2. 3. Somewhat distracting 4. 5. Very distracting
How stressful was this search task?	1. Not stressful 2. 3. Somewhat stressful 4. 5. Very stressful
How did you find the speed of the fading, in this case? [1]	1. Way too slow 2. 3. Just right 4. 5. Way too fast

Table B.1: Function Survey.

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[1] For functions that did not fade, this question was ignored

Appendix C

Broad Study Participant Data

Data is reported for each participant in the Broad Study. Where *Acc.* denotes accuracy, *Sen.* denotes sensitivity, and *Spe.* denotes specificity.

Participant 1

Gender: Male
Age Group: 23 - 27

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	7.67	18.37	1.00	1.00	1.00	2.76	0.00
C_{25}	11.29	13.47	0.70	0.60	0.80	0.88	0.23
$L_{200,0}$	9.67	11.09	0.80	0.60	1.00	1.59	0.58
$L_{200,25}$	6.82	11.45	0.90	0.80	1.00	2.05	0.35
$L_{300,0}$	5.18	10.50	0.90	0.80	1.00	2.05	0.35
$L_{300,25}$	6.31	9.83	0.90	1.00	0.80	2.05	-0.35
$S_{200,0}$	7.23	8.18	0.88	0.80	1.00	1.95	0.30
$S_{200,25}$	5.86	9.60	0.90	0.80	1.00	2.05	0.35
$S_{300,0}$	5.44	12.31	0.90	0.80	1.00	2.05	0.35
$S_{300,25}$	8.15	17.83	1.00	1.00	1.00	2.76	0.00

Table C.1: Broad Study Participant 1 Data.

Participant 2

Gender: Male
Age Group: > 32

	Mean Response Times		Performance Metrics				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	4.69	9.76	0.90	1.00	0.80	2.05	-0.35
C_{25}	7.88	14.37	1.00	1.00	1.00	2.66	0.05
$L_{200,0}$	4.39	12.44	1.00	1.00	1.00	2.76	0.00
$L_{200,25}$	7.99	10.49	0.88	0.80	1.00	1.95	0.30
$L_{300,0}$	3.54	10.97	1.00	1.00	1.00	2.76	0.00
$L_{300,25}$	8.39	12.04	0.80	0.60	1.00	1.59	0.58
$S_{200,0}$	3.74	12.30	0.90	0.80	1.00	2.05	0.35
$S_{200,25}$	4.95	10.91	1.00	1.00	1.00	2.76	0.00
$S_{300,0}$	6.37	11.31	0.90	0.80	1.00	2.05	0.35
$S_{300,25}$	6.62	10.38	1.00	1.00	1.00	2.76	0.00

Table C.2: Broad Study Participant 2 Data.

Participant 3

Gender: Female
Age Group: 23 - 27

	Mean Response Times		Performance Metrics				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	12.41	18.03	0.70	0.40	1.00	1.17	0.79
C_{25}	9.30	27.92	1.00	1.00	1.00	2.76	0.00
$L_{200,0}$	7.28	17.02	0.88	1.00	0.80	1.95	-0.30
$L_{200,25}$	8.63	22.20	1.00	1.00	1.00	2.66	0.05
$L_{300,0}$	10.33	20.37	0.90	0.80	1.00	2.05	0.35
$L_{300,25}$	14.95	13.42	0.62	0.40	1.00	0.93	0.68
$S_{200,0}$	5.81	14.34	0.88	0.75	1.00	1.90	0.42
$S_{200,25}$	9.38	14.16	0.90	0.80	1.00	2.05	0.35
$S_{300,0}$	7.73	15.43	0.90	0.80	1.00	2.05	0.35
$S_{300,25}$	5.66	13.74	1.00	1.00	1.00	2.56	0.00

Table C.3: Broad Study Participant 3 Data.

Participant 4

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	7.00	12.78	0.90	0.80	1.00	2.05	0.35
C_{25}	9.08	14.12	1.00	1.00	1.00	2.76	0.00
$L_{200,0}$	6.69	12.97	1.00	1.00	1.00	2.76	0.00
$L_{200,25}$	10.38	17.63	1.00	1.00	1.00	2.66	-0.05
$L_{300,0}$	7.62	14.54	1.00	1.00	1.00	2.76	0.00
$L_{300,25}$	10.67	14.45	0.90	0.80	1.00	2.05	0.35
$S_{200,0}$	5.66	11.31	1.00	1.00	1.00	2.66	-0.05
$S_{200,25}$	7.68	12.76	0.90	0.80	1.00	2.05	0.35
$S_{300,0}$	10.00	11.03	0.90	0.80	1.00	2.05	0.35
$S_{300,25}$	5.73	12.01	1.00	1.00	1.00	2.76	0.00

Table C.4: Broad Study Participant 4 Data.

Participant 5

Gender: Male
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	6.25	12.92	1.00	1.00	1.00	2.76	0.00
C_{25}	6.55	13.16	1.00	1.00	1.00	2.76	0.00
$L_{200,0}$	6.43	12.35	0.90	0.80	1.00	2.05	0.35
$L_{200,25}$	5.77	13.14	1.00	1.00	1.00	2.76	0.00
$L_{300,0}$	5.56	11.54	1.00	1.00	1.00	2.76	0.00
$L_{300,25}$	9.20	13.31	0.90	0.80	1.00	2.05	0.35
$S_{200,0}$	5.62	11.43	1.00	1.00	1.00	2.76	0.00
$S_{200,25}$	8.17	11.79	1.00	1.00	1.00	2.76	0.00
$S_{300,0}$	6.75	11.11	1.00	1.00	1.00	2.76	0.00
$S_{300,25}$	7.83	13.71	1.00	1.00	1.00	2.76	0.00

Table C.5: Broad Study Participant 5 Data.

Participant 6

Gender: Male
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	11.20	12.46	0.70	0.40	1.00	1.17	0.79
C_{25}	8.46	14.01	0.90	0.80	1.00	2.05	0.35
$L_{200,0}$	9.55	13.83	0.80	0.60	1.00	1.59	0.58
$L_{200,25}$	8.87	12.75	0.70	0.40	1.00	1.17	0.79
$L_{300,0}$	8.00	10.55	0.70	0.40	1.00	1.17	0.79
$L_{300,25}$	9.53	11.62	0.90	0.80	1.00	2.05	0.35
$S_{200,0}$	10.43	9.08	0.60	0.60	0.60	0.42	0.00
$S_{200,25}$	7.34	10.43	0.80	0.60	1.00	1.59	0.58
$S_{300,0}$	8.93	11.45	0.90	0.80	1.00	2.05	0.35
$S_{300,25}$	5.33	11.74	1.00	1.00	1.00	2.76	0.00

Table C.6: Broad Study Participant 6 Data.

Participant 7

Gender: Male
Age Group: 28 - 32

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	16.99	13.64	0.90	1.00	0.80	2.05	-0.35
C_{25}	11.10	22.28	0.90	0.80	1.00	2.05	0.35
$L_{200,0}$	9.85	14.95	0.88	0.80	1.00	1.95	0.30
$L_{200,25}$	10.31	21.01	1.00	1.00	1.00	2.76	0.00
$L_{300,0}$	12.42	17.22	0.80	0.60	1.00	1.59	0.58
$L_{300,25}$	8.51	12.42	0.90	1.00	0.80	2.05	-0.35
$S_{200,0}$	4.74	9.47	0.75	1.00	0.50	1.28	-0.64
$S_{200,25}$	7.96	10.99	0.66	0.80	0.50	0.67	-0.33
$S_{300,0}$	7.21	14.08	1.00	1.00	1.00	2.76	0.00
$S_{300,25}$	11.14	17.43	1.00	1.00	1.00	2.76	0.00

Table C.7: Broad Study Participant 7 Data.

Participant 8

Gender: Male
Age Group: 23 - 27

	Mean Response Times		Performance Metrics				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	6.50	12.35	0.80	0.60	1.00	1.59	0.58
C_{25}	8.70	11.95	0.90	1.00	0.80	2.05	-0.35
$L_{200,0}$	5.63	10.67	1.00	1.00	1.00	2.76	0.00
$L_{200,25}$	5.10	10.29	0.90	0.80	1.00	2.05	0.35
$L_{300,0}$	6.02	9.83	1.00	1.00	1.00	2.76	0.00
$L_{300,25}$	6.94	10.93	1.00	1.00	1.00	2.76	0.00
$S_{200,0}$	6.20	9.64	0.80	0.60	1.00	1.59	0.58
$S_{200,25}$	7.51	8.13	0.70	0.60	0.80	0.88	0.23
$S_{300,0}$	5.43	10.47	1.00	1.00	1.00	2.76	0.00
$S_{300,25}$	7.83	11.44	0.90	0.80	1.00	2.05	0.35

Table C.8: Broad Study Participant 8 Data.

Participant 9

Gender: Female
Age Group: 23 - 27

	Mean Response Times		Performance Metrics				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	5.13	10.40	1.00	1.00	1.00	2.76	0.00
C_{25}	4.00	10.79	1.00	1.00	1.00	2.76	0.00
$L_{200,0}$	4.92	9.56	0.90	0.80	1.00	2.05	0.35
$L_{200,25}$	5.60	9.68	1.00	1.00	1.00	2.76	0.00
$L_{300,0}$	8.11	10.53	0.70	0.40	1.00	1.17	0.79
$L_{300,25}$	3.95	10.00	1.00	1.00	1.00	2.76	0.00
$S_{200,0}$	6.15	8.27	1.00	1.00	1.00	2.76	0.00
$S_{200,25}$	4.42	9.31	1.00	1.00	1.00	2.76	0.00
$S_{300,0}$	8.35	13.29	1.00	1.00	1.00	2.76	0.00
$S_{300,25}$	6.34	10.90	1.00	1.00	1.00	2.76	0.00

Table C.9: Broad Study Participant 9 Data.

Participant 10

Gender: Male
Age Group: 23 - 27

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	6.00	17.67	1.00	1.00	1.00	2.76	0.00
C_{25}	7.58	15.69	1.00	1.00	1.00	2.76	0.00
$L_{200,0}$	9.65	14.65	0.90	0.80	1.00	2.05	0.35
$L_{200,25}$	6.74	14.15	0.90	0.80	1.00	2.05	0.35
$L_{300,0}$	5.48	12.71	1.00	1.00	1.00	2.76	0.00
$L_{300,25}$	4.06	13.13	1.00	1.00	1.00	2.76	0.00
$S_{200,0}$	9.78	14.36	0.80	0.60	1.00	1.59	0.58
$S_{200,25}$	5.83	14.10	1.00	1.00	1.00	2.76	0.00
$S_{300,0}$	8.92	14.13	0.90	0.80	1.00	2.05	0.35
$S_{300,25}$	8.51	17.92	1.00	1.00	1.00	2.66	-0.05

Table C.10: Broad Study Participant 10 Data.

Appendix D

Focused Study Participant Data

Data is reported for each participant in the Focused Study. Where *Acc.* denotes accuracy, *Sen.* denotes sensitivity, and *Spe.* denotes specificity.

Participant 1

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	8.30	13.65	1.00	1.00	1.00	3.01	0.22
$L_{300,0}$	9.25	14.93	1.00	1.00	1.00	3.05	0.24
$S_{300,25}$	11.50	12.77	1.00	1.00	1.00	3.05	0.24

Table D.1: Focused Study Participant 1 Data.

Participant 2

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	8.78	25.92	1.00	1.00	1.00	2.91	0.30
$L_{300,0}$	13.67	15.67	0.93	0.75	1.00	2.29	0.62
$S_{300,25}$	8.00	17.98	0.92	1.00	0.88	2.31	-0.12

Table D.2: Focused Study Participant 2 Data.

Participant 3

Gender: Male
Age Group: 23 - 27

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	9.46	9.24	0.75	0.5	0.83	0.86	0.43
$L_{300,0}$	4.97	11.86	0.75	0.75	0.75	1.213	0.04
$S_{300,25}$	6.47	9.83	0.93	0.75	1.00	2.29	0.62

Table D.3: Focused Study Participant 3 Data.

Participant 4

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	8.07	15.9	1.00	1.00	1.00	3.05	0.24
$L_{300,0}$	10.46	20.69	1.00	1.00	1.00	3.01	0.22
$S_{300,25}$	8.83	16.02	0.93	0.75	1.00	2.29	0.62

Table D.4: Focused Study Participant 4 Data.

Participant 5

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	9.38	25.52	1.00	1.00	1.00	3.01	0.22
$L_{300,0}$	11.55	17.47	1.00	1.00	1.00	3.05	0.24
$S_{300,25}$	8.58	15.22	1.00	1.00	1.00	3.05	0.24

Table D.5: Focused Study Participant 5 Data.

Participant 6

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	6.01	7.17	0.81	0.25	1.00	1.24	1.14
$L_{300,0}$	5.28	7.36	0.87	0.50	1.00	1.76	0.88
$S_{300,25}$	7.31	7.79	0.87	0.50	1.00	1.76	0.88

Table D.6: Focused Study Participant 6 Data.

Participant 7

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	10.21	12.98	0.75	0.75	0.75	1.13	0.04
$L_{300,0}$	6.67	11.25	0.93	1.00	0.91	2.47	-0.04
$S_{300,25}$	6.62	10.66	1.00	1.00	1.00	3.05	0.24

Table D.7: Focused Study Participant 7 Data.

Participant 8

Gender: Male
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	10.02	14.31	1.00	1.00	1.00	3.05	0.24
$L_{300,0}$	7.60	13.28	1.00	1.00	1.00	3.05	0.24
$S_{300,25}$	2.02	13.63	1.00	1.00	1.00	3.05	0.24

Table D.8: Focused Study Participant 8 Data.

Participant 9

Gender: Male
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	5.10	12.97	1.00	1.00	1.00	3.05	0.24
$L_{300,0}$	5.44	11.65	1.00	1.00	1.00	3.05	0.24
$S_{300,25}$	8.12	12.38	0.93	1.00	0.91	2.47	-0.04

Table D.9: Focused Study Participant 9 Data.

Participant 10

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	12.29	23.09	0.93	0.75	1.00	2.29	0.62
$L_{300,0}$	8.09	18.32	1.00	1.00	1.00	3.05	0.24
$S_{300,25}$	9.08	18.22	1.00	1.00	1.00	3.05	0.24

Table D.10: Focused Study Participant 10 Data.

Participant 11

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	16.46	23.04	1.00	1.00	1.00	3.01	0.22
$L_{300,0}$	19.71	21.23	0.83	0.33	1.00	1.32	0.98
$S_{300,25}$	6.05	20.87	1.00	1.00	1.00	2.88	0.29

Table D.11: Focused Study Participant 11 Data.

Participant 12

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	10.56	21.17	0.92	0.66	1.00	2.05	0.70
$L_{300,0}$	14.68	16.26	0.87	0.50	1.00	1.76	0.88
$S_{300,25}$	10.13	18.98	1.00	1.00	1.00	3.01	0.22

Table D.12: Focused Study Participant 12 Data.

Participant 13

Gender: Male
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	8.63	15.75	0.93	0.75	1.00	2.29	0.62
$L_{300,0}$	8.85	9.19	0.81	0.25	1.00	1.24	1.14
$S_{300,25}$	8.21	9.81	0.87	0.50	1.00	1.76	0.88

Table D.13: Focused Study Participant 13 Data.

Participant 14

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	9.48	17.37	0.93	0.75	1.00	2.29	0.62
$L_{300,0}$	10.79	14.96	0.93	0.75	1.00	2.29	0.62
$S_{300,25}$	5.06	14.69	1.00	1.00	1.00	3.05	0.24

Table D.14: Focused Study Participant 14 Data.

Participant 15

Gender: Female
Age Group: 23 - 27

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	6.51	7.53	0.93	0.75	1.00	2.29	0.62
$L_{300,0}$	5.37	6.96	0.62	0.25	0.75	0.09	0.56
$S_{300,25}$	6.14	7.44	0.87	0.50	1.00	1.76	0.88

Table D.15: Focused Study Participant 15 Data.

Participant 16

Gender: Male
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	9.16	15.50	1.00	1.00	1.00	3.05	0.24
$L_{300,0}$	6.40	12.54	1.00	1.00	1.00	3.05	0.24
$S_{300,25}$	6.33	12.97	1.00	1.00	1.00	3.05	0.24

Table D.16: Focused Study Participant 16 Data.

Participant 17

Gender: Male
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	6.77	20.37	0.93	1.00	0.91	2.47	-0.04
$L_{300,0}$	9.95	15.16	0.87	0.75	0.91	1.72	0.33
$S_{300,25}$	9.34	14.35	1.00	1.00	1.00	3.05	0.24

Table D.17: Focused Study Participant 17 Data.

Participant 18

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	3.91	10.27	1.00	1.00	1.00	3.05	0.24
$L_{300,0}$	8.27	11.23	0.93	0.75	1.00	2.29	0.62
$S_{300,25}$	7.03	9.77	1.00	1.00	1.00	3.05	0.24

Table D.18: Focused Study Participant 18 Data.

Participant 19

Gender: Male
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	6.35	10.13	0.93	0.75	1.00	2.29	0.62
$L_{300,0}$	7.12	10.96	0.87	0.50	1.00	1.76	0.88
$S_{300,25}$	6.37	9.50	0.87	0.50	1.00	1.76	0.88

Table D.19: Focused Study Participant 19 Data.

Participant 20

Gender: Female
Age Group: 23 - 27

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	4.96	12.99	1.00	1.00	1.00	3.05	0.24
$L_{300,0}$	6.34	12.41	1.00	1.00	1.00	3.05	0.24
$S_{300,25}$	6.19	13.21	1.00	1.00	1.00	3.05	0.24

Table D.20: Focused Study Participant 20 Data.

Participant 21

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	5.71	9.14	0.93	0.75	1.00	2.29	0.62
$L_{300,0}$	6.15	10.35	1.00	1.00	1.00	3.05	0.24
$S_{300,25}$	5.69	10.36	0.93	0.75	1.00	2.29	0.62

Table D.21: Focused Study Participant 21 Data.

Participant 22

Gender: Female
Age Group: 23 - 27

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	9.16	10.78	1.00	1.00	1.00	3.05	0.24
$L_{300,0}$	5.21	11.41	1.00	1.00	1.00	3.05	0.24
$S_{300,25}$	5.93	12.42	1.00	1.00	1.00	3.05	0.24

Table D.22: Focused Study Participant 22 Data.

Participant 23

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	6.73	15.10	1.00	1.00	1.00	3.05	0.24
$L_{300,0}$	11.45	11.16	0.87	0.50	1.00	1.76	0.88
$S_{300,25}$	5.02	12.60	0.93	0.75	1.00	2.29	0.62

Table D.23: Focused Study Participant 23 Data.

Participant 24

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	5.68	11.58	1.00	1.00	1.00	3.05	0.24
$L_{300,0}$	6.35	11.61	1.00	1.00	1.00	3.01	0.22
$S_{300,25}$	9.12	11.51	0.87	0.50	1.00	1.76	0.88

Table D.24: Focused Study Participant 24 Data.

Participant 25

Gender: Female
Age Group: 18 - 22

	Mean Response Times		**Performance Metrics**				
Function	**Present**	**Absent**	**Acc.**	**Sen.**	**Spe.**	d'	c
C_{100}	7.47	12.01	1.00	1.00	1.00	3.05	0.24
$L_{300,0}$	8.36	10.73	0.93	0.75	1.00	2.29	0.62
$S_{300,25}$	5.72	8.97	0.87	0.50	1.00	1.76	0.88

Table D.25: Focused Study Participant 25 Data.

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