Visual Search of Displays of Many Objects: Modeling Detailed Eye Movement Effects with Improved EPIC

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Abstract

This paper describes a new set of results on visual search of displays of 75 objects that differ in size, shape, and color, and presents a cognitive architecture model based on the active vision concept that accounts for the effects using object eccentricity and size effects, noisy saccades, and fixation memory provided by a persistent visual store. The data confirm older, less complete studies of this task. The model is a significant refinement of earlier visual search models and preliminary fits show that it promises to provide an integrated architectural account of these effects.

Keywords: cognitive architecture, visual search; cognitive modeling; eye movements

Introduction

Many everyday and work activities involve visual search, the process of visually scanning or inspecting the environment to locate an object of interest that will then be the target of further activity. An especially tractable form of visual search takes place in many human-computer interaction tasks in which a particular icon coded by color, shape, and other attributes must be located on a screen and then clicked on using a mouse. Such visual search takes place in a visual environment that is much simpler than natural scenes, and so is a both a good theoretical and practical domain to model visual search processes. It combines relative simplicity of the visual characteristics of the searched-for objects with practical relevance. The task is a natural one in the sense that such activities are very common in current technology; an example is current radar displays in military applications, which can contain a large number of icons and other objects (cf. Kieras & Marshall, 2006). Thus understanding in detail how visual search works in such domains can lead to better system designs.

Kieras (2010) presented a model for the results of a classic study by Williams (1967), who using early film-based eye tracking methodology, explored the visual search of large and dense displays of many items that can be searched by multiple attributes. He manipulated the size of the objects along with their color and shape, an unusual combination in the visual search literature. Kieras and Hornof (2014) showed how the model could be used in a simpler form applicable to interface design problems. But some key issues in the model could not be addressed because Williams reported only a small subset of the potential data, and essentially no characteristics of the eye movements themselves.

What's new. New eye movement data was collected in a Williams-like task that includes the complete eye movement trajectory and precise search completion times. This allows analysis of additional effects, such as those of object size, saccade distance, the characteristics of fixated objects that do not match the search cues, refixation effects, and so forth - far beyond what is possible with the Williams (1967) data.

The EPIC architecture was improved in two significant ways: First, the acuity functions that describe whether an object property can be detected as a function of object eccentricity and size were given the same form as psychophysical functions resulting from an especially relevant class of experiment. Second, EPIC's eye movement mechanism has been completely accurate - if the cognitive processor issued an instruction to fixate a certain object, the eyes always moved exactly to that object. However, there is abundant literature that eye movements to a target normally fall short and have variability linear with the distance. EPIC models would thus be more efficient than humans, meaning that to match human data, other parameters might have to be distorted from their realistic values. Thus, EPIC's oculomotor processor now makes "noisy" eye movements. To compensate, the visual search strategy has to be adapted to complete the task in spite of the unreliability of fixations.

Thus despite the superficial similarity of this work to the earlier, there are new challenges in the modeling. The work reported here is preliminary - there is much new ground to explore. First the experiment will be presented, followed by the architectural changes and the current modeling results.

The Visual Search Experiment

The task was to locate a target object in a field of seventy-five distractor objects. Each object on the display had a unique two-digit number and a unique combination of color, size, and shape. Participants were precued with the number of the target, and some combination of the target's color, size, and shape.

Twenty-four participants were recruited from the

University of Oregon campus community. Two were excluded because the eye tracker could not be calibrated to them. All had normal or corrected-to-normal vision. Participants received a base payment of $10 plus a bonus (ranging from $5 to $8) based on their speed and accuracy.

Search fields were presented on the central 1600 x 1200 portion of a color-calibrated Dell 2407WFP 24-inch monitor connected to a 3.06 GHz Intel Core 2 Duo Macbook Pro running Mac OS 10.8. The data collection software was written in C++, Objective-C, and Cocoa. Eye movement data were collected using a binocular 120 Hz LC Technologies Eyegaze tracker after a nine-point calibration. The monitor was positioned 60 cm from the participant.

Each participant was presented with ninety-six search fields, each with seventy-five randomly arranged objects. Figure 1 shows one of the search fields. Each search field was preceded by the presentation of a precue that described the target in text and included the target's two-digit number and, depending on the condition, some combination of the the target's color, size, and shape. Because each precue could include any combination of the three features, including none, there were a total of eight possible precue types. Each combination was used in twelve trials, resulting in the ninety-six trials per subject.

Search fields contained seventy-five objects on a 67% gray background that subtended 39° by 30° of visual angle. Each object had a unique combination of color, size, and shape. Colors were blue, green, yellow, red, and purple. Sizes were small (0.8º), medium (1.6º), and large (2.8º), measured as the diameter of the circular object of that size, with other shapes normalized to the same area. Shapes were circles, semi-circles, squares, equilateral triangles, and crosses. Each object had a one-pixel black border.

The seventy-five unique objects were randomly distributed across the search field with at least one degree of visual angle between adjacent objects. A unique two-digit number from 01 to 75 appeared in the center of each object with a height of 0.26° (10 pixels). The precue appeared in the center of the display in the same typeface, with each feature listed on a separate line. Participants started each trial by clicking on an XX above the target description.

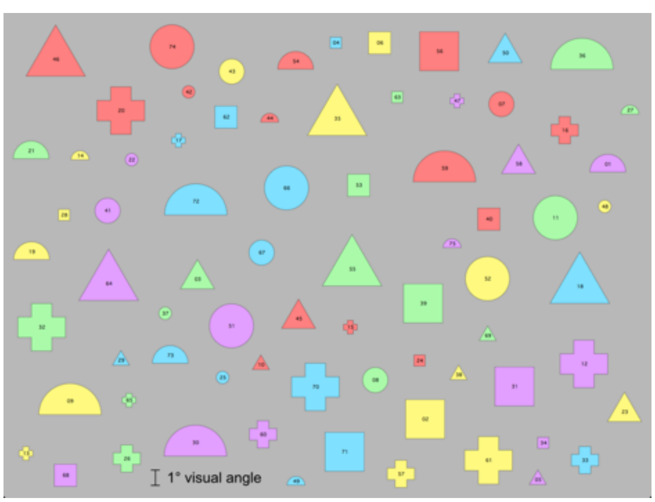

Figure 1. A sample search field used in the experiment.

Each successful trial proceeded as follows: (1) The precue appeared in the center of the display. (2) The participant moved the mouse and clicked on the XX. (3) The precue disappeared and the search field appeared. (4) The participant found the target. (5) The participant moved the mouse and clicked on the number in the target.

Participants were constrained to not move the mouse until they found the target by using a point-completion deadline (Hornof, 2001). Participants practiced until they were comfortable with the deadline.

Participants were rewarded for successful trials with a pleasant 170 ms "cha-ching" sound and penalized for error trials with a 350 ms buzzer. Participants were also financially rewarded. Each trial started with a bonus of five, twelve, or twenty-one cents, depending on the difficulty of the condition (for example, color was easiest) and the bonus diminished at a rate of 0.4, 0.3, or 0.15 cents per second until the participant clicked on the target (stopping at zero, and with faster rates for easier conditions). Errors resulted in no bonus plus a five-cent penalty. Accumulated bonuses were reported to the participants every twenty-four blocks.

Results

The fixations were identified using a dispersion-based algorithm with a maximum dispersion window size of 0.7º and a minimum fixation duration of 60 ms. The error in the eye tracking data was reduced using the method of required fixations, as described in Zhang & Hornof (2014), yielding a series of fixations for each trial by each subject, for a total of about 64 thousand fixations.

In each trial first, last, and any offscreen (and subsequent) fixations were discarded. Then the apparent target of each fixation was designated as the object on the display whose center was closest to the point of fixation; these were considered to be the fixated objects. Then the proportion of fixations in which the properties of the fixated object matched the cue properties were calculated. Similar calculations were made for other statistics, such as the *saccade distance* - the difference between the current and previous fixation. These statistics were accumulated for each subject in each condition, and means computed for each condition.

In all of the graphs shown here, the observed mean values are plotted with solid bars, and the predicted with open bars. Observed values are shown with 95% confidence intervals for the mean based on the values averaged over subjects.

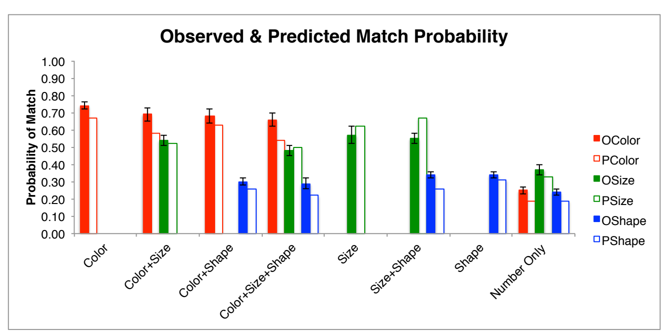

Figure 2. Proportion of fixations that match the cued properties.

The observed values will be discussed first; the predicted later in the context of the model presentation.

First, the results were consistent with those reported by Williams(1967). Figure 2 shows the proportion of fixations on objects that matched the cued properties. E.g., if the color was the only specified cue, about 74% of the fixations were on objects with the specified color. The color cue produces the highest proportion of matches, followed by object size, whereas object shape produces the lowest proportion of matches. The Number Only condition is shown for comparison; here a "match" just corresponds to whether the fixated object has the same property as the target object; the fact that the proportion of matches corresponds to their distribution in the display (five colors and shapes, three sizes) means that these fixations were basically random with regard to the color, size, or shape of the object.

These results replicate the Williams results quite well, showing that color is the most effective cue in guiding visual search, and shape is the least. But size appears to be more effective in these data compared to Williams, being similar to color, perhaps because there were only three different sizes, rather than four as in Williams that may have been difficult to discriminate.

To further compare with Williams (1967), Figure 3 shows the number of fixations required to complete the task for each cue type. The color cue requires the fewest fixations, followed by size, then shape, with the Number Only cue requiring the most. These effects also basically replicate the Williams results, but are more precise due to better eye tracking methodology.

A new effect in these data concerns the saccade distance. If a cue is more effective than another in guiding visual search, the corresponding property of an object should be visible at a greater eccentricity, meaning that saccades should be longer on the average for more effective cues. Figure 4 shows this effect; color cues produce the longest saccades, followed by size, then shape, then Number Only. The effect is fairly small, but reliable, as shown by the overlap relations of the confidence intervals. The small size of the effect could be due to averaging over both matching and mismatching objects in the effective cue conditions.

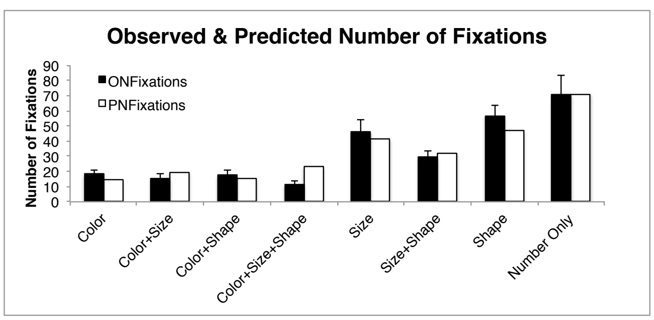

Figure 3. Mean number of fixations required to complete a trial.

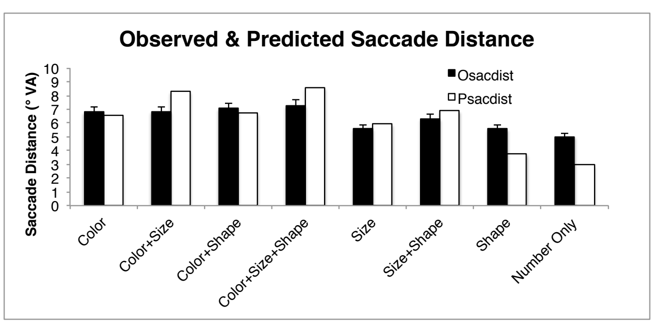

Figure 4. Mean saccade distance from the previous fixation to the fixated object.

Discussion

Visual Search and Active Vision

The empirical literature on visual search was dominated for a long time by studies that ruled out eye movements. But tasks in which the eye is free to move about a static display is more representative of the normal operation of the visual system and the role of attention in visual activity. This point was argued eloquently by Findlay & Gilchrist (2003) in presenting an *active vision* framework for understanding visual activity.

In active vision, a key process is choosing the next object for inspection. A variety of studies (see Findlay & Gilchrist, 2003, for a review) have shown that properties such as the color, shape, size, or orientation influences which object is chosen for the next fixation; the phenomenon is called *visual guidance*. These properties are available to some extent in extra-foveal or peripheral vision, meaning that visual attention, which is almost synonymous with where the eye is fixated, involves using extra-foveal information to select for detailed examination one of the objects currently perceived in the visual scene.

The importance of color in visual search is consistent with many results ranging from classic human factors studies (e.g. Sanders & McCormick, 1987). But in the active vision framework, color is not specially privileged in some way, but rather, various direct measurements show that the color of an object is visible over a wide range of eccentricity and object sizes (e.g. Gordon & Abramov, 1977), and so can often serve as an effective cue about where to look next. The relative ineffectiveness of shape is likewise not due to a fundamental problem with shape, but rather that in many cases, recognizing the shape requires resolving detailed features that can only be seen close to the fovea. As an extreme of shape recognition, recognizing the text label can require foveal vision.

Saccade accuracy

A general property of these data was that there are many fixations that appear to be between objects. The average distance between the fixation point and the center of the closest object averaged 0.99° and was similar across cue conditions. This inaccuracy could have three causes: (1) a deliberate strategy to collect information over a wider area than a precise fixation would allow, which seems unlikely given the density of the display; (2) measurement error, even after applying our error correction technique; (3) error and noise in the oculomotor system – saccades tend to fall short of the intended target and display some variability as well. In these data, there is no strong tendency for in-between fixations to be followed by a short corrective saccade to precisely fixate an object. Rather, it seems likely that depending on the extent of extra-foveal vision, the eye can collect enough information at the "missed" fixation point that a person can usually correctly decide if an object in the vicinity is the target, and fixate another object if not.

Repeat fixations and memory failures

One overall feature of these results is that many more fixations are required than should be necessary if each object only received one fixation; for example, it should require no more than 37.5 fixations on average in the Number-Only condition to find the labeled object, but about 71 are performed. The data shows that 33% of the fixations are on a previously fixated object in this condition; in contrast, the four color-cue conditions have a lower repeat rate of 21%.

In contrast, some observations and modeling of repeat fixations (Peterson et al. 2001, Kieras & Marshall, 2006, Kieras, 2009, 2010) suggests that repeat fixations are relatively rare, around 5%, implying a good memory for previous fixations, and almost all are performed immediately, being due to recognition (encoding) failures rather than failures of the memory for previous fixations.

However, in these data, immediate repeats average about 14% with little variation between cue conditions, and the average lag between repeat fixations is about 2.4 in the color cue conditions, and much higher at 12.5 in the Number-Only condition (lag = 0 is an immediate refixation). So perhaps repeat fixations in these data are due to both factors: there are some encoding failures leading to immediate or almost immediate fixations, and some memory failures, especially in the conditions that take much longer.

The EPIC Cognitive Architecture

The EPIC architecture for human cognition and performance directly supports an active vision approach to visual search and provides a general framework for simulating a human interacting with an environment to accomplish a task. The reader is referred to Meyer & Kieras (1997) or Kieras (in press), for a more complete description of EPIC; here is only the necessary minimum description.

In the EPIC architecture, the *eye processor* contains *acuity functions* that specify whether each visual property of each object is currently visible as a function of the size of the object and its eccentricity. The currently available visual properties for each object are represented in the *sensory store*; the *perceptual processor* then encodes the properties of each object, possibly in relation to other objects, and passes the encoded representation on to the *perceptual store* where they are available to the cognitive processor to match the conditions of production rules. The perceptual store contains the current representation of the visual world that cognition can reason and make decisions about, including decisions about where to move the eyes next by commanding the *ocular motor processor*.

When the eyes move away from an object, the properties of the object persist for a short time (e.g. 200 ms) in the sensory store, and when lost, the perceptual processor notes that the corresponding property in the perceptual store no longer has sensory support. After a relatively long time, the property will then be lost from the perceptual store. But if the object disappears completely, it and all of its properties will be removed from the perceptual store fairly quickly. The notion that the representation persists for a considerable time as long as the scene is present is supported by studies summarized by Henderson & Castelhano (2005); memory for previously fixated objects was assessed in natural visual scenes, and retention times of at least several seconds were observed. Since this form of memory has not been studied extensively, its properties and duration must be chosen to fit the modeled data.

Model for the Search Task

The model is an instantiation of the active vision concept; constructing it requires a choice of (1) visual acuity functions and parameters, (2) a model of the "noise" in the eye movements, (3) a parameter for the persistence time of visual properties in the perceptual store that are no longer sensorily supported, and (4) a set of production rules that implement the visual search strategy. Each of these will be described, with emphasis on the new features in this work.

New acuity functions

The availability of a perceptual property in extra-foveal vision depends heavily on the *eccentricity* (the distance in degrees of visual angle from the center of gaze) of the object, normally referred to in degrees of visual angle, and on the *size* of the object (also measured in degrees of visual angle), and on the specific property involved. Despite the many decades of research on vision, the literature does not contain a comprehensive set of parametric data on acuity for different visual properties as a function of their eccentricity and size, especially for the density and properties typical of computer displays. Space limitations do not allow a review of the available data (see Findlay & Gilchrist, 2003).

Previously, EPIC used simple forms of acuity functions that were adequate to fit the limited data such as Williams(1967). The new work here was to anchor the acuity functions closer to the available psychophysical data. Of special interest are studies of "cortical magnification" which is based on the reasoning that a constant amount of visual cortex (presumably supporting a certain number of receptive fields) are required for performing discrimination at a certain level, and since anatomically, the density of cortical representation declines with distance from the fovea, the size of the stimulus must increase to involve the same amount of cortex. Such functions have been measured in psychophysical experiments; a typical result (e.g. Virsu & Rovamo, 1979) is that to maintain discriminability, the size of the object must increase as a cubic function of eccentricity; the required size increases linearly for a moderate eccentricity, and then quite sharply in the further periphery. A cubic function with a moderate linear coefficient, a zero quadratic coefficient and a very small cubic coefficient provides a good fit.Visual search studies such as Carrasco & Frieder (1996) show that if object size is constant, then targets at greater eccentricity are located more slowly, whereas if peripheral objects are magnified in size according to the measured functions, search time becomes flat with eccentricity. However, it appears that magnification functions measured for individual objects greatly overestimate the acuity for objects in dense visual fields (e.g. see discussion in Anstis, 1974). To measure acuity in dense displays would be very difficult, and the literature does not contain useful parametric studies.

To deal with this non-definitive picture, a simple family of acuity functions are proposed, and their parameters determined by a combination of general constraints set by the literature and iterative maximization of fit in the models. A separate function was specified for each property: color, encoded size (small, medium, large), shape, and text label. The acuity function is a Gaussian detection function that gives the probability that the property will be detected (be available) for an object with size s at eccentricity e:

$$P(detection) = P(s > N(\mu, \sigma))$$

$$\mu = a + be + ce^2 + de^3,\ \sigma = a\ constant$$

The form for μ (which can be interpreted as the 50% threshold for object size) reflects the commonly fitted form of cortical magnification functions. The value of σ governs the steepness of the ogival detection function; smaller values of σ make it look more like an all-or-none threshold-like process.

In the preliminary predicted results presented here, the acuity parameters were determined by informal iterative fitting. The a term was held at 0.05, b was estimated as 0.2 for color, size, and shape, and 0.1 for text, c was held at 0, d was 0.0004 for color and size, .025 for shape, .05 for text, and σ was 0.5 for color, size, and shape, and 1.0 for text.

The availability for each property is independently resampled for all objects whenever the eye is moved. As the eye moves around, the available properties of the same object can fluctuate, and will not be reliably available from one fixation to the next. However, the information, once acquired, will remain for some time in the perceptual store.

New model of saccade accuracy

A variety of studies (see Harris, 1995 for a review) have shown that saccades tend to fall short of the actual fixation target, and the standard deviation of the saccade distance tends to be proportional to the distance. Following Harris (1995), the new oculomotor processor samples the distance for a saccade to an object at eccentricity e from a Gaussian distribution:

$$saccade\ length = N(\mu, \sigma)$$

$$\mu = g \cdot e,\ \sigma = s \cdot \mu$$

Typical values for g (gain) range from 0.85 - 0.95, and s (spread) is typically around 10%. The current preliminary fits use the values suggested by Harris as optimal, namely g=0.95, s=10%. Unlike previous EPIC models, this model thus often misses the object to be fixated, which decreases the probability that (e.g.) its text label will be available, meaning that the task strategy must either attempt to fixate the object again, or choose a entirely different object to fixate. On the other hand, if the acuity functions are such that most fixations are close enough, there may be little effect of inaccurate saccades.

Fixation memory

As summarized in the task strategy below, memory for previous fixations was implemented by only choosing objects to fixate whose relevant properties are currently unknown, either because the object was never fixated, its properties were not detected, or it was fixated a long time ago but the properties have been lost from the perceptual store. As mentioned below, the duration of properties of visible objects in perceptual store interacts with the acuity functions and model strategy in predicting the properties of repeat fixations. For the model predictions presented here, this duration was set at 15 s.

New task strategy

The visual search strategy in the model is a new variation of a basic strategy that has been used in several EPIC visual search models. There are now three concurrent threads of execution. In the first thread, *nomination rules* now continuously propose objects to fixate whose available visual properties match the cued properties. In the second thread, *choice rules* pick a single candidate from the nominated objects according to a priority scheme, and launch an eye movement to the chosen candidate. The priority scheme favors the more widely available attributes, and so chooses an object with a matching color over one with a matching size over one with a matching shape. If there are no nominations, a “guessed” object is chosen whose cued properties are currently unknown. Objects are only nominated or chosen if their text label property is currently unknown, which serves as a memory for fixations, and if more than one object qualifies, the closest one is chosen. The *response rules* in the third thread wait for the eye movement to the candidate to be complete and either click on the object if its text label matches the target label, or discard it if not, which enables the next choice of object to fixate. If the text label is not available (e.g. the saccade may have fallen short) the strategy waits for up to three additional cycles and then nominates the object for the next eye movement, which takes priority.

Model Results

Using the parameter values and task strategy described above, the model was run using the actual set of stimuli used in the experiment, which consisted of 2112 combinations of cue condition, search fields, and target object within that search field, with 4 repetitions of these stimuli, giving 1056 trials in each experimental condition, and the simulated eye movement and response time data were collected. These fits are preliminary, but encouraging; further work is in progress.

Figures 2-4 above show the observed and predicted statistics in each condition. As a summary measure of the goodness of fit of predicted to observed, r^2=0.89 for the proportions of matching fixations in Figure 2; r^2=0.92 for the number of fixations in Figure 3, and r^2=0.79 for the saccade distances in Figure 4, where it is clear that the distances for the weak cues of Shape and Number-Only are seriously under-predicted. In results not shown graphically, the predicted RTs are well correlated with the observed (r^2=0.92), but the model over-predicts them substantially, probably due to suboptimal methods for disqualifying a fixated object. Most seriously, the overall predicted repeat rates are too high (41 vs 25% in the observed data), especially in the weak cue conditions; increasing the property decay time from 15 s to 20 s or more improves the fit, but then the number of fixations is under-predicted in the weak cue conditions.

Guided versus unguided fixation choices

An insight from this preliminary modeling work is that there are basically two kinds of fixation choices: a guided fixation when the object matches a cue, and an unguided fixation when there is no candidate that has a matching cue property. While unguided fixations dominate the Number-Only condition, they clearly play a role in the other cue conditions, because fixations to non-matching objects make up a quarter or more of the fixations in these conditions.

For unguided fixations, the model strategy must choose a next object on some basis; if this strategy is incorrect, then all of the summary statistics for a cue condition will be mis-predicted. Several strategies have been explored, but no clear winner is yet evident - for example, choosing a qualified candidate at random, rather than the closest, produces a different pattern of mis-predictions in the weak cue conditions. The next steps in this work will separate fixations on matching objects from non-matching, which should help characterize guided versus unguided fixation choice strategies.

Conclusion

This model represents a realization of the active vision concept in terms of a computational cognitive architecture whose components incorporate noisy saccades, size and eccentricity effects in perception, and a persistent visual perceptual store that represents the current visual situation and provides a memory for previous fixations. The task strategy implements visual guidance by using the supplied target properties and the information in the visual perceptual store to choose the next object to fixate. The adequacy of the architecture, and a deeper understanding of the functional properties of the visual system, will emerge as the model is developed to more closely account for the eye movement data.

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