Using Model Tracing and Evolutionary Algorithms to Determine Parameter Settings for Cognitive Models From Time Series Data such as Visual Scanpaths

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Time-series data such as eye movements or mouse movements contain rich information about the dependencies between successive human actions. This poster demonstrates how model tracing, which simulates a task by tracking time-series data, along with the use of an evolutionary optimization algorithm, led to robust estimates for parameters of visual acuity functions needed by visual search models.

Model Tracing

Model tracing involves predicting an observable human action with the task context that the participant experienced before making that action. Model tracing is different from conventional cognitive modeling in the following two ways:

1. A tracing model continually realigns itself with the observed human actions.
2. A tracing model predicts the likelihood of the observed event rather than providing conventional summary statistics such as the number of fixations in a trial.

Visual Acuity Functions

Model tracing is applied in this study to estimate the parameters of visual acuity functions, which describe how the visibility of object features gradually diminishes as objects move further from the point of gaze. Figure 1 illustrates the effect. We model this effect using the following functions proposed by Kieras' (2010):

$$threshold = ae^2 + be + c$$
$$P(available) = P(s + X > threshold) \qquad (1)$$
$$X \sim N(0, vs)$$

where e represents the eccentricity, s represents object size, and X represents a noise that is sampled from a Gaussian distribution with a standard deviation of v times s. The parameters a, b, and c vary for different object features such as color,

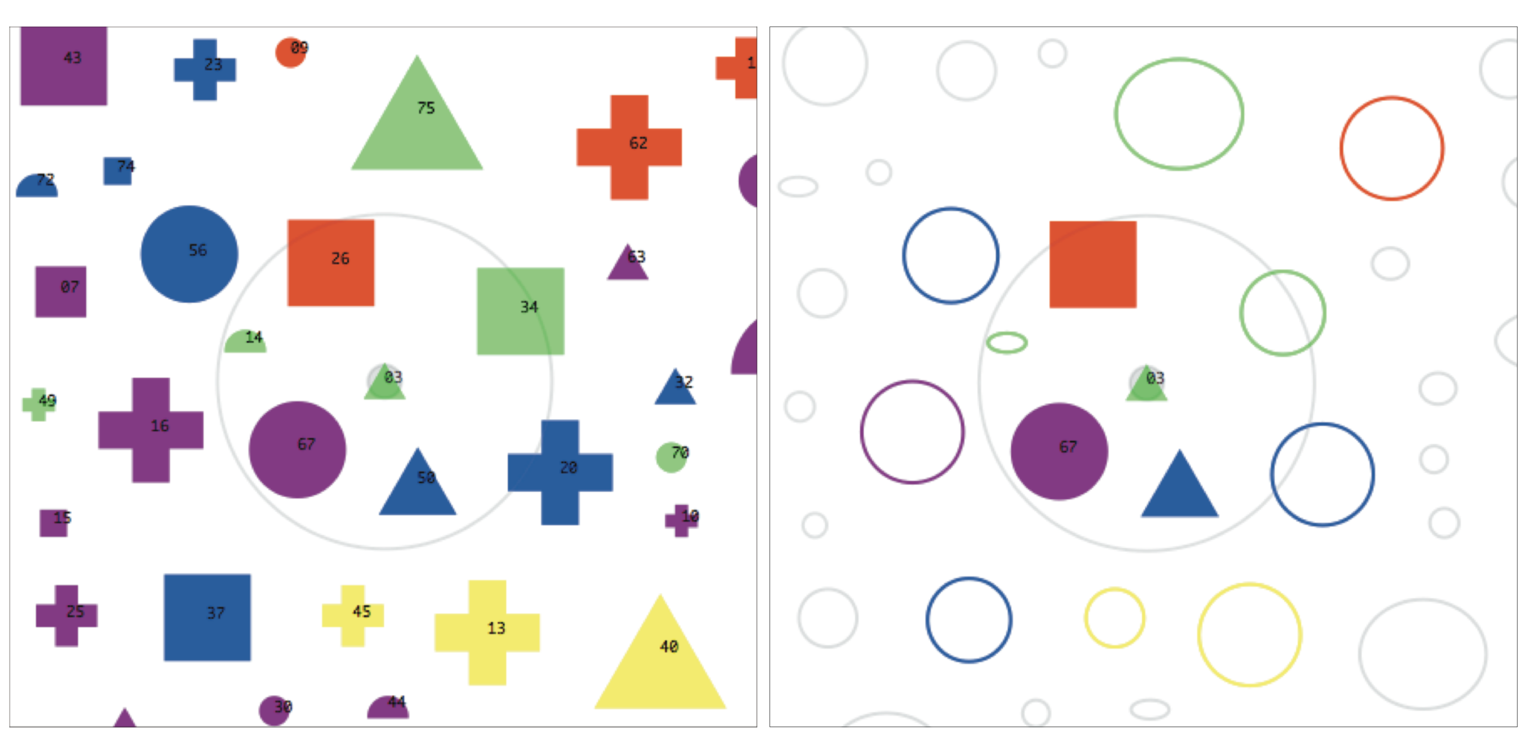

Figure 1. An illustration of how object features gradually diminishes as they move further from the point of gaze (center of the big gray circle). The left panel shows a portion of the physical display, and the right panel shows the features perceived by the simulated vision as determined by the visual acuity functions. Some objects have all of their features available; some have just color (colored circles); and some have just their position (gray circles).

shape, and size to simulate different rates of visibility degradation.

The goal of this paper is to use model tracing to estimate the free parameters of this function—a, b, c, and v—for different visual features in a visual search task.

The Williams Visual Search Task (Replicated)

We replicated the Williams (1966) experiment to collect more eye tracking data. The task is to search for a target in a grid of 75 objects that have different colors, shapes, and sizes. The search objects are similar to those in Figure 1, and the search display occupies a 39° by 30° screen area. Each object has a unique two-digit number in the center. Search precues were shown before each trial and included the number of the target object and, depending on the precue condition, some combination of the target's color, size, and shape, with each feature optional, resulting in eight possible precue conditions, such as "17 small blue cross" which was the "All" feature condition. The precue always included the target number. After finding the target, the participant clicked on it to proceed to the next trial.

Figures 2 and 3 show the participants' performance (black bars), along with the model data (gray bars) discussed below. Our experiment successfully replicated Williams' observation that color is more useful in guiding visual search than size and shape. This can be seen in Figure 2 in that the precue conditions that specified color had larger proportions of fixations landing on objects with the specified feature, which suggests that the participants may be able to see color in a wide area of their visual periphery and use that information to effectively plan their next saccade to objects that are likely to be the target.

Estimate Parameters Using Tracing

We developed a standalone computational model, a scanpath tracing model, to simulate a person doing this visual search task. The scanpath tracing model adopts the theoretical concepts of the visual acuity function and a visual perceptual store (VPS) adapted in part from the EPIC cognitive architecture (Kieras, 2010). If an object feature is determined to be available by the visual acuity function, it is deposited in the VPS for a short time period (e.g, 300 ms). Figure 1 illustrates what features might be perceived by the acuity functions shortly after the eyes arrive on an object.

The scanpath tracing model simulates the task by cycling through these three steps:

1. Move the gaze to the observed fixation location and set the simulation time to the fixation time.
2. Delete from VPS (visual perceptual store) the items that should have decayed based on the passing of time, and add the objects and features that the visual acuity functions determine are available based on the current gaze position.
3. Based on the contents of the VPS, calculate how likely that for the following fixation, the model would fixate the same location as the participant.

In every cycle, the contents of VPS will contain some combination of the following:

- *Viable-candidates* – objects that have a feature in common with the target.
- *Non-targets* – objects that have a feature that is known and which makes it not possibly the target (such as a red object when looking for a blue target).
- *Unknown-objects* – objects that are visible but have no known color, size, or shape features.

Table 1 shows the likelihood that the model's visual search strategy will move the eyes to each of the above three types of objects, and to the space between objects. The model uses this table to calculate the likelihood of the observed fixation location (in Step 3, above).

Table 1. The likelihood that the visual search strategy will move the gaze to the four possible destinations under each of the four visual-perceptual store states.

	If the Visual-Perceptual Store (VPS) Contains		The Search Strategy Prefers Object Types as Follows			
State	Viable-candidates	Non- targets	Viable-candidates	Non-targets	Unknown-Objects	Between Objects
1	no	no	0.0%	0.0%	66.0%	34.0%
2	no	yes	0.0%	48.0%	34.3%	17.7%
3	yes	no	95.0%	0.0%	3.3%	1.7%
4	yes	yes	95.0%	2.4%	1.7%	0.9%

The parameters of the visual acuity function directly affect the contents of VPS, and thus the model's predictions about the likelihood of each observed fixation location. Because a higher likelihood indicates a better fit to the data, our goal is to find the parameter settings that generate the highest likelihood for the observed scanpath.

A *differential evolution algorithm* was used to search for the optimal parameters of the tracing model in the following four steps: (1) The algorithm instantiates a set of scanpath tracing models (100 models for our study) with random parameter settings (Generation 0). (2) It runs each instantiated tracing model, and each model calculates the goodness of fit to the human scanpath data (the average log-likelihood of all fixations). For our study, the scanpath data include 24,821 fixations collected from the visual search trials that specified a single target feature. (3) The algorithm creates a new generation of parameter settings by moving the parameters that generated low likelihoods towards those that generated high likelihoods (following Vesterstrom and Thomsen, 2004). (4) The algorithm repeats steps (2) and (3) for many generations until the termination condition has been reached. For this study, the search was set to terminate after 300 generations. Because in each generation the parameters are slightly improved, the parameters found after many generations provide a sufficiently good fit to the scanpath data, though they are not guaranteed to be optimal.

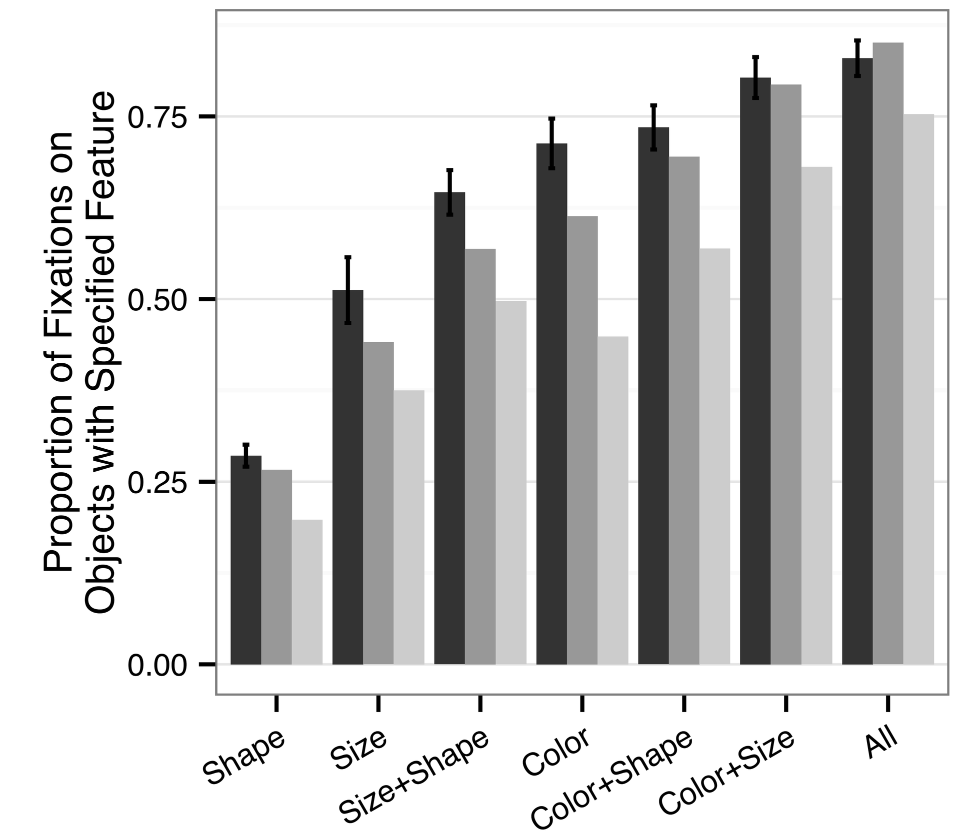

Figure 2. The proportion of fixations on objects with at least one of the cued features. AAPE: Tracing, 8%; Original, 24%.

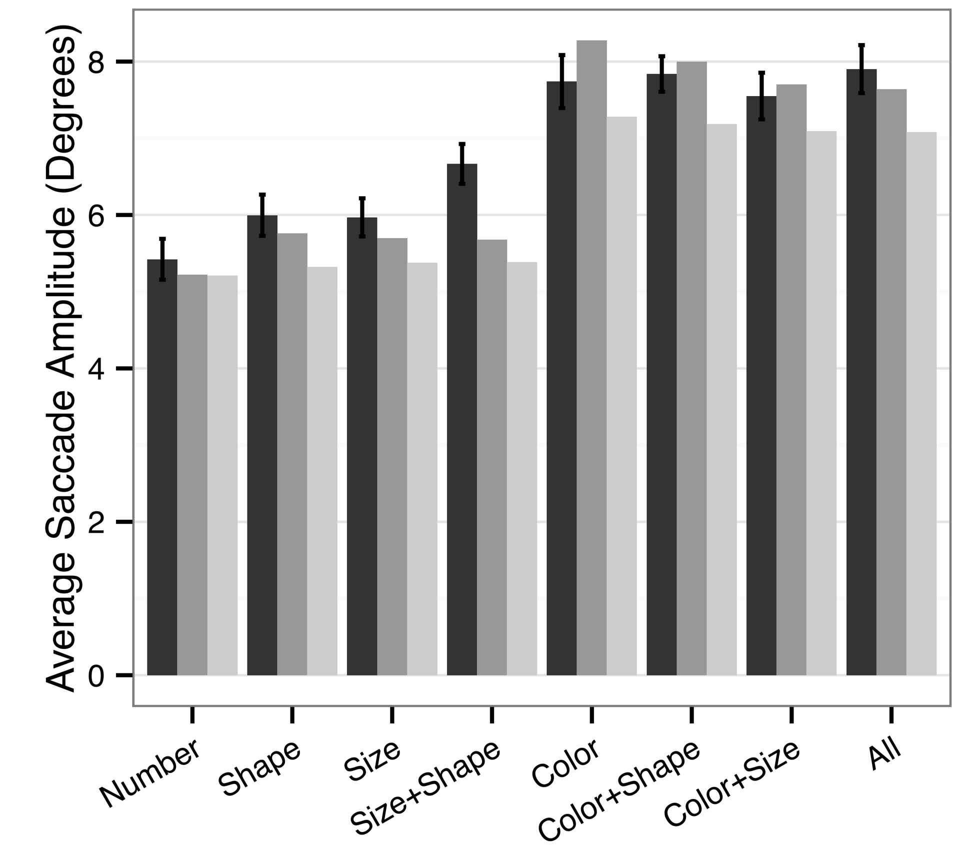

Figure 3. Average saccade amplitude across conditions. AAPE: Tracing, 5%; Original, 9%.

Results

Figure 4 shows the visual acuity functions estimated from our new tracing model and from the original EPIC model (which can be found in Kieras, 2010). The curves determine the threshold object size for a feature to be available. That is, an object feature is available when it is above (or to the left of) that feature's curve. The estimated parameters allowed the tracing model to fit the scanpath data better (log-likelihood is -3.61) than the the original EPIC parameters (log-likelihood is -3.74). In Figure 4, both sets of functions show similar trends across the three features: Color is more visible than size, and size is generally more visible than shape. The main difference is that our parameters allow greater availability for all features than the original EPIC parameters.

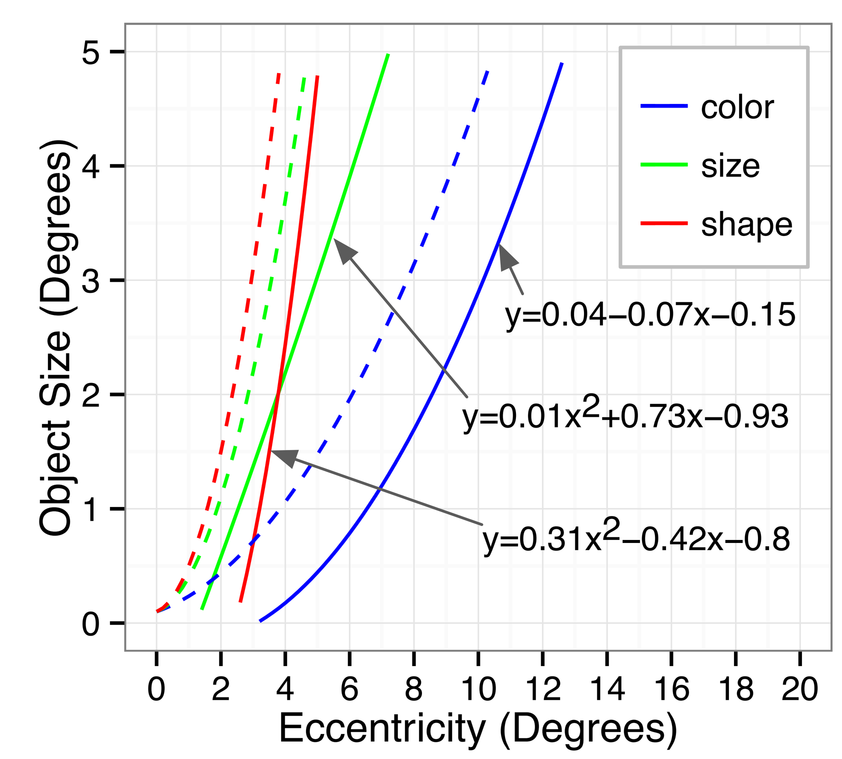

Figure 4. The visual acuity function estimated from tracing (solid) and from the original EPIC model (dashed). An object feature is available when it is above or to the left of that feature's curve.

The estimated visual acuity function parameters were further validated by transferring them into Kieras' EPIC-based visual search model to see whether the model can fit the summary statistics of the eye movement data. Figures 2 and 3 compare the models' predictions with the observed data on two critical aspects of the visual search performance. The results show that the new parameters estimated by the tracing model explain the human data well, and in most cases, outperform the original EPIC parameters that were specifically adjusted to fit the summary eye movement statistics.

Conclusion

Model tracing is a novel and useful approach to explaining human data that may have great potential for developing and evaluating accurate computational cognitive models of human performance. By fitting the model to a large amount of data, tracing improves the statistical power of parameter estimation, which helps to address the challenge of parameter fitting discussed in Howes et al. (2009).

References

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