Computational Cognitive Science

Lecture 20: Visual Search

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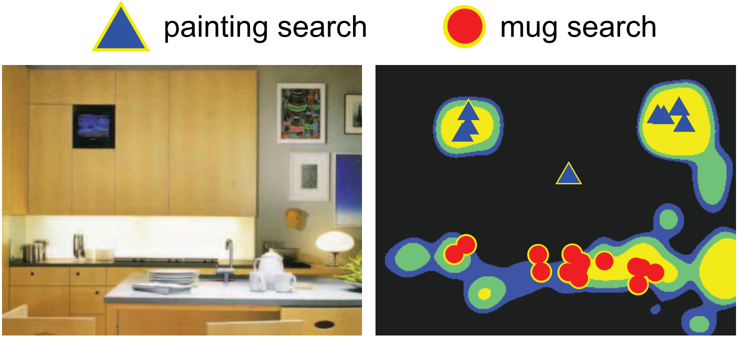
Reading: Najemnik and Geisler (2005).

Visual Search

In the last lecture, we saw how context and saliency can be used to predict fixation *locations* in visual search.



But how about the fixation *sequence* in search? Which strategy is used to decide where to look next?

Visual Search

The optimal search strategy needs to take into account:

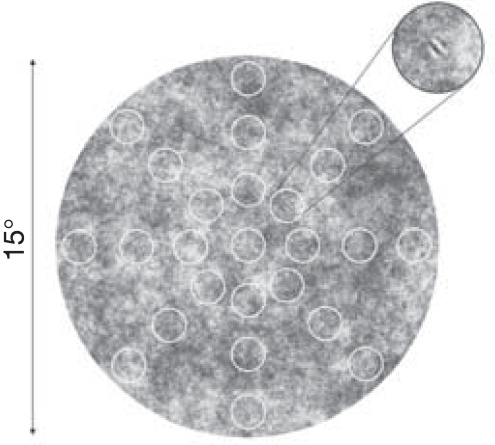
- the visibility of the target decreases with its eccentricity (distance from the center of the retina);
- the visibility of the target increases with target contrast and decreases with background contrast.

Experiment: determine *visibility map.* Use artificial stimuli to exclude influence of saliency, context, top-down knowledge, etc.

Search target: sine wave grating; background: $1/f$ noise.

Detection and Search Experiments

Search starts at the center; target can be at any of 85 locations[1]. Vary eccentricity, target contrast, background contrast; measure detection accuracy; compute visibility d'.



[1] 25 locations in detection experiment

Visual Search

Visibility is defined using the discriminability index d' from signal detection theory:

$$d' = \Phi^{-1}(H) - \Phi^{-1}(F)$$

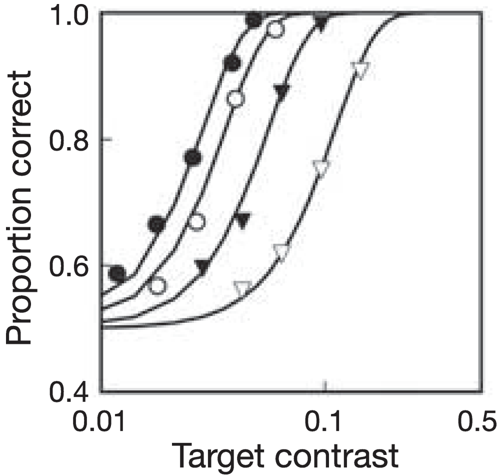
where H is the hit rate and F is the false alarm rate and Φ^{-1} is the inverse of the cumulative Gaussian distribution.

Contrast is defined as the root mean square of intensity:

$$c_{\mathrm{RMS}} = \sqrt{\frac{1}{MN}\sum_{i=1}^{N}\sum_{j=1}^{M}(I_{ij} - \bar{I})^2}$$

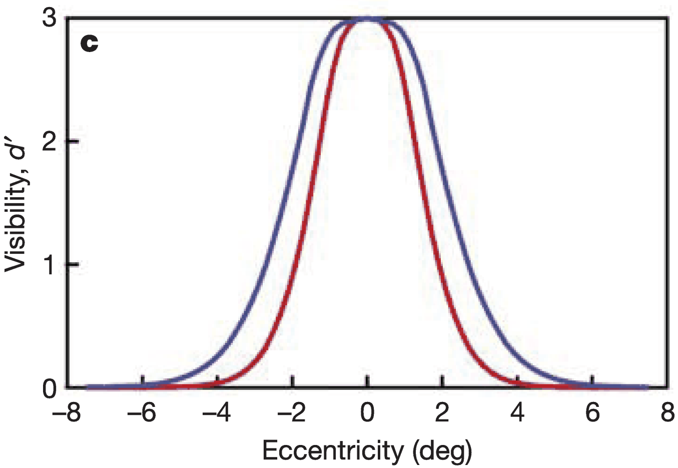
where I_{ij} are the intensity values of the region (size $M \times N$) and $\bar{I}$ is the average intensity.

Search Experiment



background contrast: filled circles, 0; open circles, 0.05; filled triangles, 0.10; open triangles, 0.20.

Visual Search



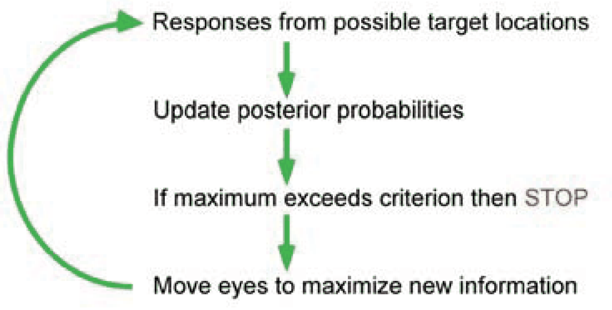
red: background contrast 0.05, target contrast 0.07;
blue: background contrast 0.20, target contrast 0.19.

The Ideal Searcher

A model with an optimal strategy for visual search needs to:

- optimally integrate information across fixations;
- optimally select successive fixation locations.

Architecture of Najemnik and Geisler (2005)'s Ideal Searcher:



Simulating Fixations

The Ideal Searcher computes $p_i(T)$, the posterior probability that the target is at location i for fixation T:

$$p_i(T) = \frac{\text{prior}(i)\exp\left(\sum_{t=1}^{T} {d'}^2_{ik(t)} W_{ik(t)}\right)}{\sum_{j=1}^{n}\text{prior}(j)\exp\left(\sum_{t=1}^{T} {d'}^2_{jk(t)} W_{jk(t)}\right)} \tag{1}$$

where t is fixation number, $d'_{ik(t)}$ is the visibility, and $W_{ik(t)}$ the template response, at location i when location $k(t)$ is fixated.

Template response: match between search target (template) and retinal image at a given location.

Simulating Fixations

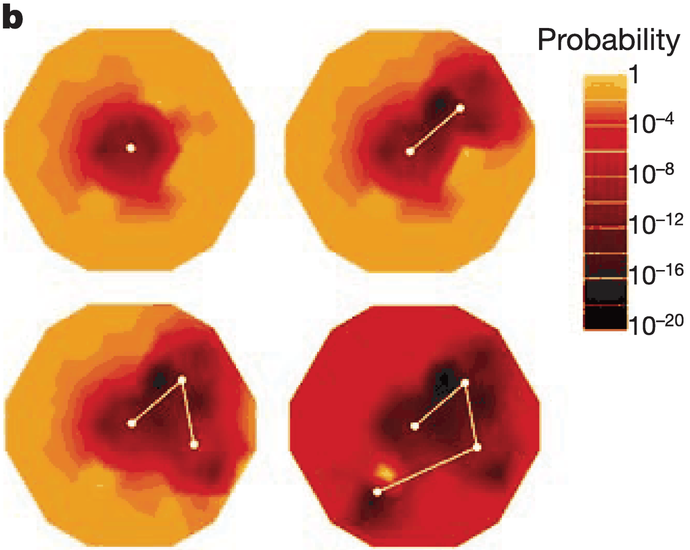
Compute the next fixation location, $k_{\text{opt}}(T+1)$, by maximizing the probability of identifying the target if that point is fixated:

$$k_{\text{opt}}(T+1) = \underset{k(T+1)}{\arg\max} \left(\sum_{i=1}^{n} p_i(T) p(C|i, k(T+1)) \right) \quad (2)$$

where $p_i(T)$ is the posterior at location i for fixation T, and $p(C|i, k(T+1))$ is the probability of correctly identifying the target at i when fixating $k(T+1)$.

These equations can be used to simulate fixation sequences: map of posterior probabilities (next page).

Simulating Fixations



Simulating Fixations

The simulations were obtained as follows:

1. fixate the center of the display;
2. select a target location at random with $\text{prior}(i) = 1/85$;
3. generate Gaussian noise for each of the 85 potential target locations with $\sigma = 1/d'$, where d' is visibility at location;
4. calculate posterior probability for each potential target location using eq. (1);
5. stop search if the maximum posterior probability exceeds criterion (criterion s.t. error rate same as human error rate);
6. select next fixation location using eq. (2); then go to step 3.

Note that the specific characteristics of the target and $1/f$ noise enter the simulation through the visibility maps.

Properties of the Model

The Ideal Searcher shows the following interesting behaviors:

- sometimes fixates location with maximal posterior probability of containing the target (MAP fixations);
- sometimes fixates location near the centroid of a cluster of locations with high posterior (center-of-gravity fixations).
- makes saccades of moderate size;
- does not fixate locations that were recently fixated (inhibition of return): nearby posteriors depressed (high d', but low W).
- sometimes makes long saccades into regions with low posterior probabilities, followed by a return saccade (exclusion saccade).

Experimental evidence for these behaviors in humans (except exclusion saccades).

Evaluation

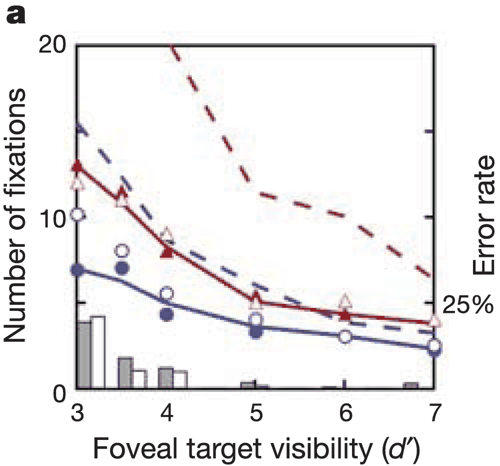
Evaluate Ideal Searcher:

- investigate search performance for sine-wave target randomly embedded at one of the 85 locations;
- two levels of $1/f$ background contrast (0.05 and 0.2) and six levels of target visibility ($d' = 3, 3.5, 4, 5, 6, 7$);
- measure number of fixations humans need to find target.

Results:

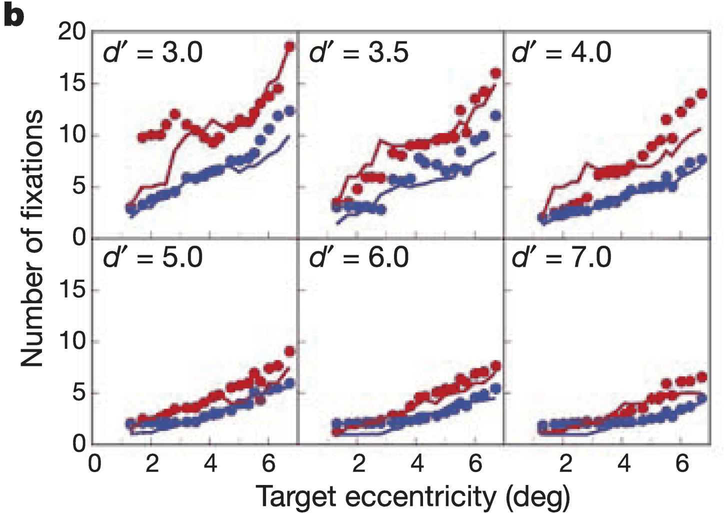
- search performance improves as the visibility of the target increases and is better in the high-noise condition;
- humans nearly reach the performance of the ideal searcher.

Evaluation: Visibility



Background contrast: red, 0.05; blue, 0.20. Ideal Searcher: solid line; random searcher: dashed line; humans: circles and triangles. Histogram: error rates of human (gray) and Ideal Searcher (white).

Evaluation: Eccentricity



Contrast: red, 0.05; blue, 0.20. Ideal Searcher: lines; humans: dots.

Why Humans Perform so Well

The ideal searcher does three things optimally:

1. parallel search at all possible target locations;
2. integration of information across fixations;
3. selection of the next fixation location.

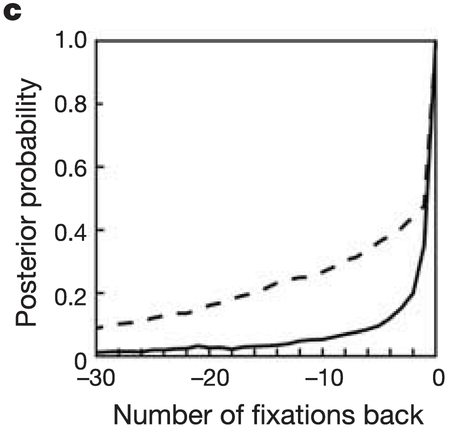
Previous experimental results show that humans:

1. process multiple target locations in parallel (e.g., in brief presentations with no eye-movements possible);
2. are not efficient at integrating information across fixations;
3. no previous evidence for optimal selection of next location.

Investigate (2) and (3) by comparing to a *random searcher.*

Comparison with Random Searcher

Posterior at target location as a function of the number of fixations before target was found:



Ideal Searcher: solid line; random searcher: dashed line.

Comparison with Random Searcher

Comparison with random searcher shows:

- humans outperform a searcher that computes posteriors and integrates them optimally across fixations, but makes random fixations (Figure a);
- most of the probability mass is in the posterior of the previous 1–2 fixations, so integrating across more fixations is not necessary (Figure c);
- limited memory (enough to support inhibition of return) is sufficient to achieve near-optimal behavior.

Summary

- The ideal searcher models eye-movements in visual search;
- takes into account how visibility of the target varies with eccentricity and contrast;
- optimally integrates information across fixations by computing the posterior probability of the target location;
- optimally selects fixation locations by maximizing posterior;
- but: simulations show little benefit from perfect integration of information across fixations;
- humans performance mirrors this; humans achieve near-optimal search behavior with limited memory.

References

Najemnik, J. & Geisler, W. S. (2005). Optimal eye movement strategies in visual search. *Nature*, *434*, 387–391.