Optimal feature gain modulation during visual search

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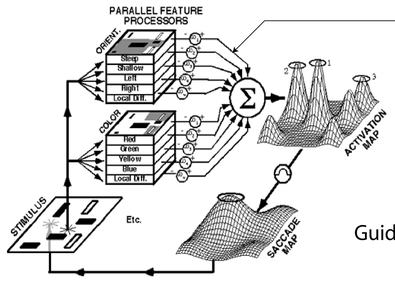
1 Background and Motivation

Beware of tigers...

How does our visual system select and promote the relevant visual features (e.g., color, orientation...) such that search speed is maximized?

Better knowledge of the target and distractors yields faster search (Muller et. al 1995, Braithwaite & Humphreys 2003 , Wolfe et. al 2004, Vickery et. al 2005)

What is the underlying mechanism?



Multiplicative gain modulation (Treue & Trujillo, '99)

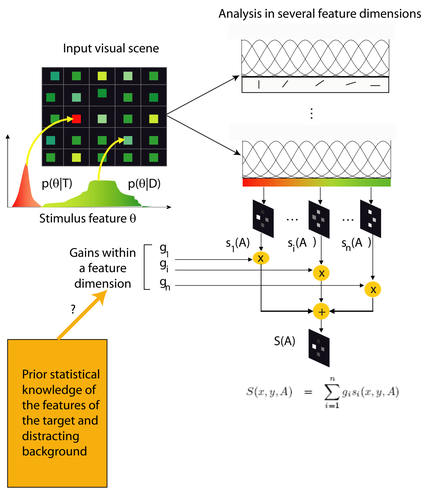
Guided search theory (Wolfe '94)

Open question: How to choose these gains for any given target and distractors?

2 Formalizing visual search

Relevant objective function is to maximize Signal-to-noise ratio (SNR) defined as the ratio of strength of the guiding signal (target salience) over noise (distractor salience).

High SNR leads to low reaction times and easy search (Wolfe et. al, '03).



$S(x,y,A) = \sum_{i=1}^{n} g_i s_i(x,y,A)$

θ|T = Target features
θ|D = Distractor features
C = Spatial configuration of Target and Distractors
η = Noise in neural response
$S_T(A)$ = Salience of the target
$s_{iT}(A)$ = Salience of the target in the i^{th} map
g_i = Top-down gain on the i^{th} map

$$E[S_T(A)] = E_{\Theta|T,C,\eta}\left[\sum_{i=1}^{n} g_i s_{iT}(A)\right] = \sum_{i=1}^{n} g_i E_{\Theta|T}[E_C[E_\eta[s_{iT}(A)]]]$$

$$E[S_D(A)] = \sum_{i=1}^{n} g_i E_{\Theta|D}[E_C[E_\eta[s_{iD}(A)]]]$$

$$\mathcal{SNR} = \frac{\sum_{i=1}^{n} g_i E_{\Theta|T}[E_C[E_\eta[s_{iT}(A)]]]}{\sum_{i=1}^{n} g_i E_{\Theta|D}[E_C[E_\eta[s_{iD}(A)]]]}$$

$$\mathcal{SNR}_i = \frac{E_{\Theta|T}[E_C[E_\eta[s_{iT}(A)]]]}{E_{\Theta|D}[E_C[E_\eta[s_{iD}(A)]]]}$$

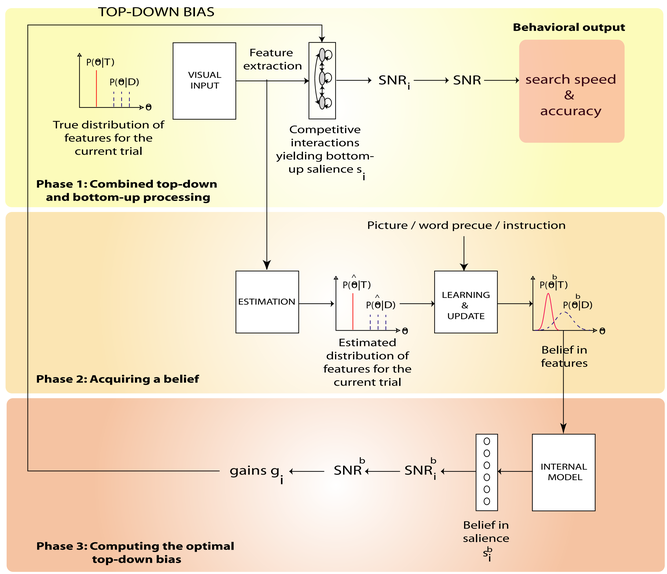
Maximizing $\mathcal{SNR}$ wrt g_i yields

$$g_i = \frac{\mathcal{SNR}_i}{\frac{1}{n}\sum_{j=1}^{n}\mathcal{SNR}_j}$$

Intuitive interpretation:

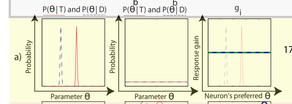
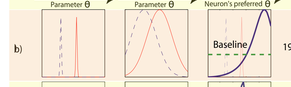
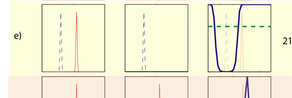
Boost a cue according to its SNR

3 Model



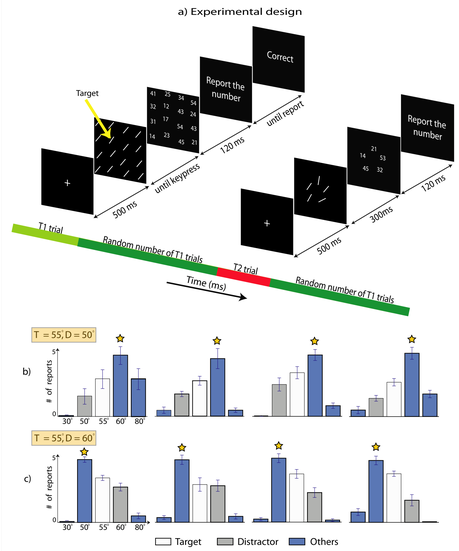
This model applies optimal top-down gains on bottom-up saliency maps such that SNR is maximized, thereby increasing search speed.

4 Simulation Results

	True distribution	Observer's belief	Optimal gains	SNR	Remarks	
a)				17.5dB	**NO PRIMING / TOP-DOWN GUIDANCE**: - No prior knowledge of T and D features, no top-down benefit - Baseline gains (unity) - Bottom-up guidance contributes to SNR	Shiffrin & Schneider, '77
b)				19.7dB	**MINIMAL PRIMING / TOP-DOWN GUIDANCE**: - Partial knowledge of T and D features - Partial top-down priming - SNR increases by 2.2dB compared to (a), search becomes faster	Maljkovic & Nakayama, '94 Wolfe et. al '03
c)				23.0dB	**MAXIMAL PRIMING**: - Complete knowledge of T and D features - Maximal top-down priming - SNR increases by 5.5dB compared to (a), search is efficient	Wolfe et. al '04 Vickery et. al, '05
d)				22.9dB	**TARGET ENHANCEMENT:** - Knowledge of T features allows target enhancement - SNR increases by 5.4dB compared to (a) - Similar gains observed in physiology of feature-based attention	Martinez-Trujillo & Treue, '04 Bichot & Schall, '02
e)				21.9dB	**DISTRACTOR SUPPRESSION**: - Knowledge of D features allows distractor suppression - SNR increases by 4.4dB compared to (a)	Braithwaite & Humphreys, '03
f)				13.3dB	**EFFECT OF DISTRACTOR HETEROGENEITY:** - Increasing distractor heterogeneity decreases search speed - SNR decreases by 9.7dB compared to homogeneous distractors condition (c)	Duncan & Humphreys, '89
g)				7.4dB	**EFFECT OF LINEAR SEPARABILITY:** - T is not linearly separable from D (unlike f) - SNR decreases by 5.9dB compared to (f) - Top-down benefit is smaller (0.5dB) compared to above (3.3dB)	D'Zmura, '91 Bauer. et al, '96 Hodsoll & Humphreys, '01
h)				4.6dB	**EFFECT OF TARGET-DISTRACTOR DISCRIMINABILITY:** - T is less discriminable from D - SNR decreases by 18.4dB compared to (c) - *A neuron that is sub-optimally tuned to the target's feature is boosted maximally compared to a neuron that is optimally tuned*	Pashler, '87 Duncan & Humphreys, '89

5 Psychophysics experiments

Surprising prediction: It is sometimes optimal to boost a non-target feature.
To test this prediction, we design the following psychophysics experiments.



a) Experimental design:

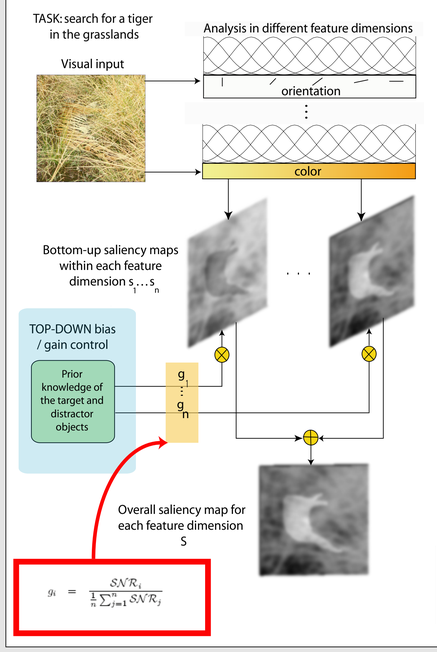
- Set up the gains using T1 trials (search for 55° among 50° items)

- Test the gains by randomly inserting T2 trials (where the target must be reported among probes all orientations)

b) As predicted by the theory, although subjects searched for a 55° target, they reported 60° significantly higher number of times (paired t-test, $p < 0.05$)

c) Additional controls show a reversal in the trend of biasing when the distractor is reversed

6 Discussion and Conclusion



1. Our theory can successfully account for a large body of existing visual search literature

   - Bottom-up effects: Target-distractor discriminability, distractor heterogeneity, linear separability, pop-out

   - Top-down effects: Role of priming, uncertainty, target enhancement, distractor suppression

2. These results suggest that humans may modulate gains optimally during visual search

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For more details, please see:
V. Navalpakkam, L. Itti, **An Integrated Model of Top-down and Bottom-up Attention for Optimal Object Detection**, In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), 2006.
V. Navalpakkam, L. Itti, **Optimal cue selection strategy**, In: Neural Information Processing Systems (NIPS), 2005.