An Active Sequential Hypothesis Testing model for Visual Search

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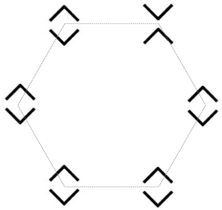
Components of the visual search task



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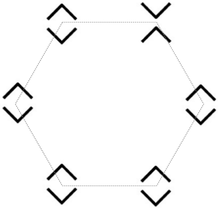
- Observation: The neuronal firing patterns generated in the brain.



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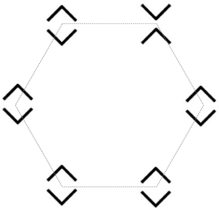

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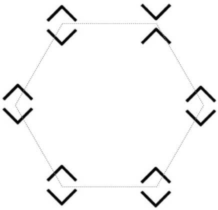

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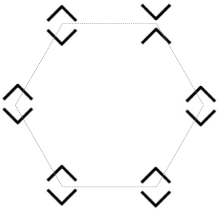

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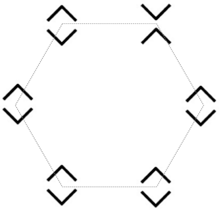
- It is active, as the subject has the ability to focus his attention on any location of his choice.
- Changing your focus of attention incurs a cost.
- The odd-ball and distractor images are learned during the task.



Components of the visual search task

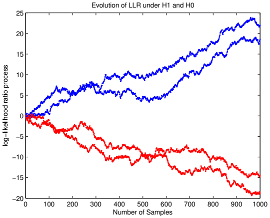
For a given image pair (k, l), sequential detection framework suggests a relation of the form:

$$\text{Stopping time} \approx \frac{-\log(P_e)}{\boxed{\text{diff}(k, l)}},$$

where P_e is the probability of false detection.

$\text{diff}(k, l)$ - drift of the appropriate log-likelihood ratio function.

Can we find a suitable $\text{diff}(k, l)$?



Active Sequential Hypothesis Testing - Known firing rates model

Basic Notation - For simplicity let us consider the case of one neuron. (The results easily extend to the case of multiple neurons.)

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- H - Index of the odd process.
- R_k - Rate elicited by image k (known).
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- $\Psi = (H, R_k, R_l)$ specifies the configuration.

Neuronal dissimilarity index

$$\tilde{D}(\Psi) = \tilde{D}(R_k, R_l) := \max_{\lambda \in \mathcal{P}(K)} \min_{\Psi' \neq \Psi} \sum_{m=1}^{K} \lambda(m) KL(P_{\Psi}^{m} \| P_{\Psi'}^{m})$$

$$= \frac{(K-2)D(R_k\|R_l)D(R_l\|R_k)}{(K-1)D(R_k\|R_l) + (K-3)D(R_l\|R_k)}$$

$D(x\|y) := x\log(x/y) - x + y$ is the KL-divergence between two Poisson random variables with means x and y.

Note that $\tilde{D}(R_k, R_l) \neq \tilde{D}(R_l, R_k)$ because relative entropy is not a symmetric metric. Thus our dissimilarity index suggests asymmetry, which is seen in many visual search experiments.

Active Sequential Hypothesis Testing - Learning based model

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- H - Index of the odd process.
- R_1 - Rate of the odd process (unknown).

Active Sequential Hypothesis Testing - Learning based model

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- R_2 - Rate of the non-odd processes (unknown).
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Active Sequential Hypothesis Testing - Learning based model

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- K - Number of locations.
- H - Index of the odd process.
- R_1 - Rate of the odd process (unknown).
- R_2 - Rate of the non-odd processes (unknown).
- $\Psi = (H, R_1, R_2)$ specifies the configuration.
- The task is one of finding the odd-arm, similar to best arm identification problems in multi-arm bandit problems.

Neuronal dissimilarity index

$$D^*(i, R_1, R_2) := \max_{\lambda \in \mathcal{P}(K)} \min_{\substack{\Psi' = (j, R_1', R_2') \\ j \neq i}} \sum_{k=1}^{K} \lambda(k) KL(P_\Psi^k \| P_{\Psi'}^k)$$

Can be extended to multi-dimensional Poisson point processes.

Back to visual search - Performance

If we assume that an ideal *diff* metric should satisfy $E[\text{Stopping Time}]\mathit{diff}(k,l) = \mathit{constant}$ for all image pairs (k,l). Then a measure of their performance can be an equality of means test.

Table : Equality of means test using various test statistics - Lesser the better

diff	ANOVA statistic	ANOVA p-values	log(AM/GM)
$\tilde{D}$	06.30	9.35×10^{-19}	0.0200
KL	06.68	2.88×10^{-20}	0.0211
Chernoff	06.74	1.61×10^{-20}	0.0252
L^1	24.00	3.42×10^{-87}	0.0678
D^*	06.34	6.93×10^{-19}	0.0233

Conclusion

- Framed the visual search problem as an Active Sequential Hypothesis Testing problem.
- ASHT suggests a neuronal dissimilarity $\tilde{D}$ index which explains the behavioural data as good as or better than L^1.
- Obtained D^* as an index when there is no prior knowledge of the image pairs.