

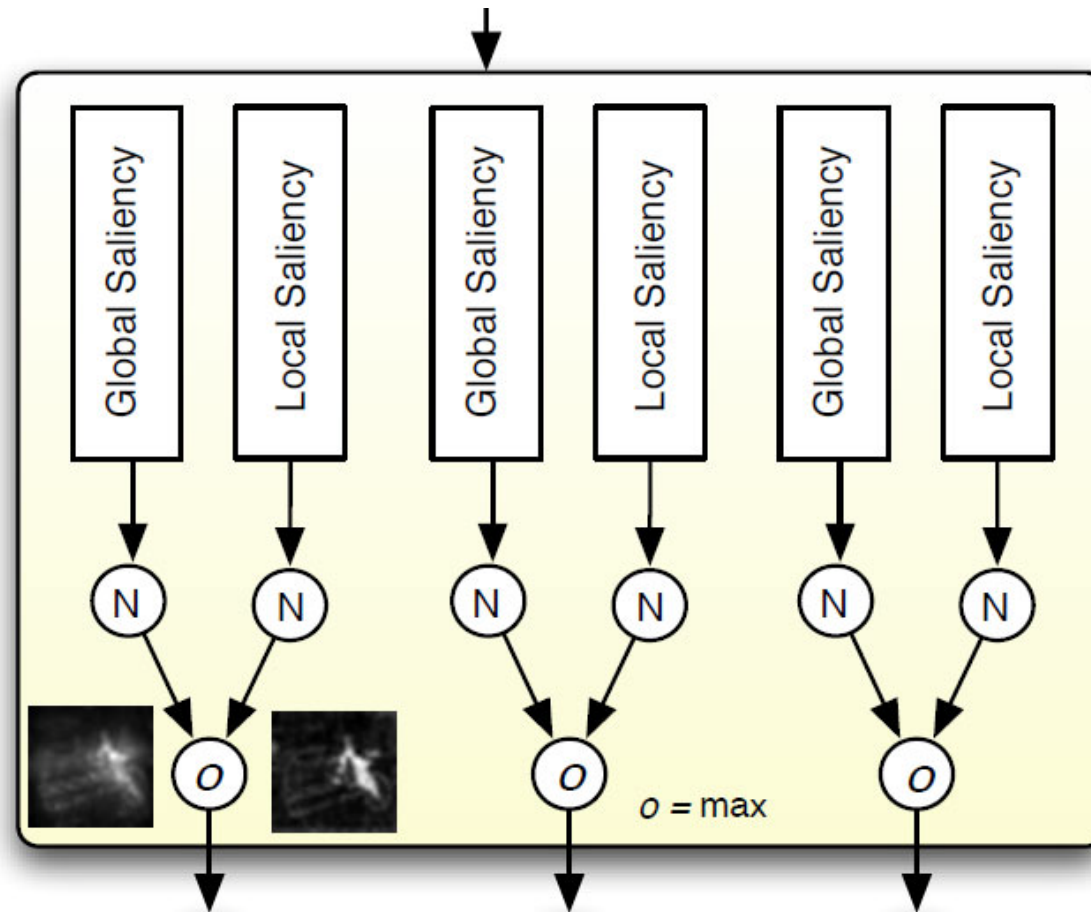
# Exploiting Local and Global Patch Rarities for Saliency Detection

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# General Idea

Saliency Model based on local and global salient points



# Previous Work

## **Feature Integration Theory** (1980 by Anne Treisman and Garry Gelade)

When perceiving a stimuli:

Features (color, intensity..) are registered early, automatically and in parallel,

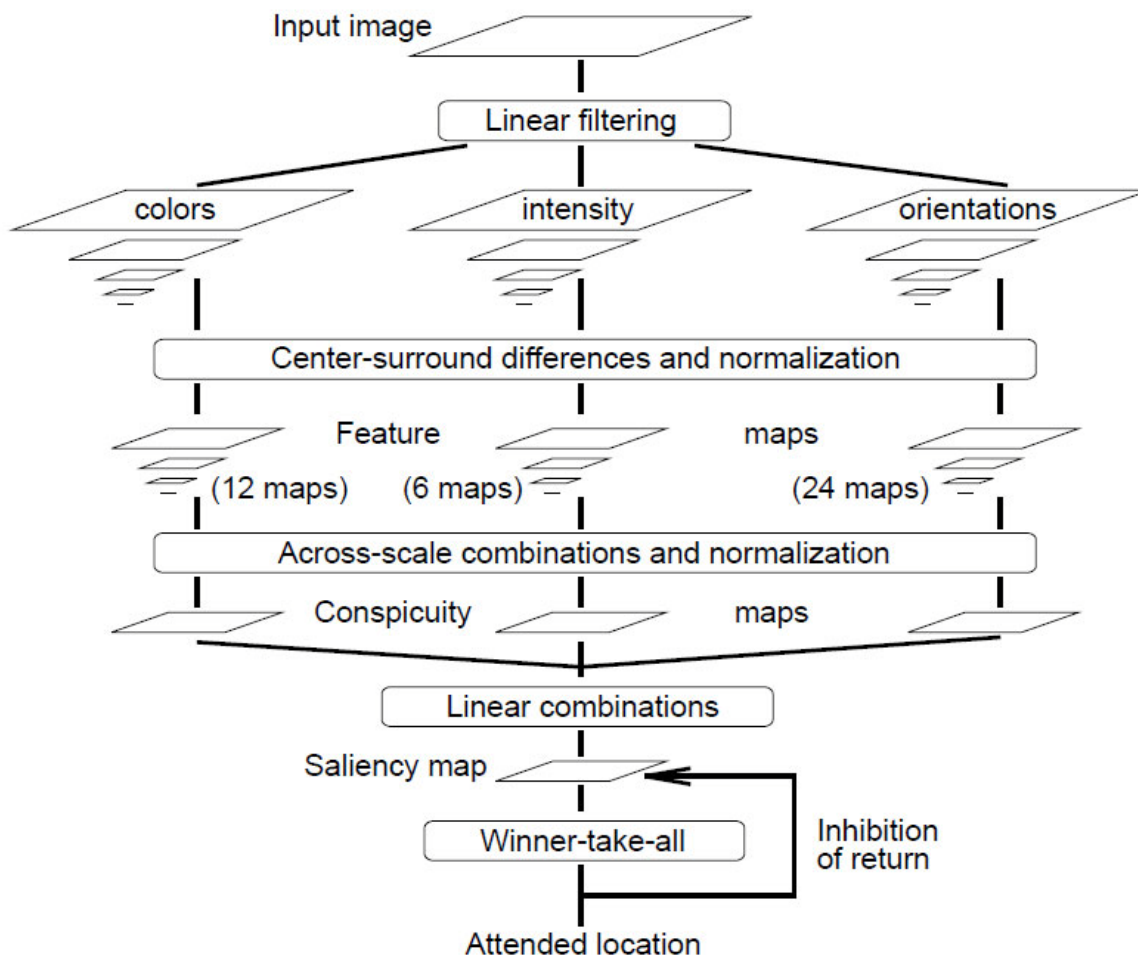
Objects are identified seperately at a later stage of processing

## **Guided Search Model** (1989 by Wolfe JM, Cave KR, Franzel SL)

Information from top-down and bottom-up processing of the stimulus is used to create a ranking of items in order of their attentional priority

# Previous Work

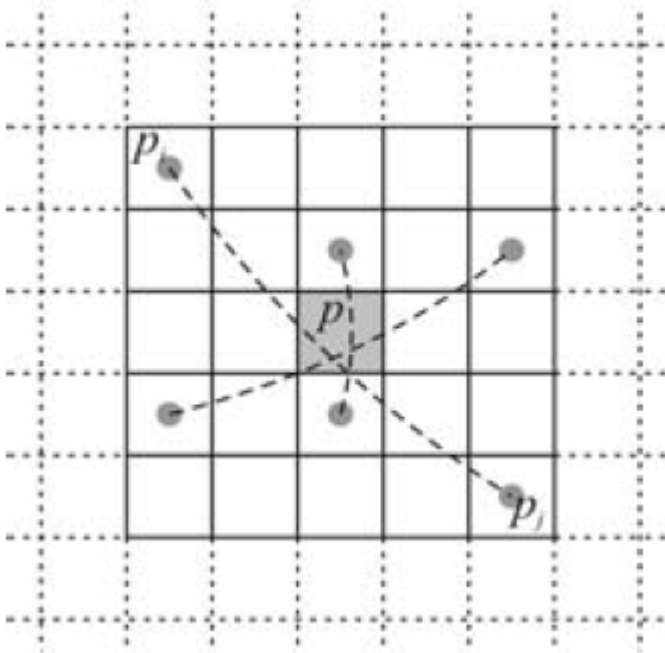
## Saliency-Based Visual Attention for Rapid Scene Analysis



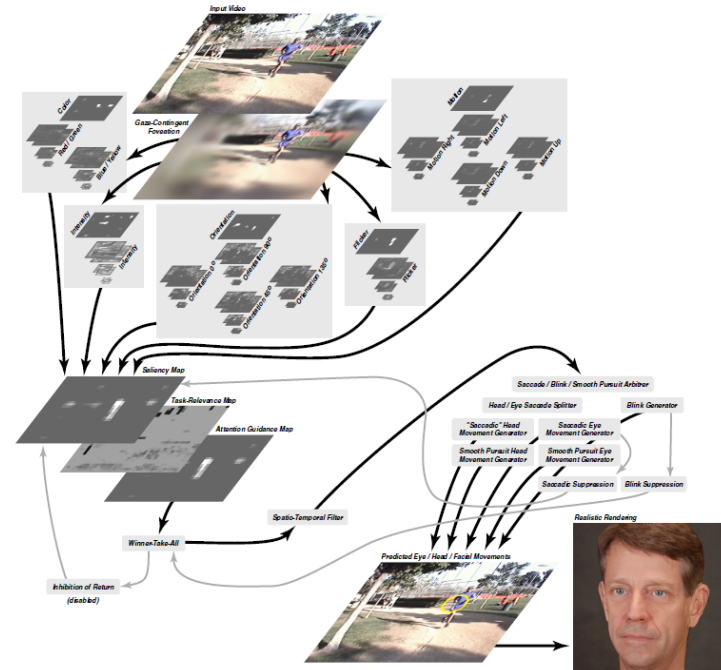
Compute saliency for simple features:  
color, intensity, orientation

Laurent Itti, Christof Koch, Ernst Niebur  
PAMI 1998

# Previous Work



Symmetry feature for saliency (2008)



Motion feature for saliency (2003)

Texture contrast (2002), Curvedness (2009)

# Previous Work

## **Probabilistic Models**

Graph Based Visual Saliency (Torralba – 2006)

Graph Algorithms and a dissimilarity measure

Saliency Using Natural Statistics (SUN) (Zhang – 2008)

Combine top-down and bottom-up info for real world object search

Saliency as Maximizing Classification Accuracy (Gao & Vasconcelos – 2003)

Measure mutual information between features

# Previous Work

## **Saliency in Frequency Domain**

### **Spectral Residual Approach (Hou & Zhang – 2007)**

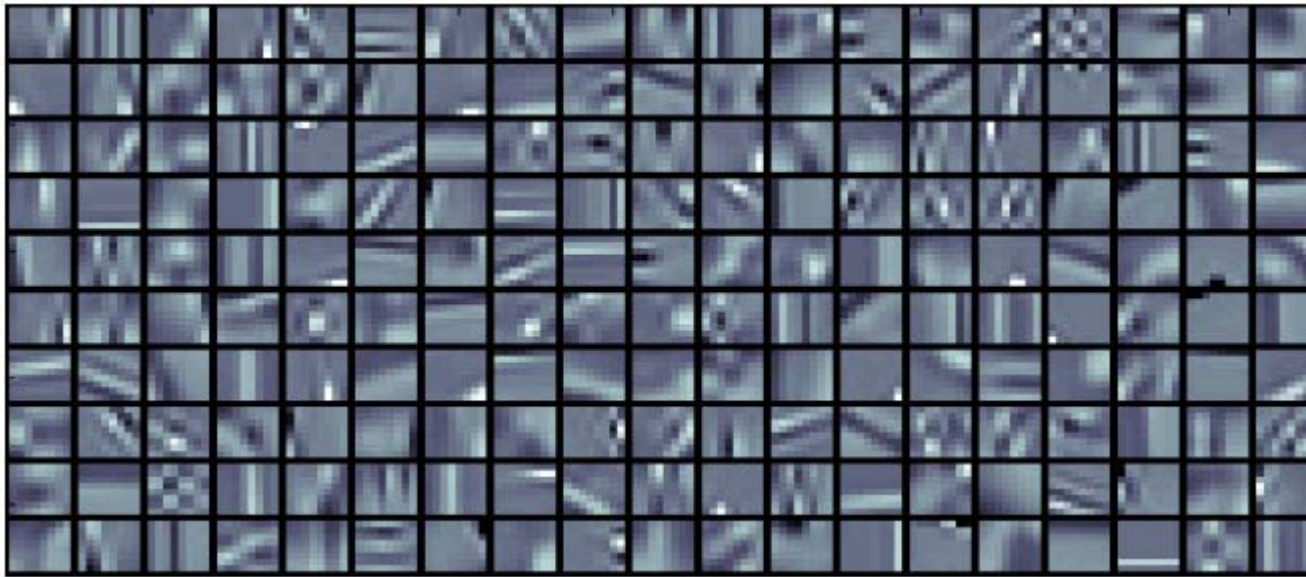
Relating extracted spectral residual features in the spectral domain

### **Multiresolution Spatiotemporal Saliency Detection Model (Gou– 2010)**

Incorporating Phase spectrum of the Quaternion Fourier Transform (PQFT)

# Details

## Image Representation



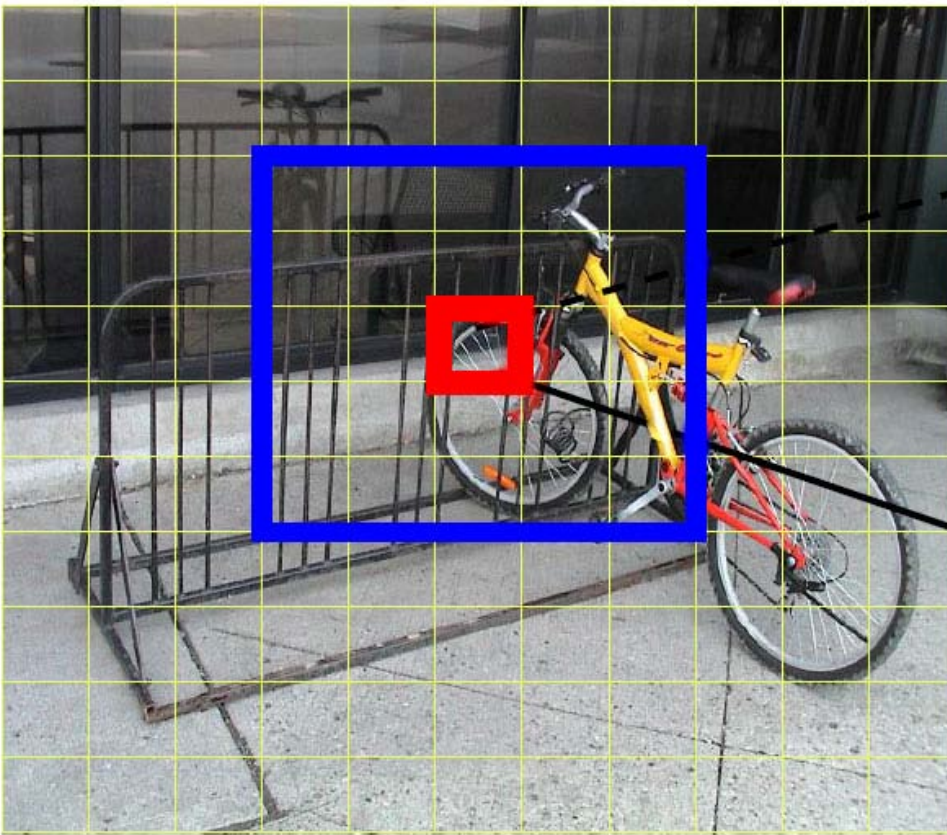
Dictionary of 200 basis functions – from natural images

$$\alpha^*(\mathbf{x}, \mathbf{D}) = \arg \min_{\alpha \in \mathbb{R}^n} \frac{1}{2} \|\mathbf{x} - \mathbf{D}\alpha\|_2^2 + \lambda_1 \|\alpha\|_1$$



# Details

## Local Saliency



$$S_l^c(\mathbf{p}_i) = \frac{1}{L} \sum_{j=1}^L W_{ij}^{-1} D_{ij}^c$$

**Average weighted dissimilarity**

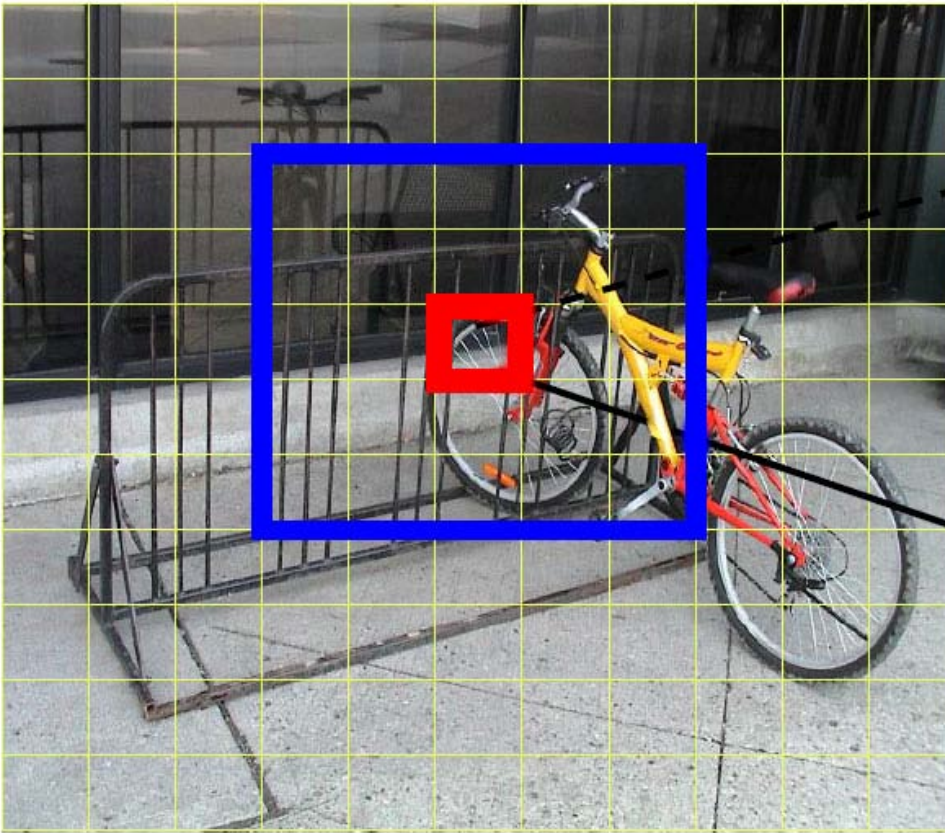
$W_{ij}$ : Euclidean distance of patches

$D_{ij}$ : Euclidean distance of coeff vectors

Further patches have less influence

# Details

## Global Saliency



$$S_g^c(\mathbf{p}_i) = P(\mathbf{p}_i)^{-1} = \left( \prod_{j=1}^n P(\alpha_{ij}) \right)^{-1}$$

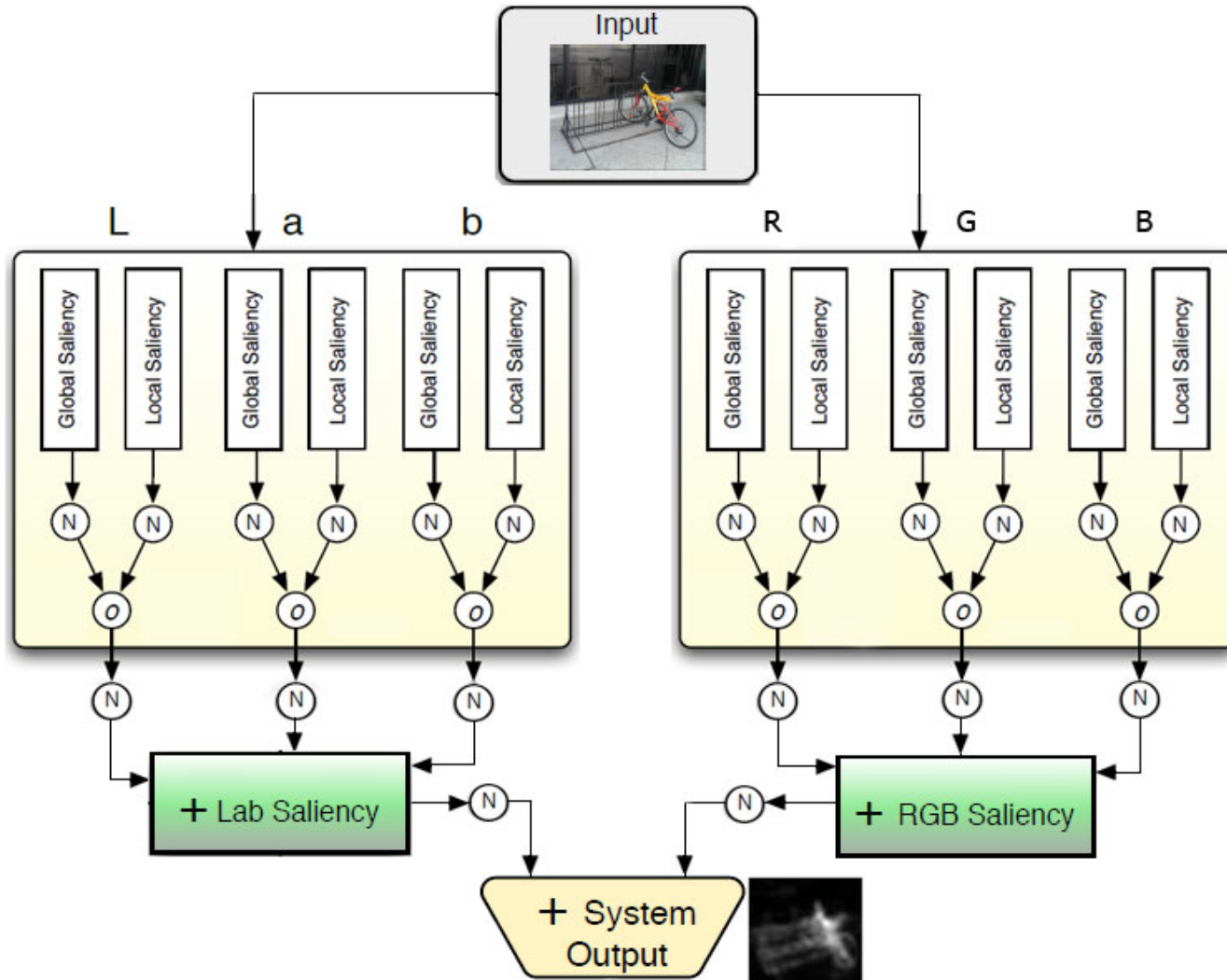
**Inverse of probability of patch over scene**

$\alpha_{ij}$ : coeff j of patch i

$P(\alpha_{ij})$ : probability density function

# Details

## Combined Saliency



# Experiments & Results

## AUC (Area Under Curve) Metric

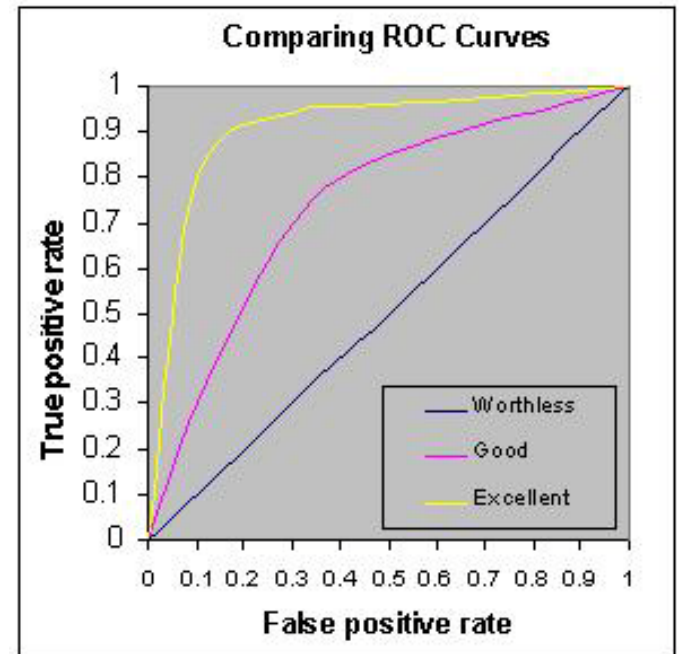
**Positive Set** : human selected saliency points

**Negative Set** : uniform random chosen points

**shuffled AUC**: all human fixations – positive set

**Saliency Map** : binary classifier

**ROC Curve** : threshold over map  
and plot true positive rate vs  
false positive rate



# Experiments & Results

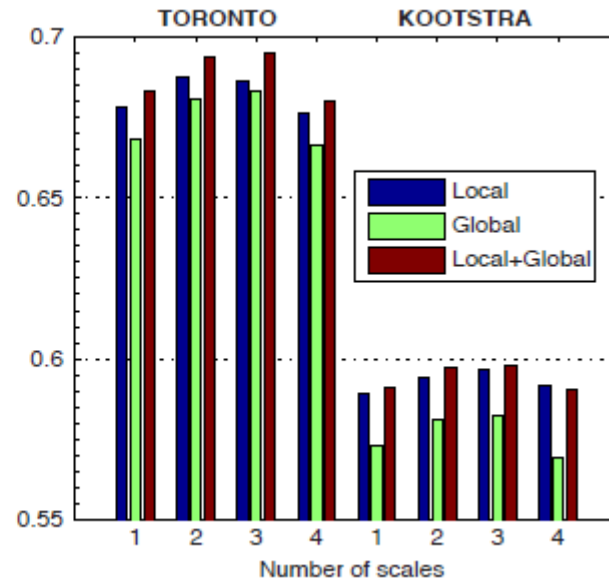
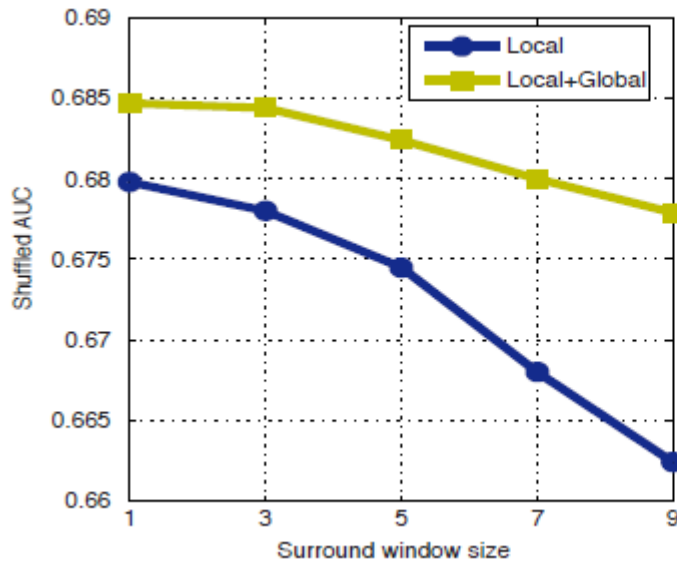
Dataset	AIM	GBVS	SRM	ICL	Itti	Judd	PQFT	SDSR	SUN	Surprise	Local $S_l$	Global $S_g$	LG $S_{lg}$	Gauss	IO
TORONTO Optimal $\sigma$	0.67 0.01	0.647 0.02	0.685 0.05	<b>0.691</b> 0.01	0.61 0.07	0.68 0.03	0.657 0.04	0.687 0.05	0.66 0.03	0.605 0.06	<b>0.691</b> 0.04	0.69 0.03	<b>0.696</b> 0.03	0.50 -	<b>0.73</b> -
MIT Optimal $\sigma$	0.664 0.02	0.637 0.02	0.65 0.05	<b>0.666</b> 0.03	0.61 0.06	0.658 0.02	0.65 0.04	0.646 0.05	0.649 0.04	0.62 0.05	0.653 0.04	<b>0.676</b> 0.04	<b>0.678</b> 0.03	0.50 -	<b>0.75</b> -
KOOTSTRA Optimal $\sigma$	0.575 0.01	0.563 0.01	0.576 0.04	0.589 0.01	0.57 0.07	0.587 0.02	0.57 0.03	<b>0.59</b> 0.03	0.55 0.02	0.566 0.07	<b>0.591</b> 0.03	0.578 0.02	<b>0.593</b> 0.03	0.50 -	<b>0.62</b> -
NUSEF Optimal $\sigma$	<b>0.623</b> 0.04	0.595 0.01	0.62 0.06	0.614 0.03	0.56 0.09	0.61 0.03	0.60 0.05	0.60 0.04	0.60 0.04	0.58 0.06	0.583 0.05	<b>0.627</b> 0.04	<b>0.632</b> 0.05	0.49 -	<b>0.66</b> -



# Experiments & Results

Dataset	<b>RGB</b>			<b>Lab</b>			<b>RGB + Lab</b>		
	$S_l$	$S_g$	$S_{lg}$	$S_l$	$S_g$	$S_{lg}$	$S_l$	$S_g$	$S_{lg}$
TORONTO	0.646	0.647	0.653	0.670	0.660	0.660	0.678	0.668	<b>0.683</b>
MIT	0.627	0.639	0.640	0.646	0.644	0.651	0.658	0.663	<b>0.667</b>
KOOTSTRA	0.574	0.572	0.578	0.572	0.555	0.570	0.589	0.573	<b>0.591</b>
NUSEF	0.599	0.610	0.610	0.556	0.596	0.592	0.569	0.614	<b>0.616</b>

# Experiments & Results



Thank You