A Corner-based Saliency Model

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A Corner-based Saliency Model

Visual Saliency

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Visual Saliency

"amount of attention spent on these pixels"

Saliency Modelling

=

Calculate visual saliency as our brain does

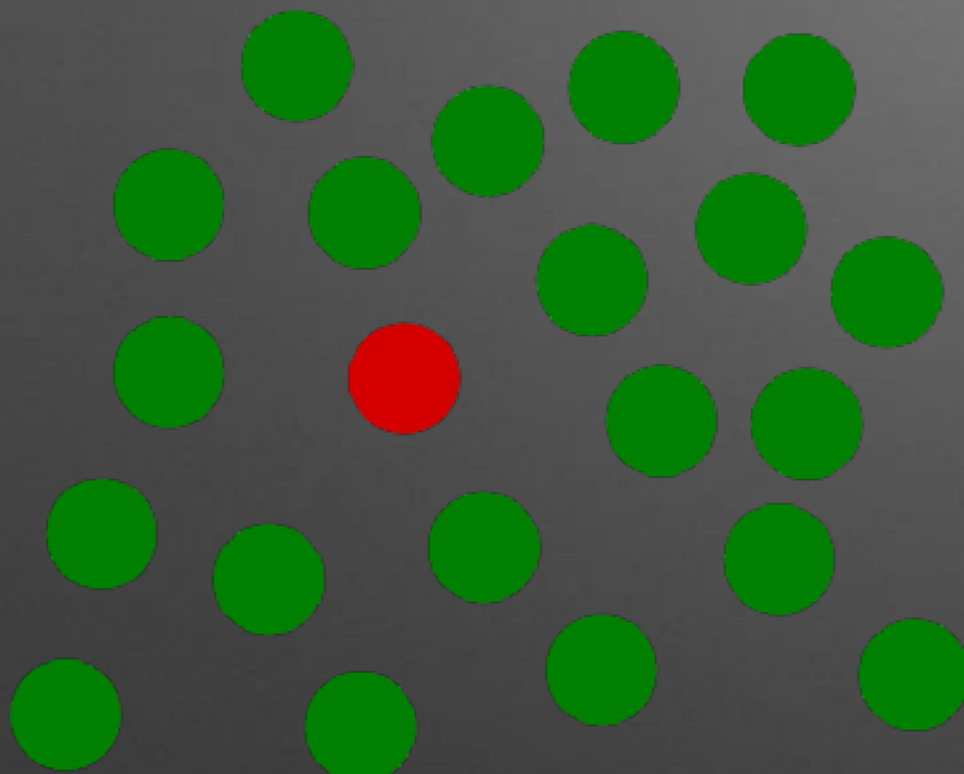
Input & Output

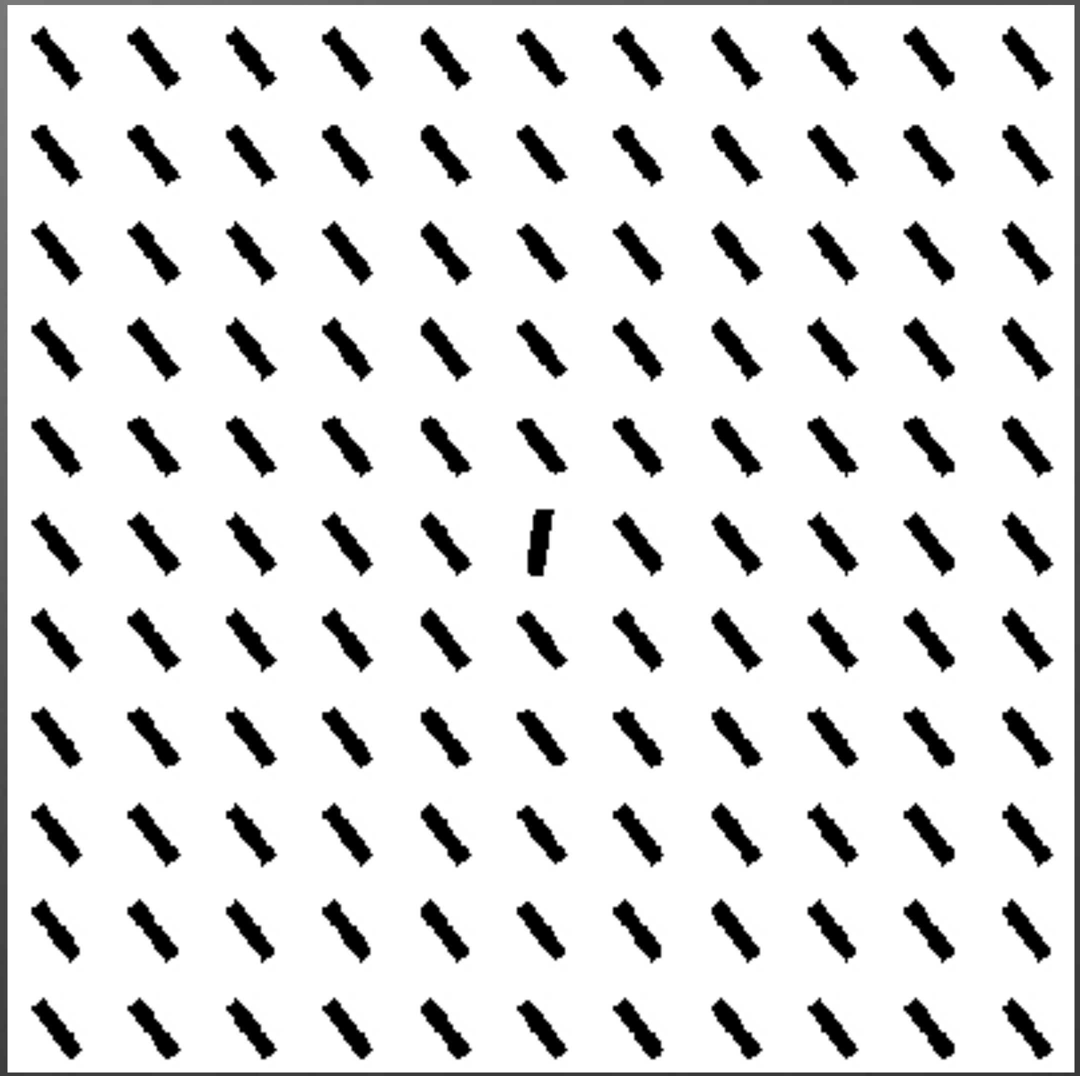
“Saliency map”

Factors

- Internal goals
- Knowledge - deers are meaningful than trees and grasses
- Features - brown colours are rare in this scene

Other kind of features





Colour and orientation

A Corner-based Saliency Model

Past works

- Custom definition of rareness
  - Patch dissimilarity
  - Information theory
  - Graph-based, face & object detection, etc.
- Machine learning
- Biological-inspired model

Itti & Koch (1998)

Intensity Colour Orientation

center-surround difference normalizations

Saliency map

Outline

- Hypothesis: why corner?
- Algorithm
- Results

Why corner?

Corner: general shape description

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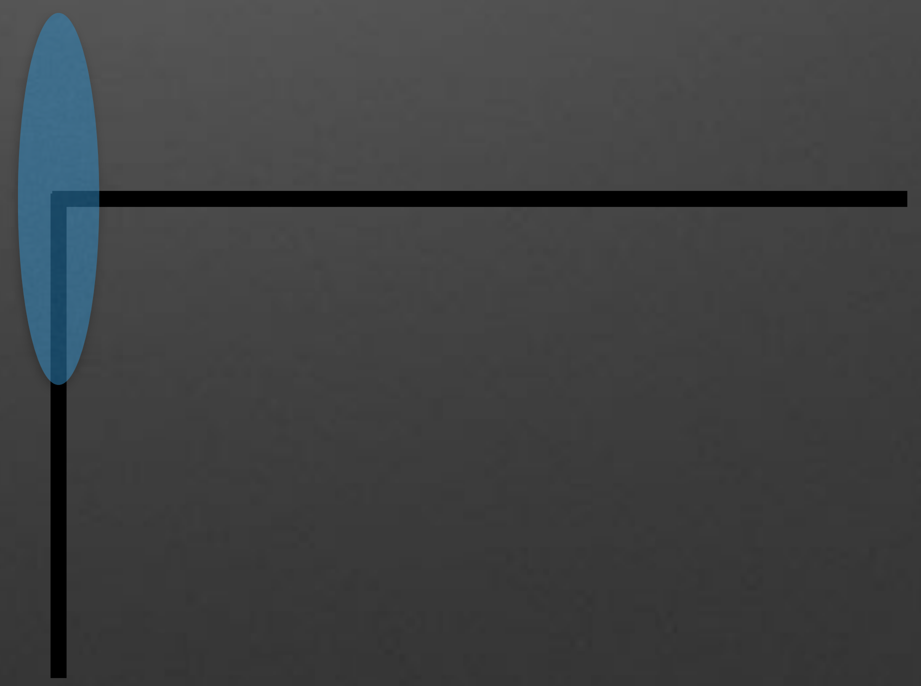
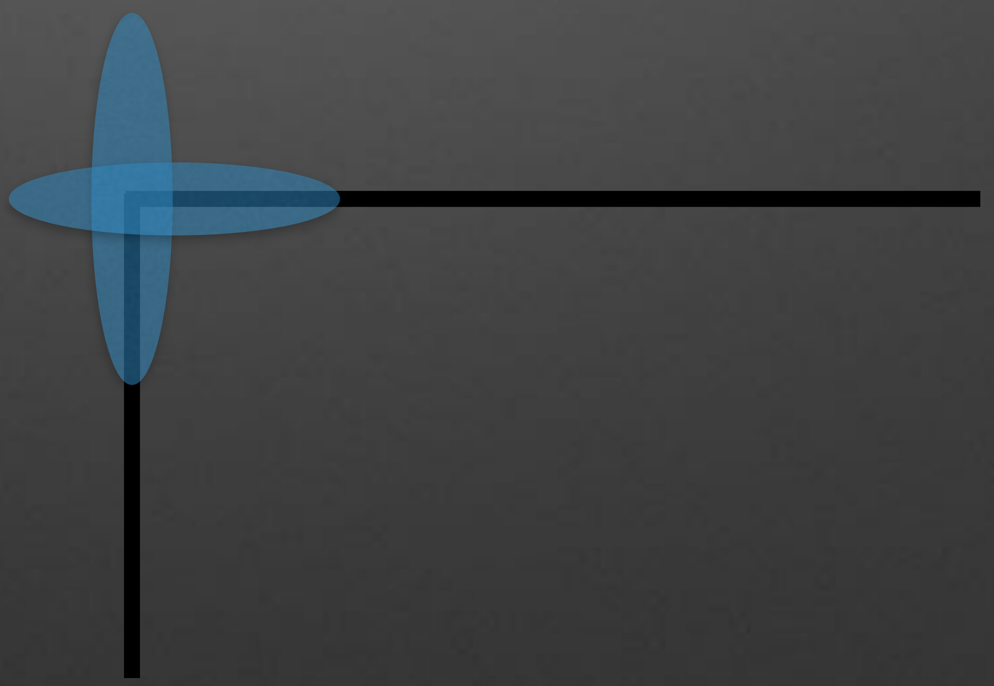


Gabor filters

Corner: general shape description



Gabor filters

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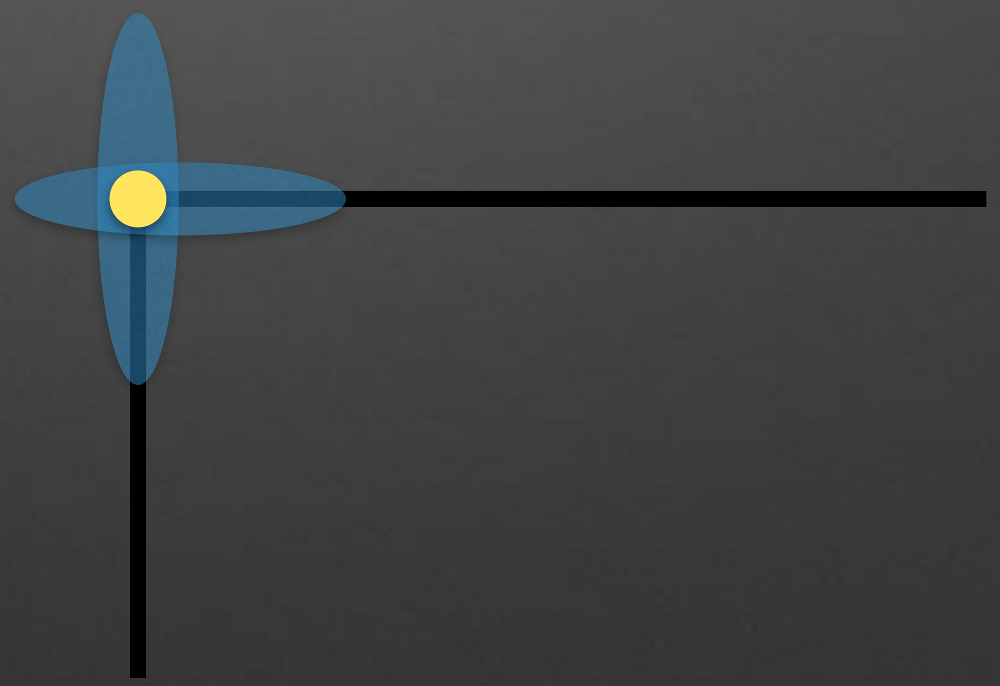

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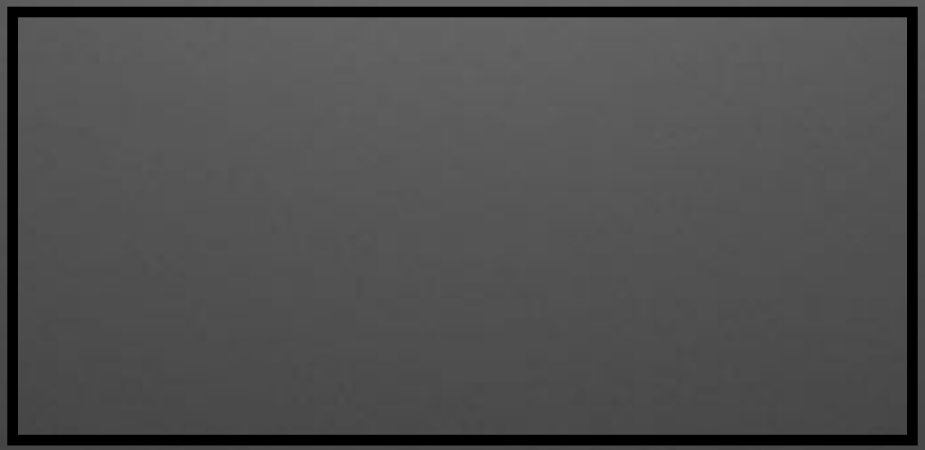

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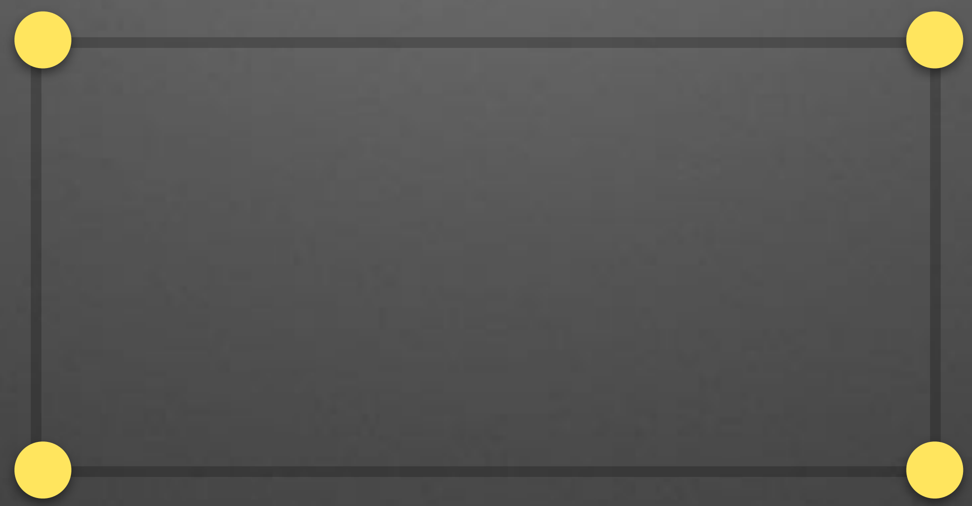

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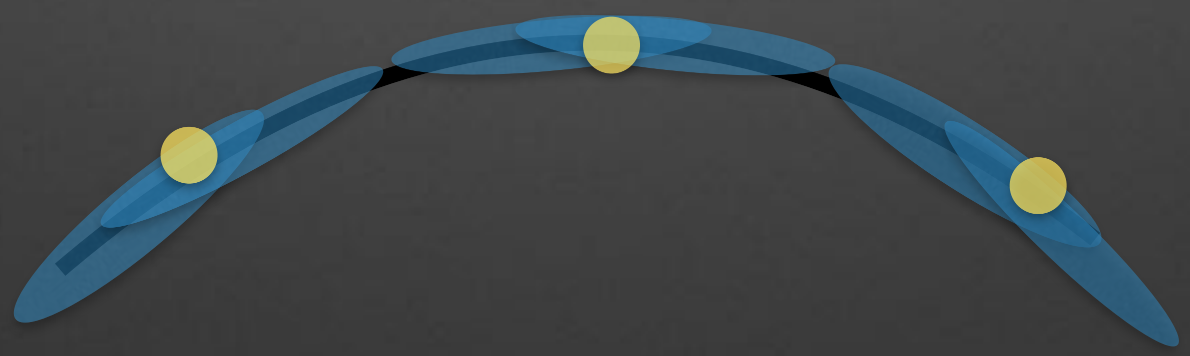

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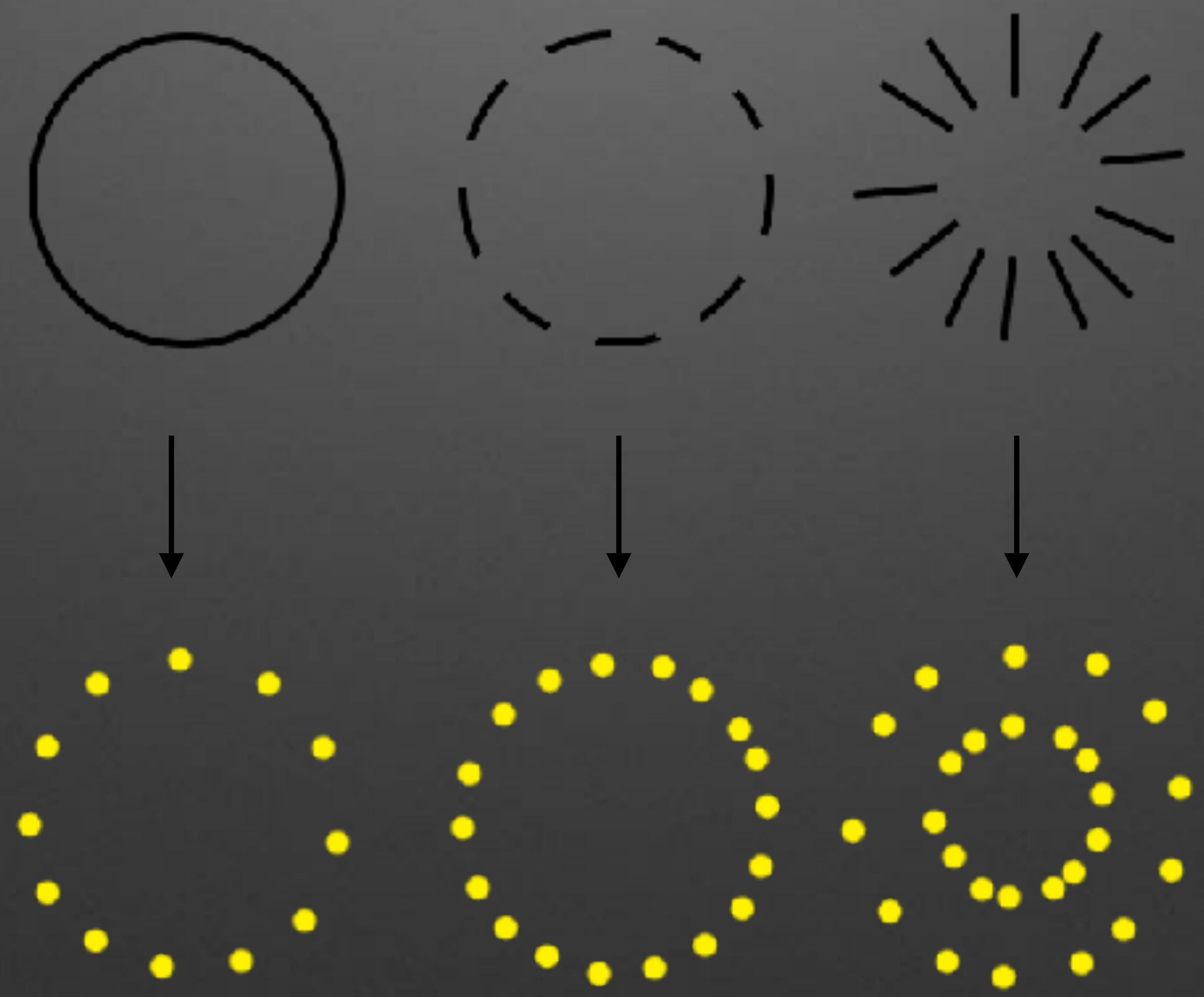

Corner: important information

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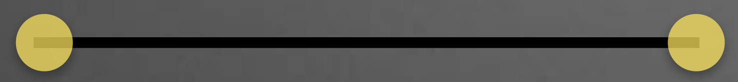

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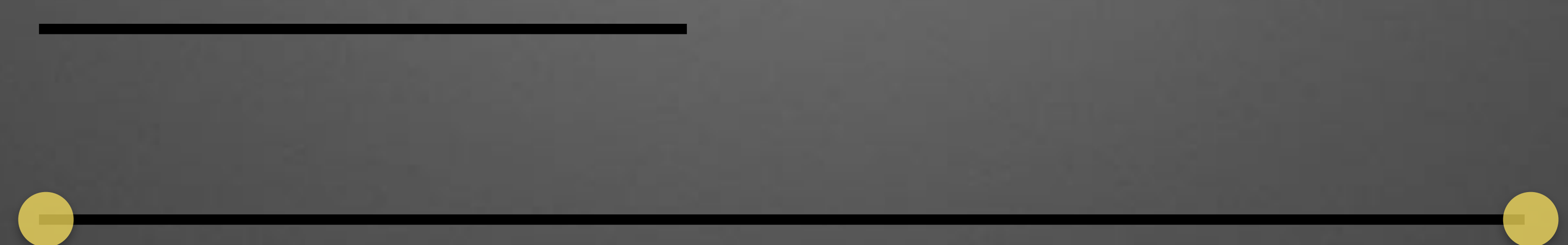

Corner: important information

...

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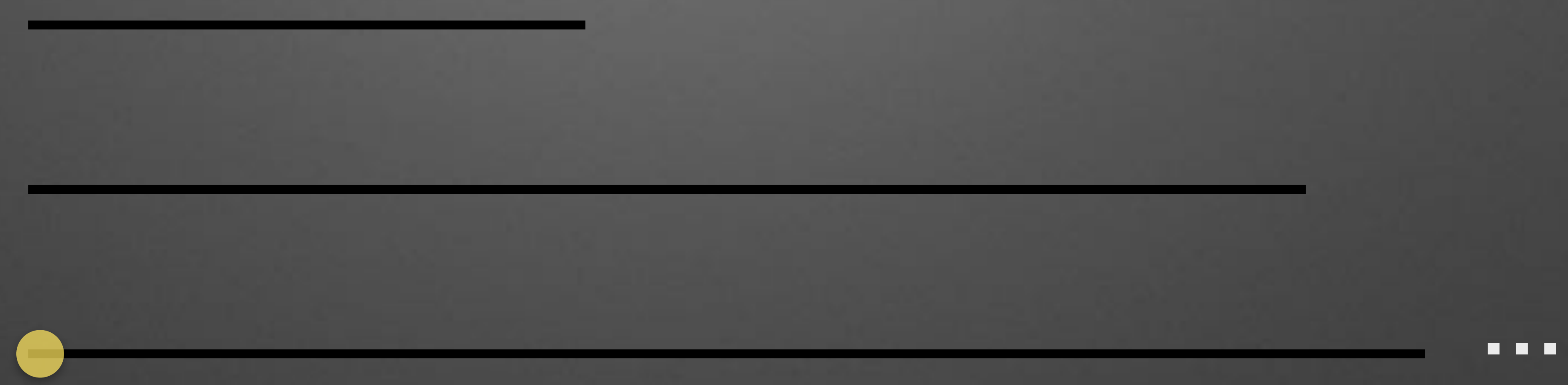

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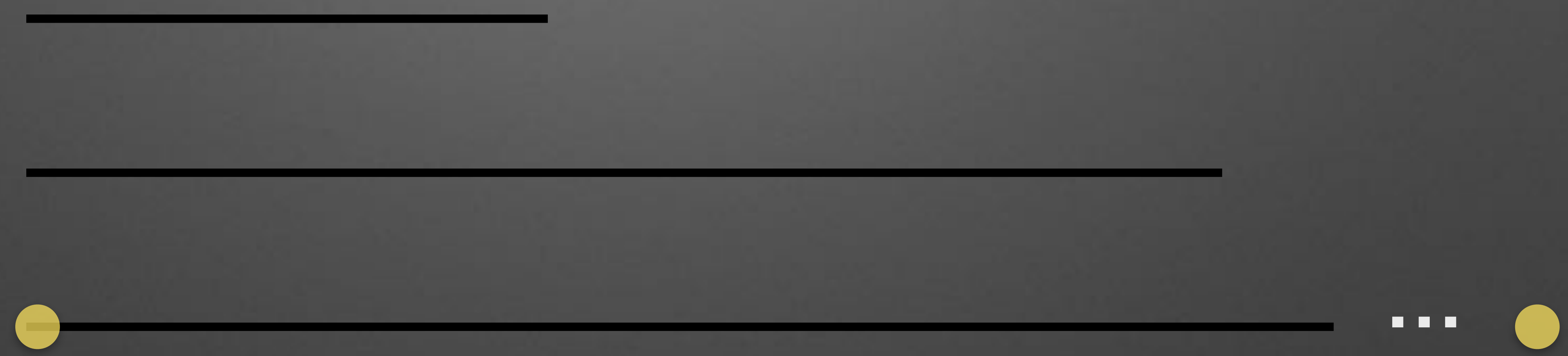

Algorithm

Algorithm

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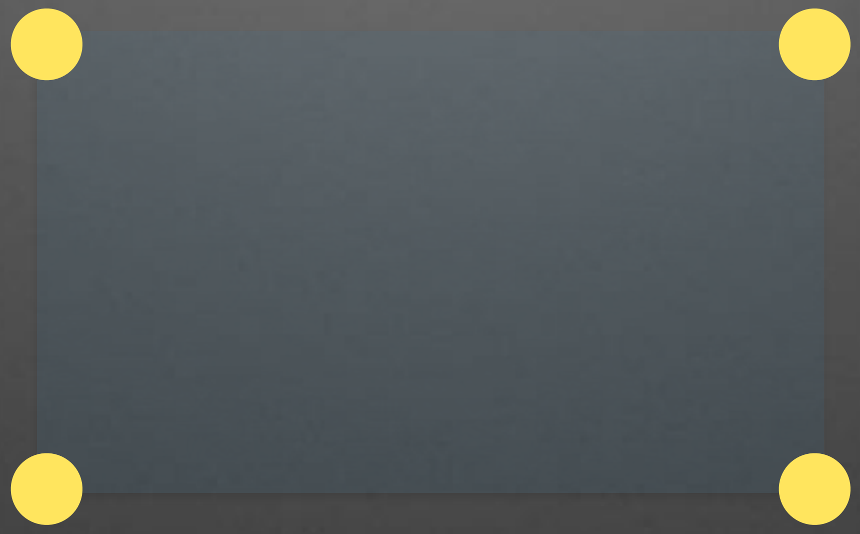

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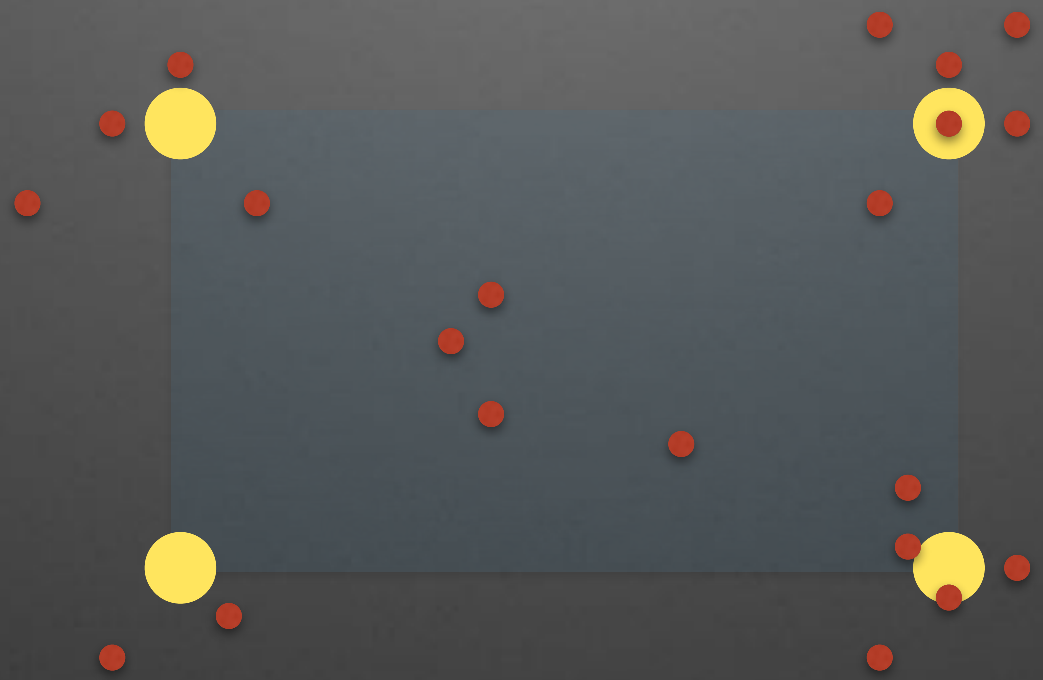

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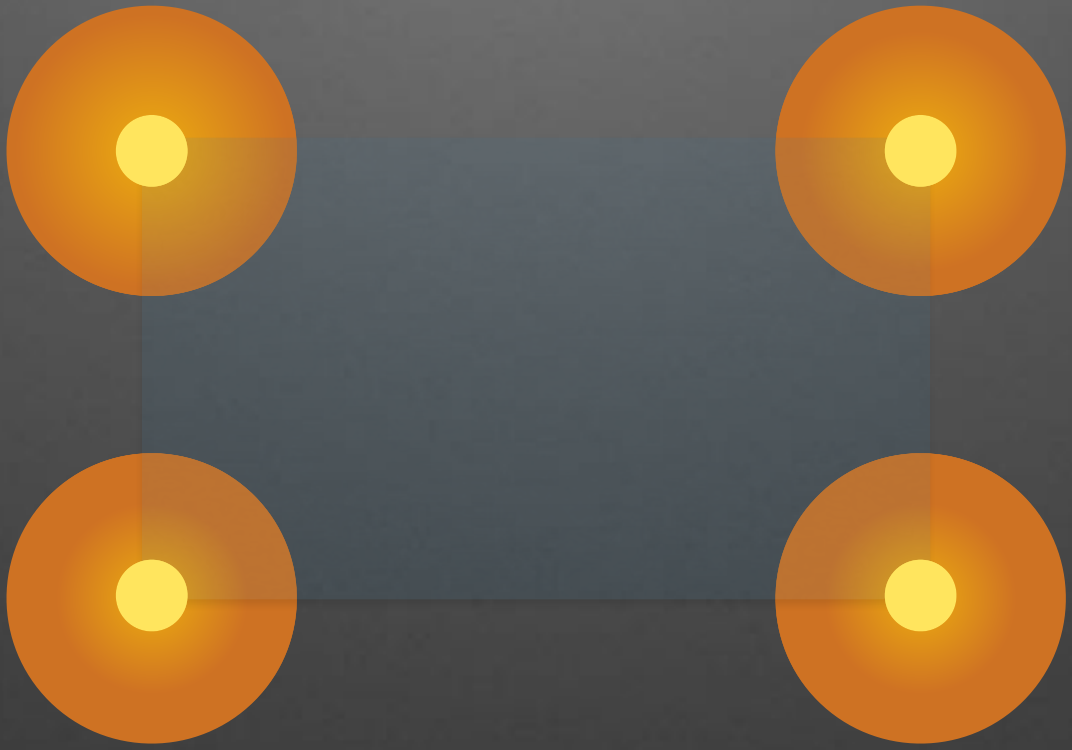

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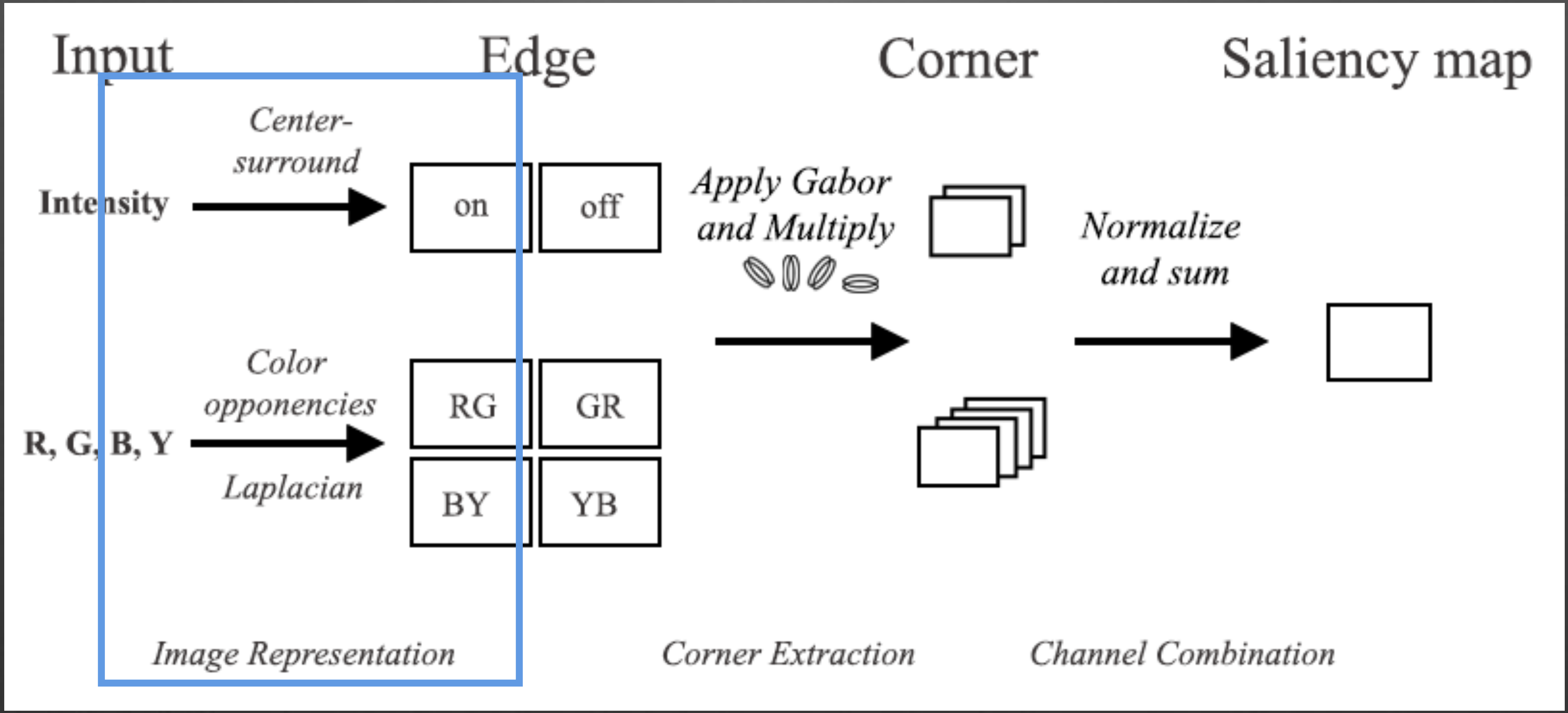
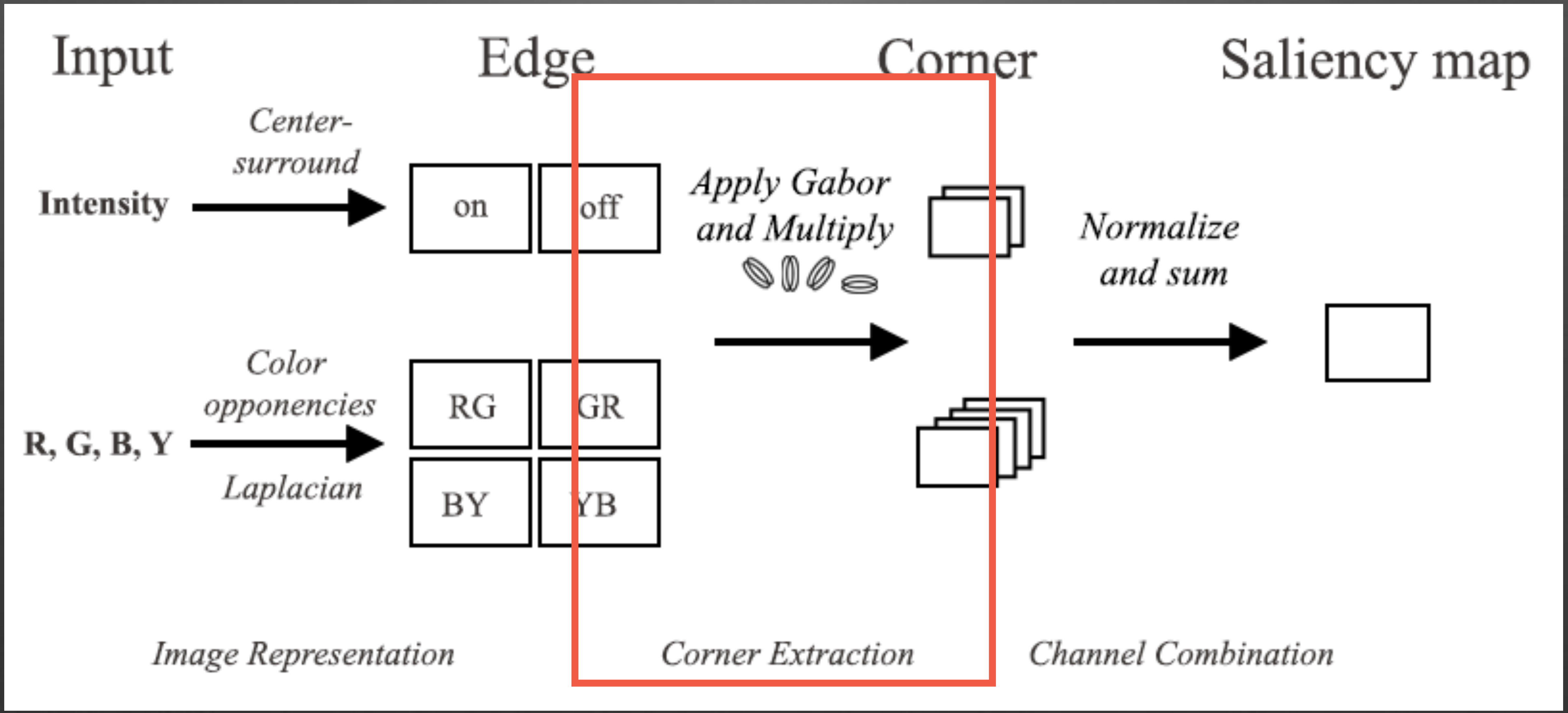


Input
Edge
Corner
Saliency map
Center-surround
Intensity
on
off
Apply Gabor and Multiply
Normalize and sum
Color opponencies
R, G, B, Y
Laplacian
RG
GR
BY
YB
Image Representation
Corner Extraction
Channel Combination

Algorithm



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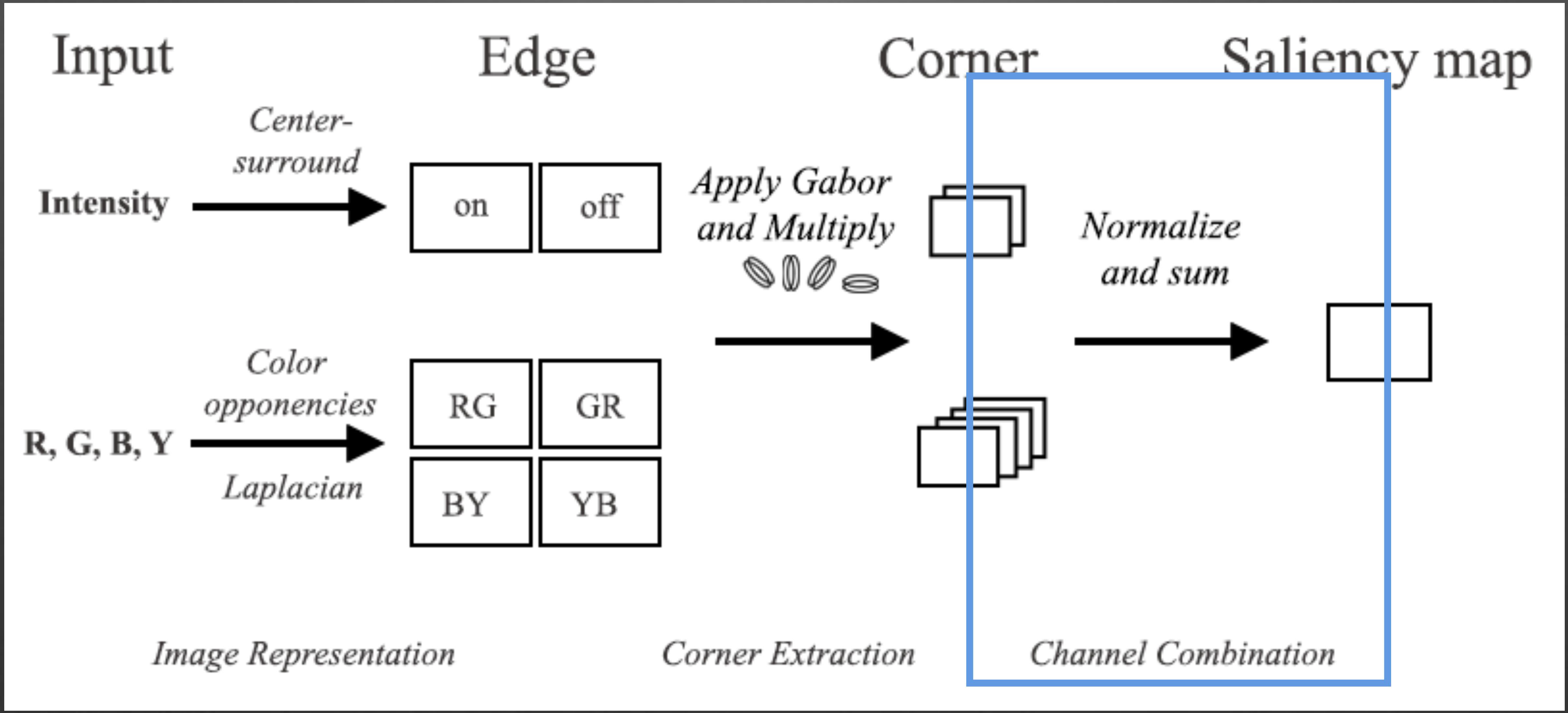
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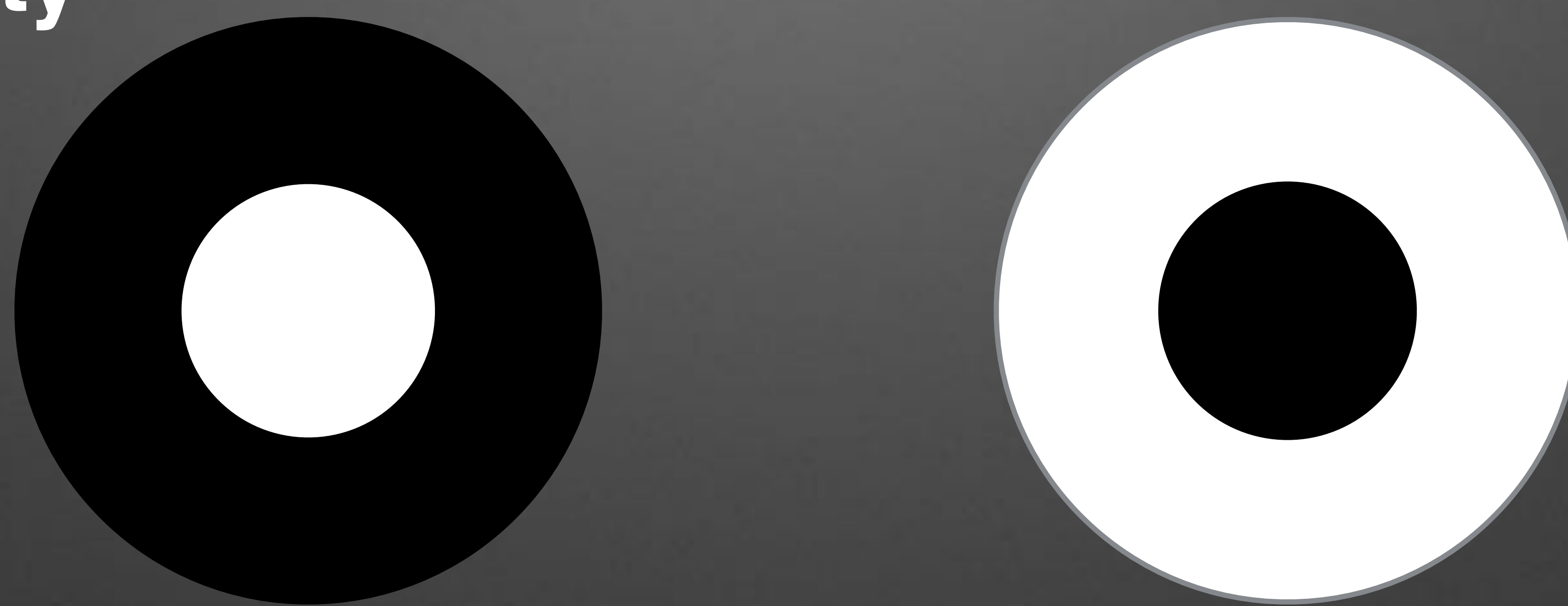
Intensity



ON OFF

$$\text{on}(x,y) = \lfloor \text{intensity}(x,y) - \text{avg. of surrounding intensity} \rfloor$$

$$\text{off}(x,y) = \lfloor \text{avg. of surrounding intensity} - \text{intensity}(x,y) \rfloor$$

Image Representation | Corner Extraction | Channel Combination

RGB

$$R = \left\lfloor r - \frac{g+b}{2} \right\rfloor$$

$$G = \left\lfloor g - \frac{r+b}{2} \right\rfloor$$

$$B = \left\lfloor b - \frac{r+g}{2} \right\rfloor$$

$$Y = \left\lfloor \frac{r+g}{2} - \frac{|r-g|}{2} - b \right\rfloor,$$

Colour opponency

$$RG = \lfloor R - G \rfloor$$

$$GR = \lfloor G - R \rfloor$$

$$BY = \lfloor B - Y \rfloor$$

$$YB = \lfloor Y - B \rfloor.$$

Intensity: on, off

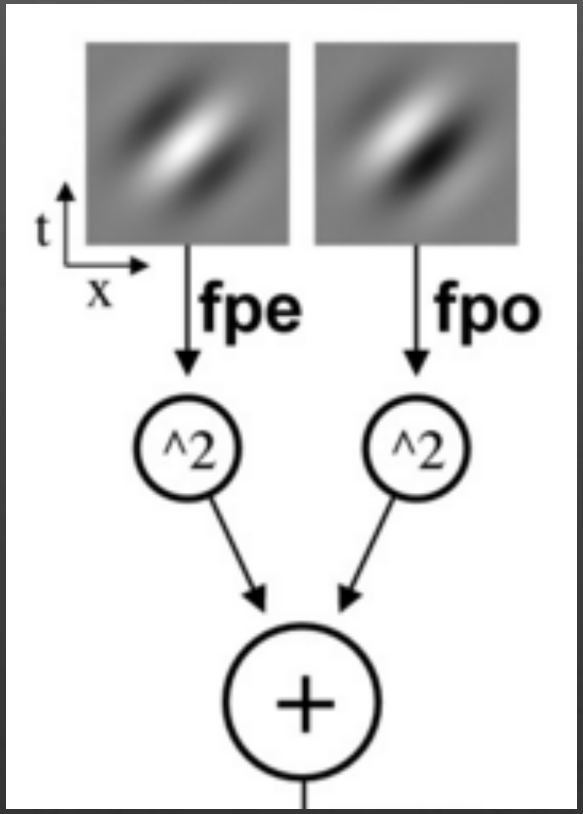
4 color opponencies

Laplacian Filter

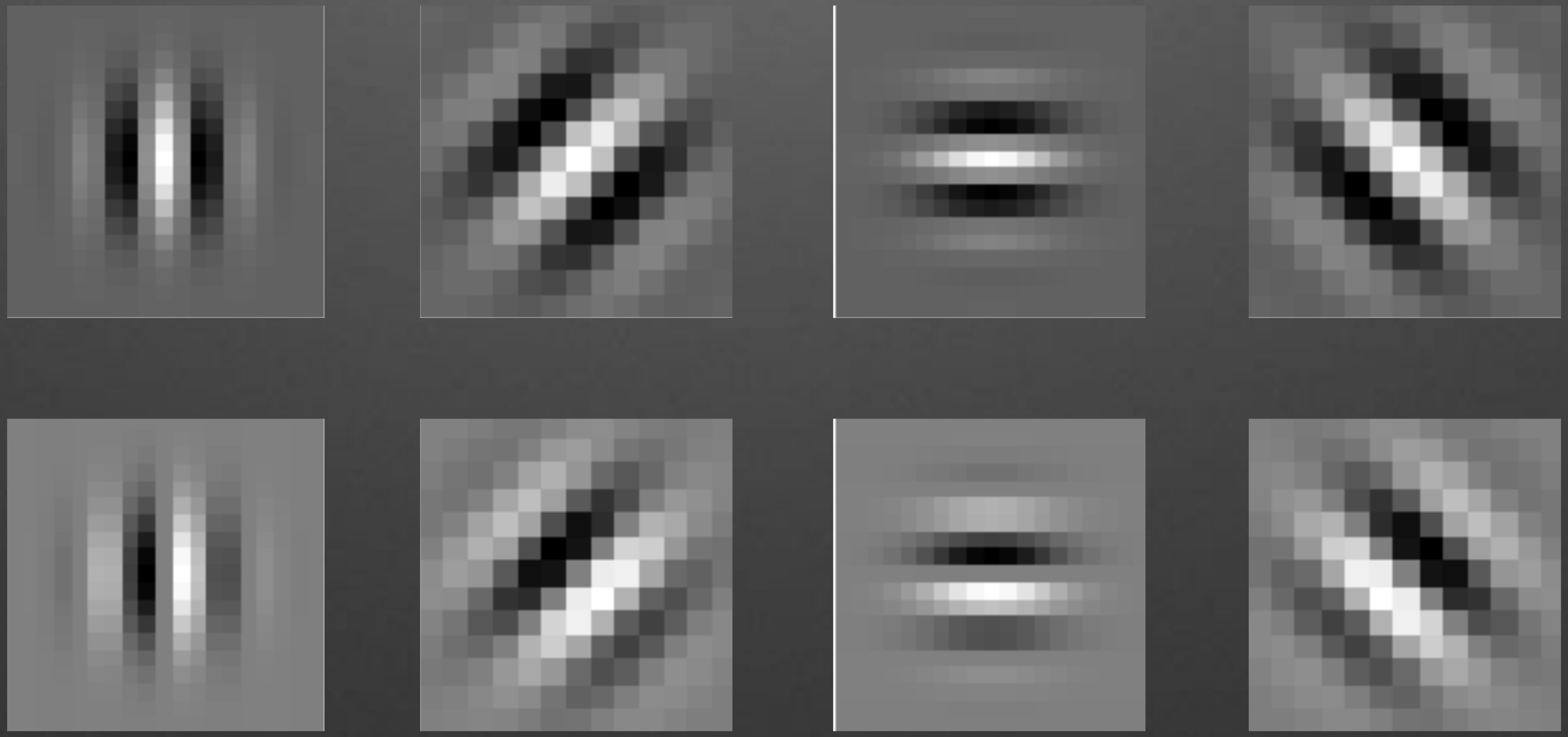
Edge features

Orientations

Gabor Energy Filter

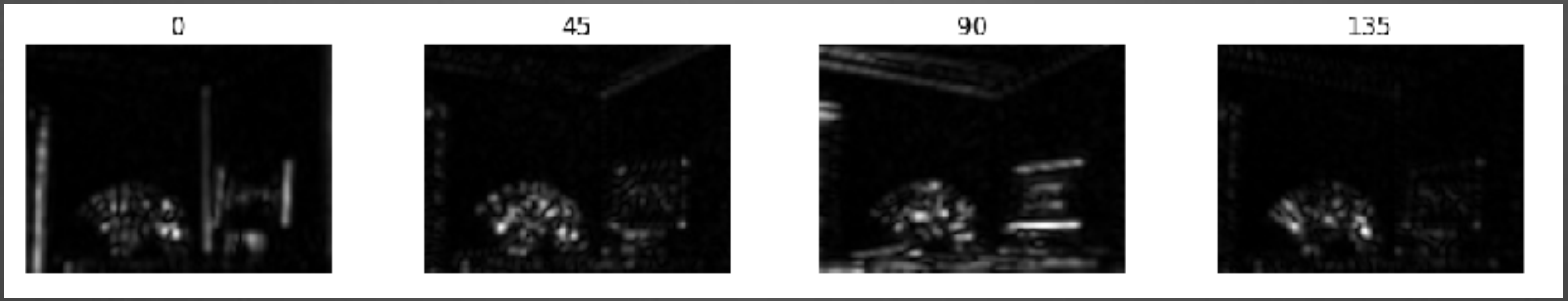


Orientations



4 orientations

Image Representation | **Corner Extraction** | Channel Combination



multiply pixelwise

↓

Enhance by Logarithm

↓

Corners

Image Representation

Corner Extraction

Channel Combination

(promote individual clusters)

(suppress boring information)

Linear Combination

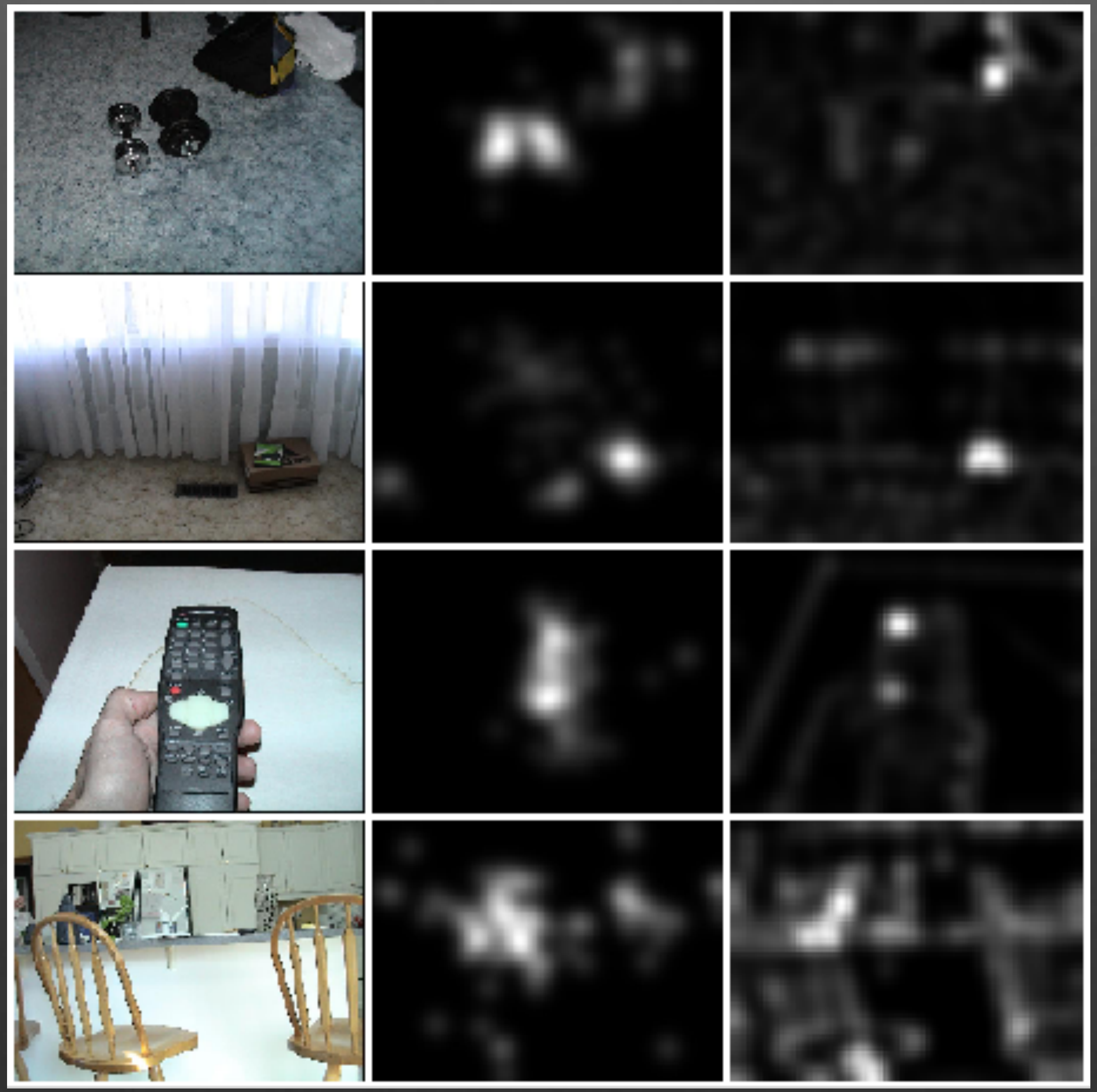
Results

Results

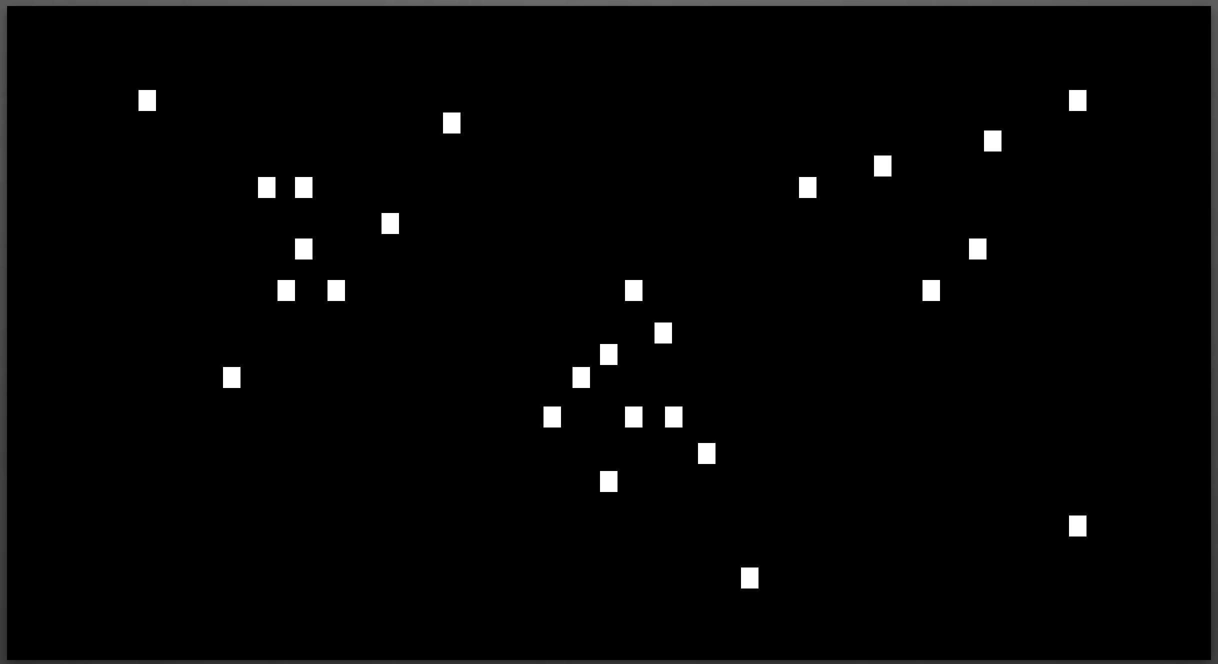
Toronto Dataset
(Bruce et al.)

120 indoor & outdoor images

Examples



Results



Bitmap of fixations

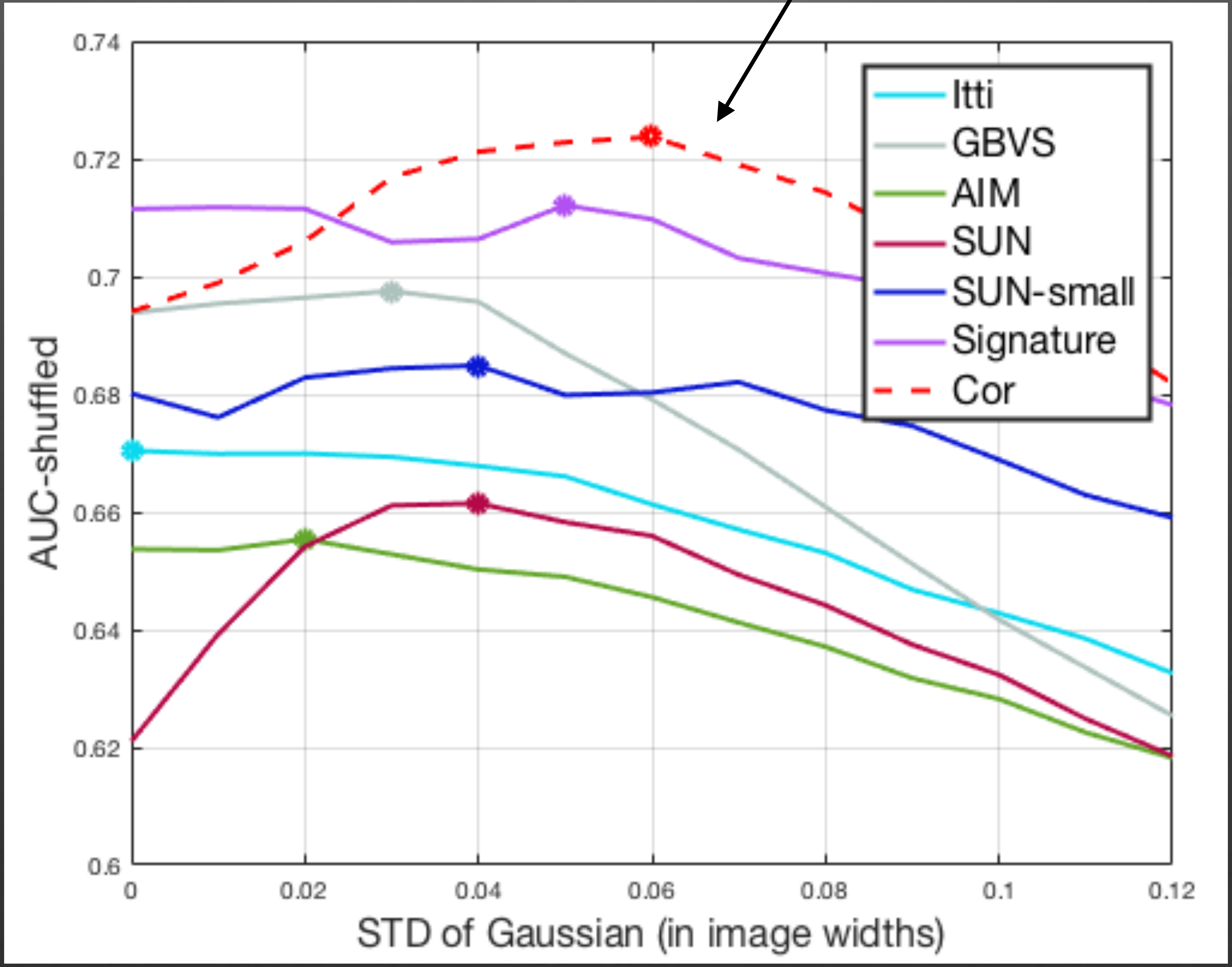
Results

Metric: AUC-shuffled

(Area Under ROC Curve)

Results

our model



Results

TABLE I. PERFORMANCE OF 7 ALGORITHMS ON TORONTO DATASET

Algorithm	AUC-shuffled (mean STD)	AUC-shuffled (optimal STD)
Itti et al. [3]	0.6573	0.6704
GBVS [9]	0.6714	0.6975
AIM [1]	0.6415	0.6554
SUN [16]	0.6429	0.6615
SUN-small	0.6764	0.6849
Signature [19]	0.7016	0.7121
Cor (8)	**0.7074**	**0.7237**

Results

MIT Saliency benchmark: dataset MIT300

17th of 61 models

Sorted by AUC-shuffled score

models

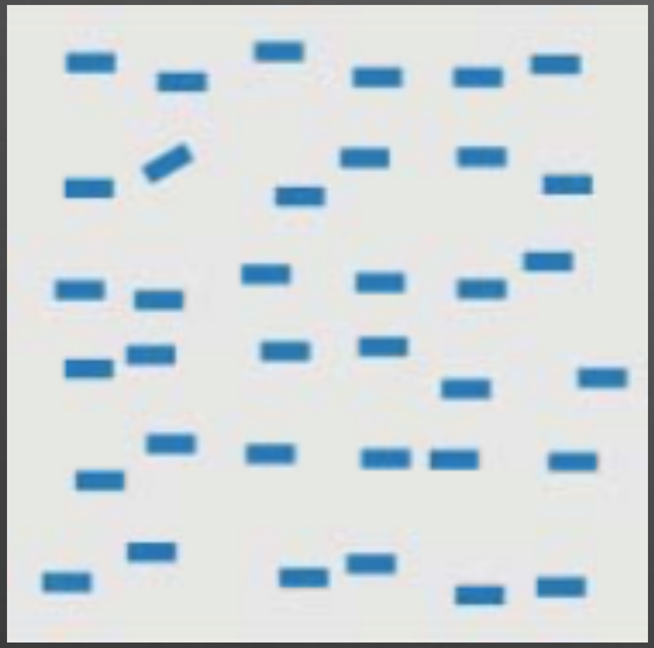
Deep Gaze 1	I: Boosting Saliency Prediction with Feature Maps Trained on ImageNet [arxiv 2014]		0.84	0.39	4.97	0.83	0.66	0.48	1.22	1.23	last tested: 15/11/2015 maps from authors	
AIM	Neil Bruce, John Tsotsos. Attention based on information maximization [JoV 2007]	matlab	0.77	0.40	4.73	0.75	0.66	0.31	0.79	1.18	last tested: 23/09/2014 maps from code (DL:15/01/2014) with params: resize=0.5, convolve=1, thebasis='31infomax975'	
Image Signature	Xiaodi Hou, Jonathan Harel, Christof Koch. Image Signature: Highlighting Sparse Salient Regions [PAMI 2011]	matlab	0.75	0.43	4.49	0.74	0.66	0.38	1.01	1.09	first tested: 19/06/2014 last tested: 15/11/2015 maps from authors	
Local+Global Saliency Model (LGS)	Ali Borji, Laurent Itti. Exploiting local and global patch rarities for saliency detection. [CVPR 2012]	matlab	0.76	0.42	4.63	[illegible]	0.66	0.39	1.02	1.11	first tested: 27/11/2014 last tested: 15/11/2015 maps from authors	
RARE2012 - Improved	Pierre Marighetto, Nicolas Riche, Matei Mancas. LSUN SALICON Challenge (http://lsun.cs.princeton.edu/leaderboard/#saliencysalicon)	improved from: matlab	0.81	0.48	3.74	0.80	0.66	0.51	1.34	0.89	first tested: 23/10/2015 last tested: 23/10/2015 maps from authors	
Corner-based Saliency (CORS)	Wirawit Rueopas	Python	0.79	0.47	3.91	0.77	0.66	0.46	1.22	1.03	first tested: 30/03/2016 last tested: 30/03/2016 maps from authors	
Salient Point Parzen Map (SPPM)	Saulo Oliveira		0.77	0.46	4.17	0.76	0.66	0.42	1.10	1.18	first tested: 23/10/2016 last tested: 23/10/2016 maps from authors	
Boolean Map based Saliency	Jianming Zhang, Stan Sclaroff. Saliency detection: a boolean map approach [ICCV 2013]	matlab, executable	0.83	0.51	3.35	0.82	0.65	0.55	1.41	0.81	first tested: 14/05/2014 last tested: 23/09/2014	

http://saliency.mit.edu

Weaknesses

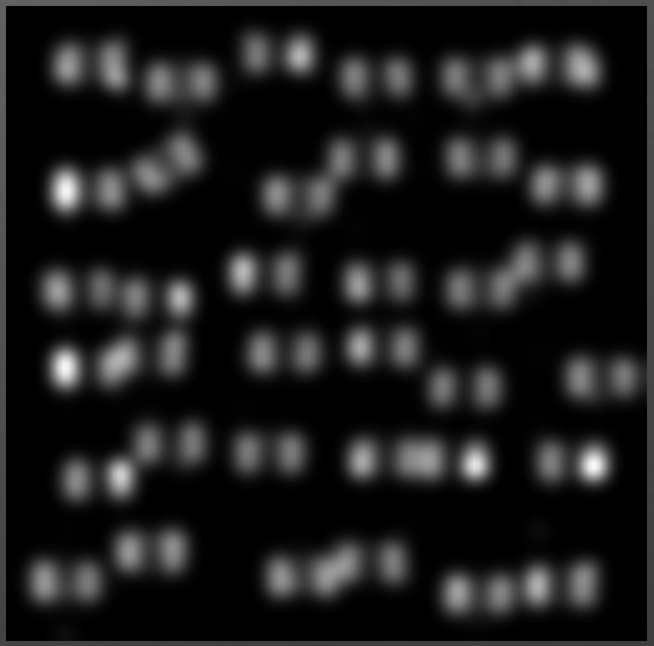
- Predict well only on natural images

Weaknesses



Input

Orientational pop-out



Saliency map by proposed model

Weaknesses

- No higher knowledge
  - Shape
  - Faces
  - Object

Conclusion

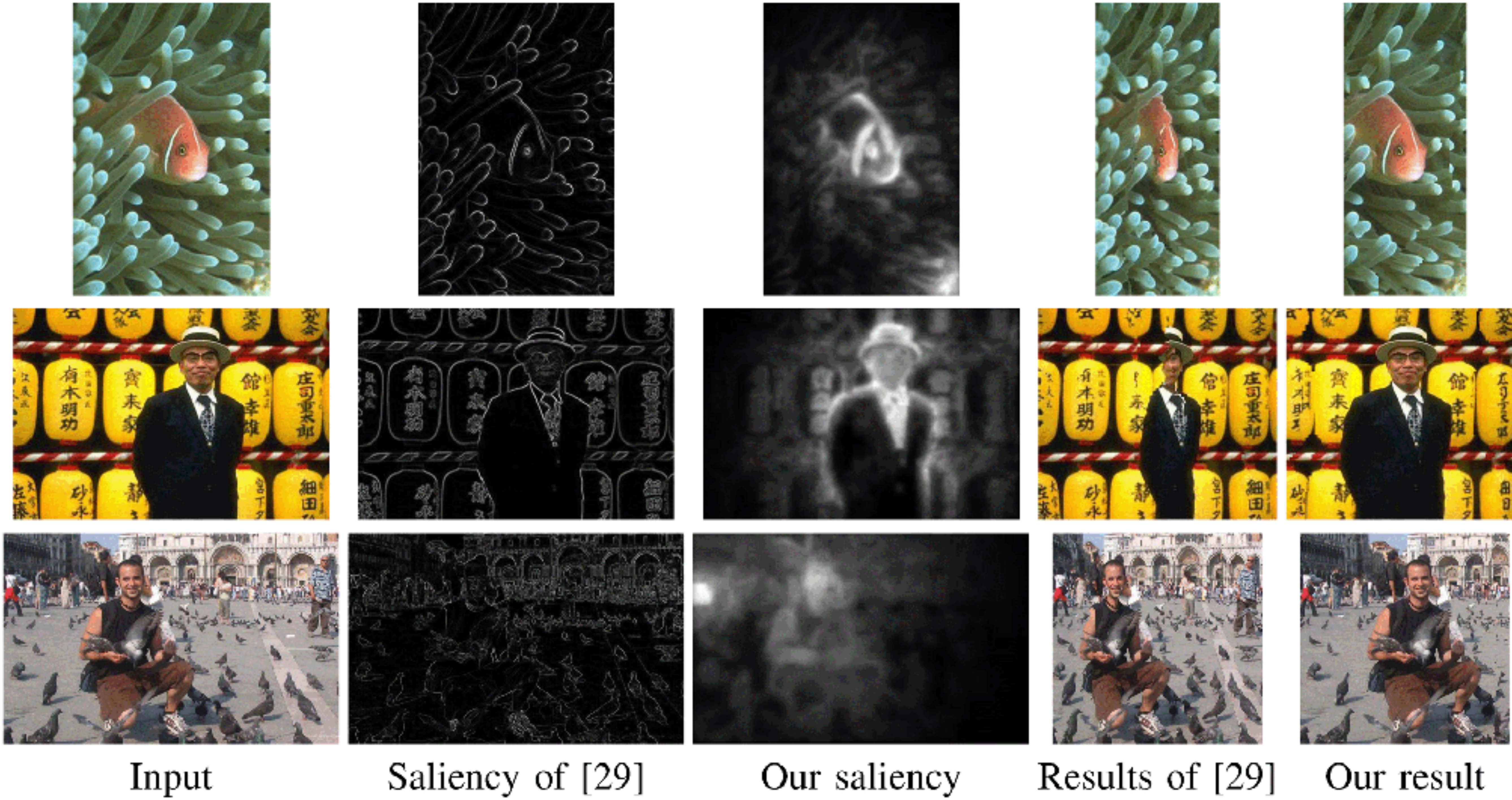
- Corners
  - Predict saliency well
  - Biologically plausible
  - Good shape descriptor

Thank You :)

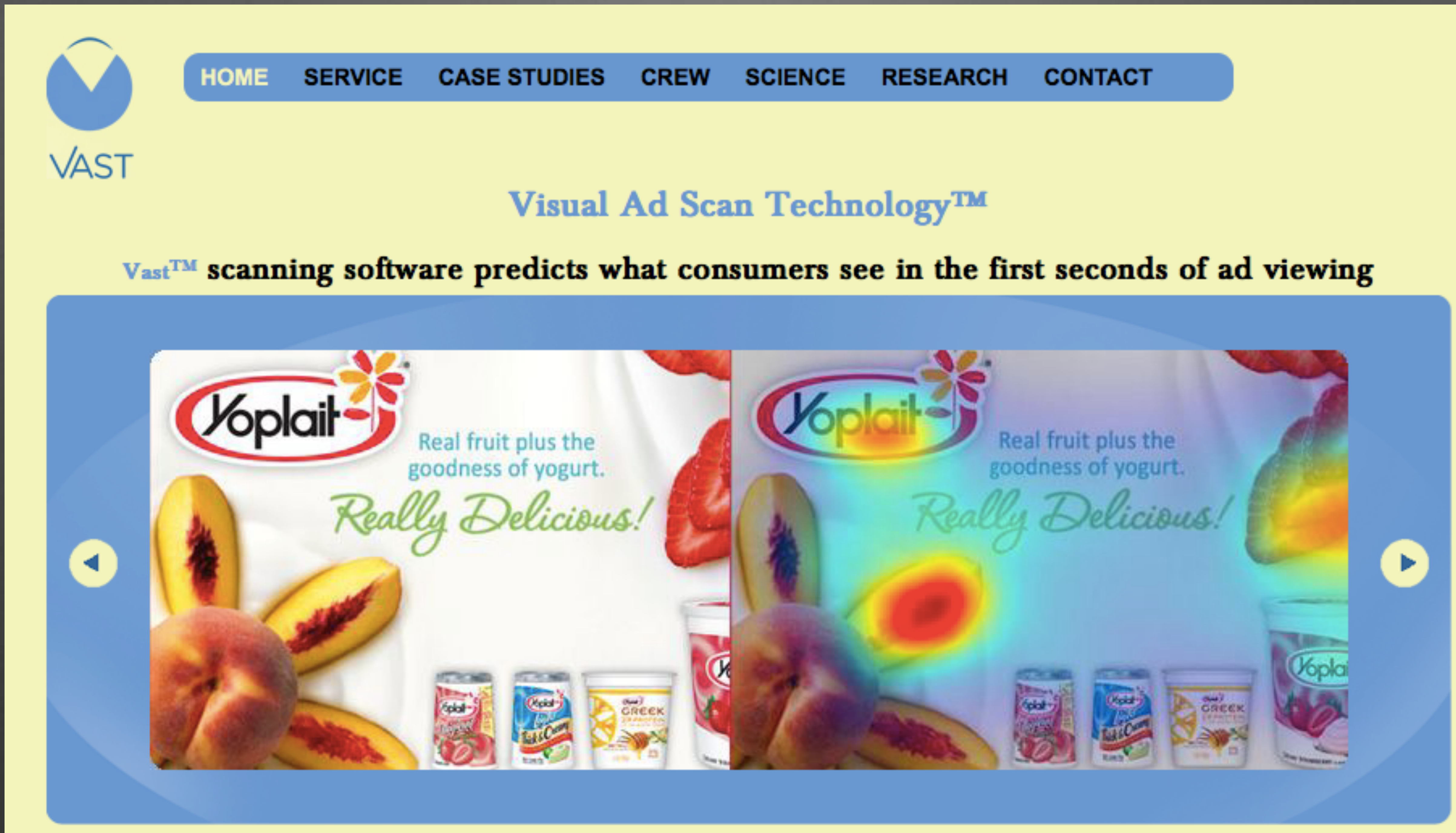
Q & A

Applications

- Reduce the object detection time
- Video compression
- Image retargeting
- Advertisement validation



https://www.computer.org/csdl/trans/tp/2012/10/ttp2012101915-abs.html



http://www.visualadscan.com

Why not machine learning?

- Clear contribution of feature
- System is easier to get up and running

Resources

http://www.imodel.org/m/09/MEO_Gabor/g/MEO_Gabor.jpg