Scallops to Subway Cars

-Detection and Counting

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Outline

- Subway car Detection
- Scallop Detection and Counting
  - Visual Attention
  - Eigen value shape descriptors

Redbird Reef

- 1996-2009 objects added
  - 2001: First subway cars
- Over 900 NYC subway cars and other objects

**Slide adapted from Effects of Artificial Reef Structures on the Geology and Biology of the Seafloor: example from the inner continental shelf off Delaware, Raineault, Art Trembanis and Doug Miller.*

Redbird Reef: Backscatter Image

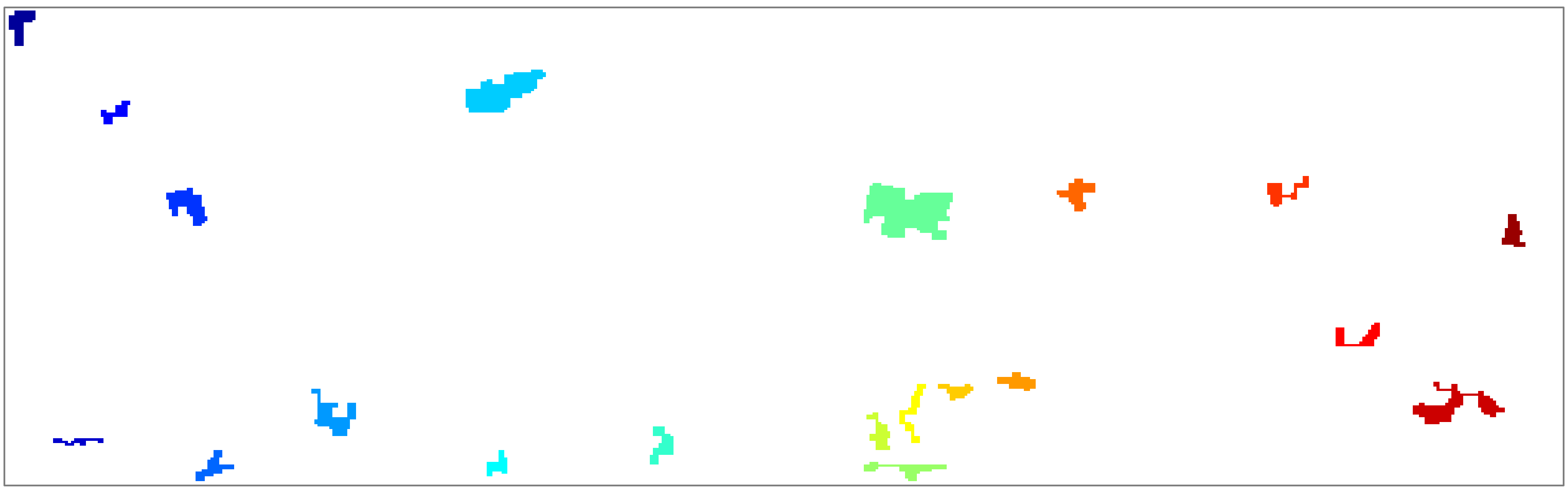


Fig 1(top). *Backscatter image* **Fig 2(bottom).** *Detected features*

Detecting Subway Cars

- The problem of detecting subway cars can be simplified to
  - Segmenting objects with distinctive edges
  - Detecting rectangles among segmented objects
- Points that help segmentation of cars
  - Distinctive rectangular edges
  - The edges are fairly unbroken

Scallops

*http://www.myrecipes.com

One way we think about scallops.

Sea Scallops (*Placopecten magellanicus*)

*http://www.edc.uri.edu/

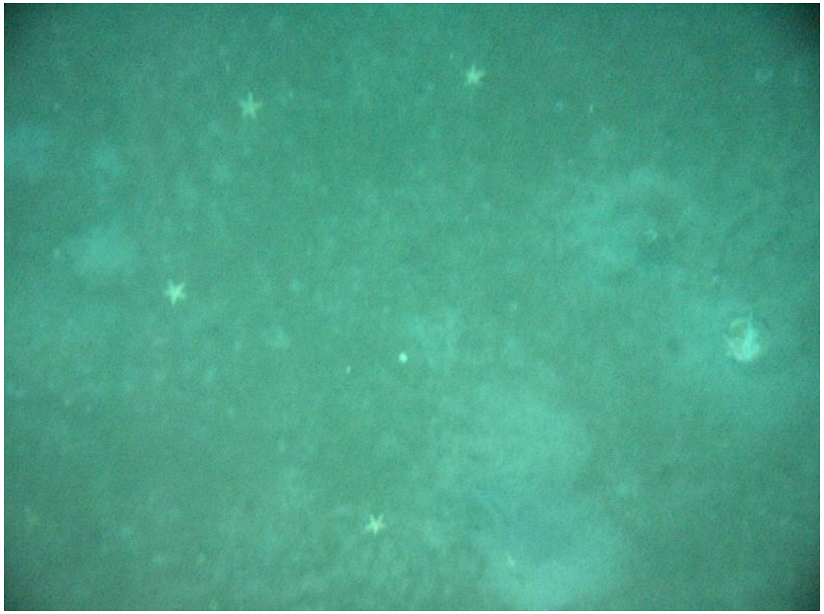
Scallop Counting

- Why count scallops?
  - Scallop counting is important in regulating the fishing areas and keep track of abundance of scallops.
- Tradition methods used for counting
  - Dredge the sea floor using a commercial dredge with a sieve. The sieve collects the scallops. The dredge sediment is then manually counted.
- Current counting method involves using images from an AUV
  - Its non-invasive compared to dredging
  - It might give a more complete idea on scallop densities

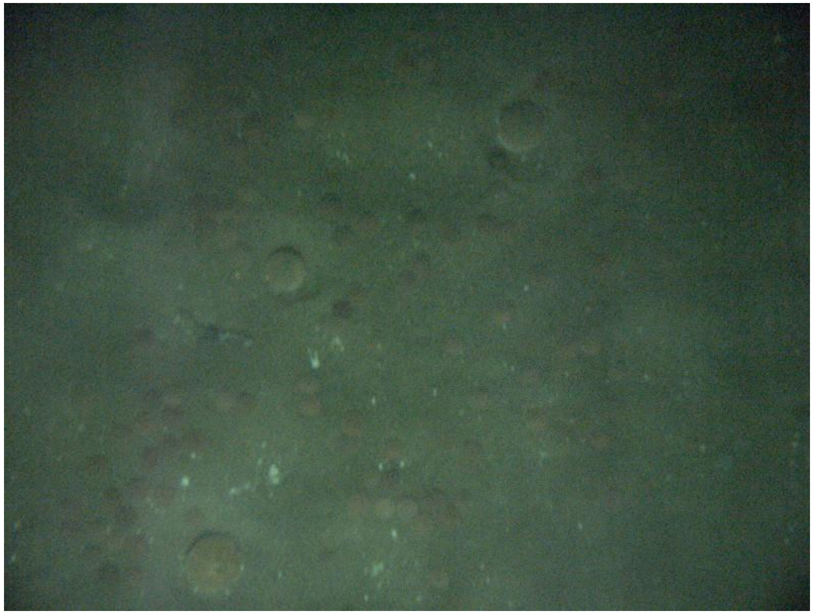
Scallops

Example image with scallops shown in red circles

Day and Night Illumination Variation and Vignetting effects



Daytime Image



Nighttime Image

Identifying Scallops

- Some possible features that can be used to identify scallops
  - Dark crescent on top
  - Bright crescent on the periphery
  - Yellowish color

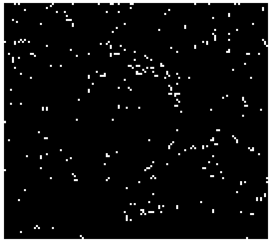
Some sample scallop images

Difficulties in Identifying Scallops

- The images contain a lot of noise (grainy appearance) so edge detection or thresholding fail.
- The edges/crescents in the scallop are often not very distinct
- The crescents are often discontinuous due to noise
- Major part of the scallop looks texturally identical to the background
- They can often be partly or almost fully covered by sediments

Original Image

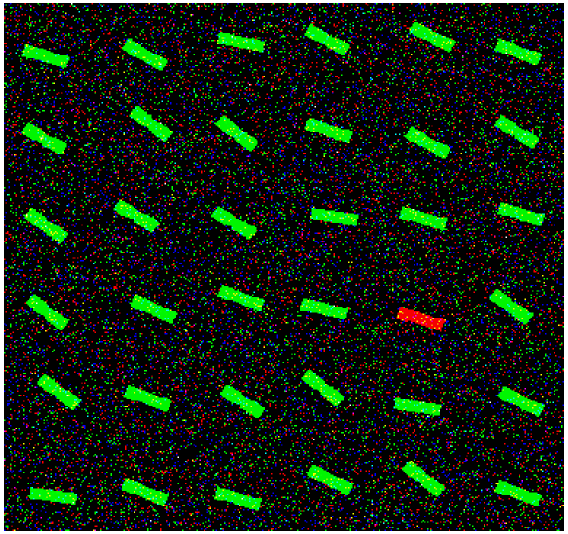
Thresholded



Edge Filtered

Visual Attention

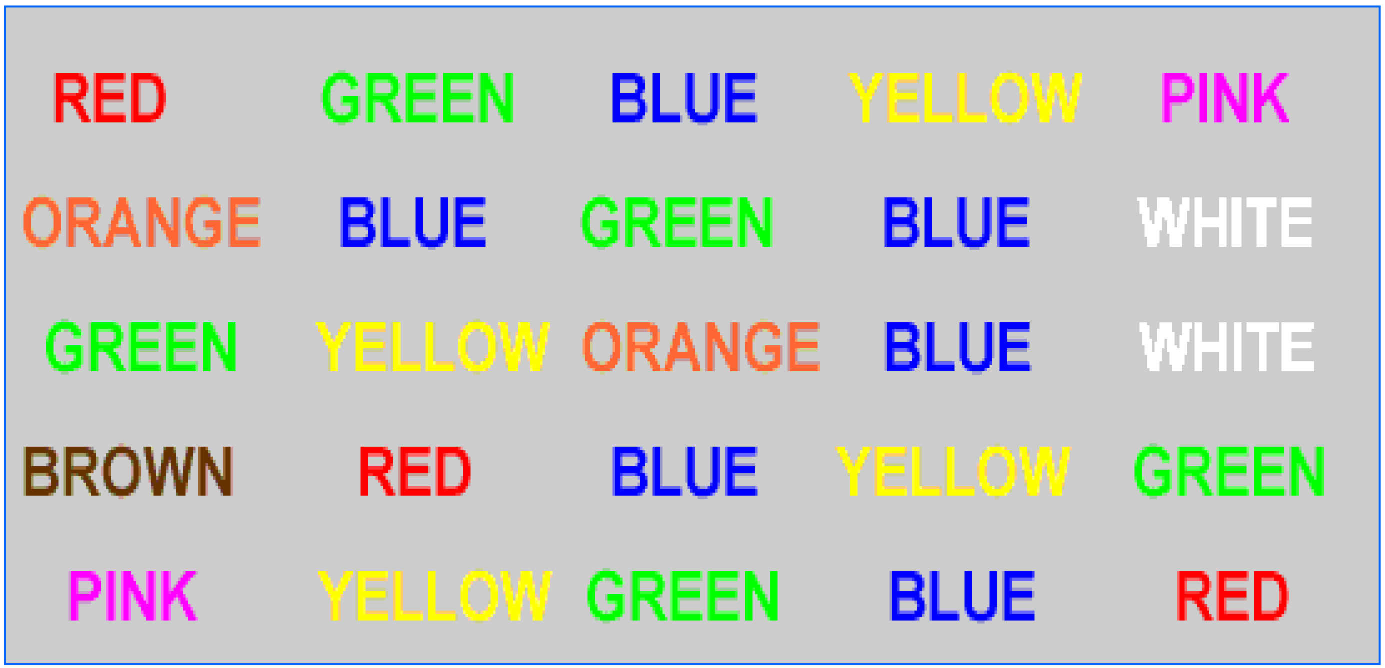
- Information comes in through the optic nerve at the rate of 10^7-10^8 bits per second.
- We employ selective attention to process parts of the images preferentially over the others.



Example to illustrate visual attention

**Computational Architectures in Biological Vision, Itti*

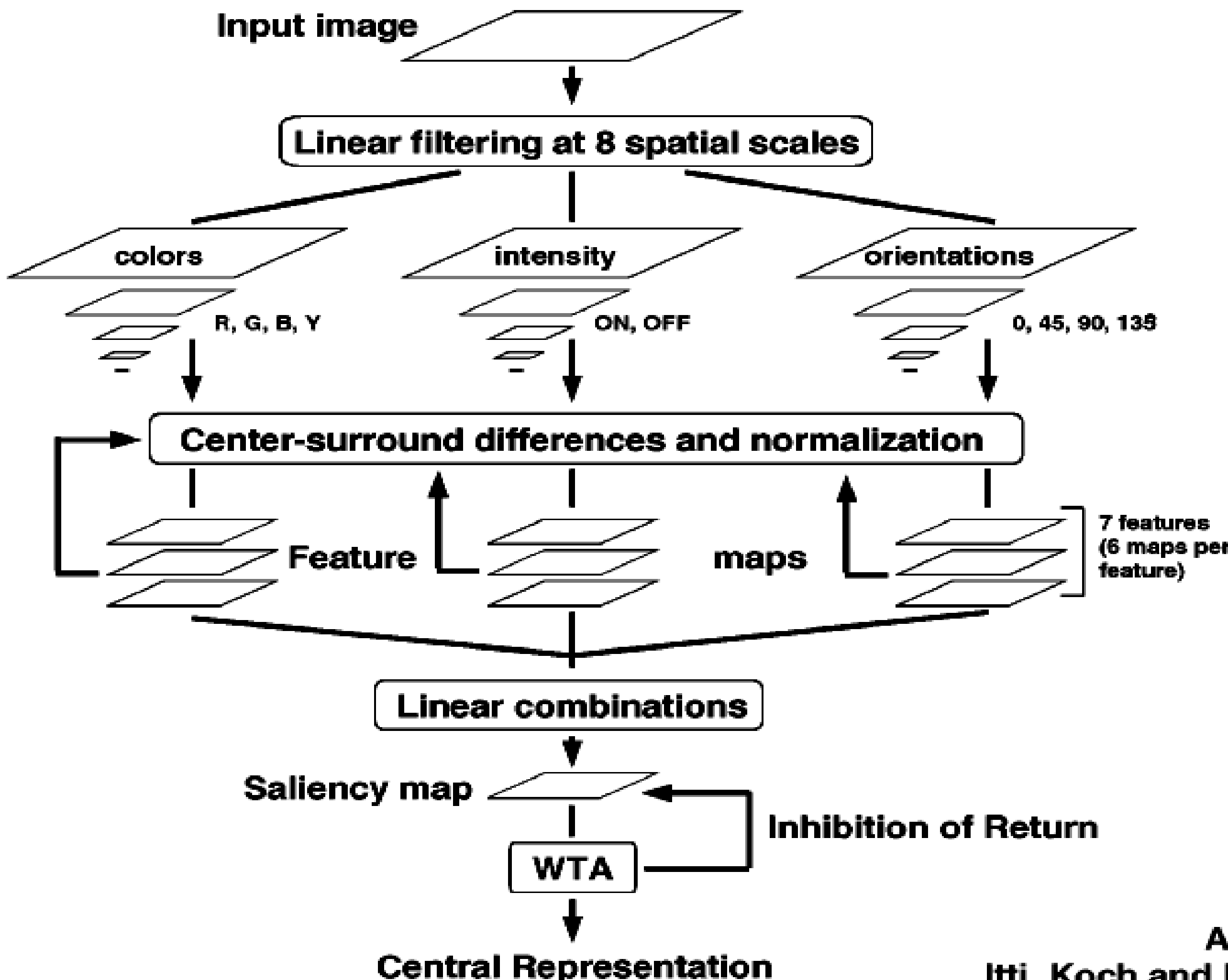
Visual Attention Mechanism
Bottom Up vs Top Down



Example to illustrate the difference between bottom up and top down attention

**Attention, Effort, and Resource Allocation, Bauer R*.

Computational Model of Visual Attention



Adapted from
Itti, Koch and Niebur (1998)

Center-Surround differences and Feature Maps

- Feature Maps

$$I(c,s) = |I(c) \ominus I(s)|$$

where $s = c + \delta, c \in \{2,3,4\}$ and $s \in \{3,4\}$ and $\ominus$ is the center-surround difference operator.

Similarly,

$$RG(c,s) = |(R(c) - G(c)) \ominus (R(s) - G(s))|$$

$$BY(c,s) = |(B(c) - Y(c)) \ominus (B(s) - Y(s))|$$

$$O(c,s,\theta) = |O(c,\theta) \ominus O(s,\theta)|$$

Where $\theta \in \{0°, 45°, 90°, 135°\}$

Conspicuity and Saliency Maps

- Conspicuity Map

$$\bar{I} = \bigoplus_{c=2}^{4} \bigoplus_{s=c+3}^{c+4} N(I(c,s))$$

$$\bar{C} = \bigoplus_{c=2}^{4} \bigoplus_{s=c+3}^{c+4} [N(RG(c,s)) + N(BY(c,s))]$$

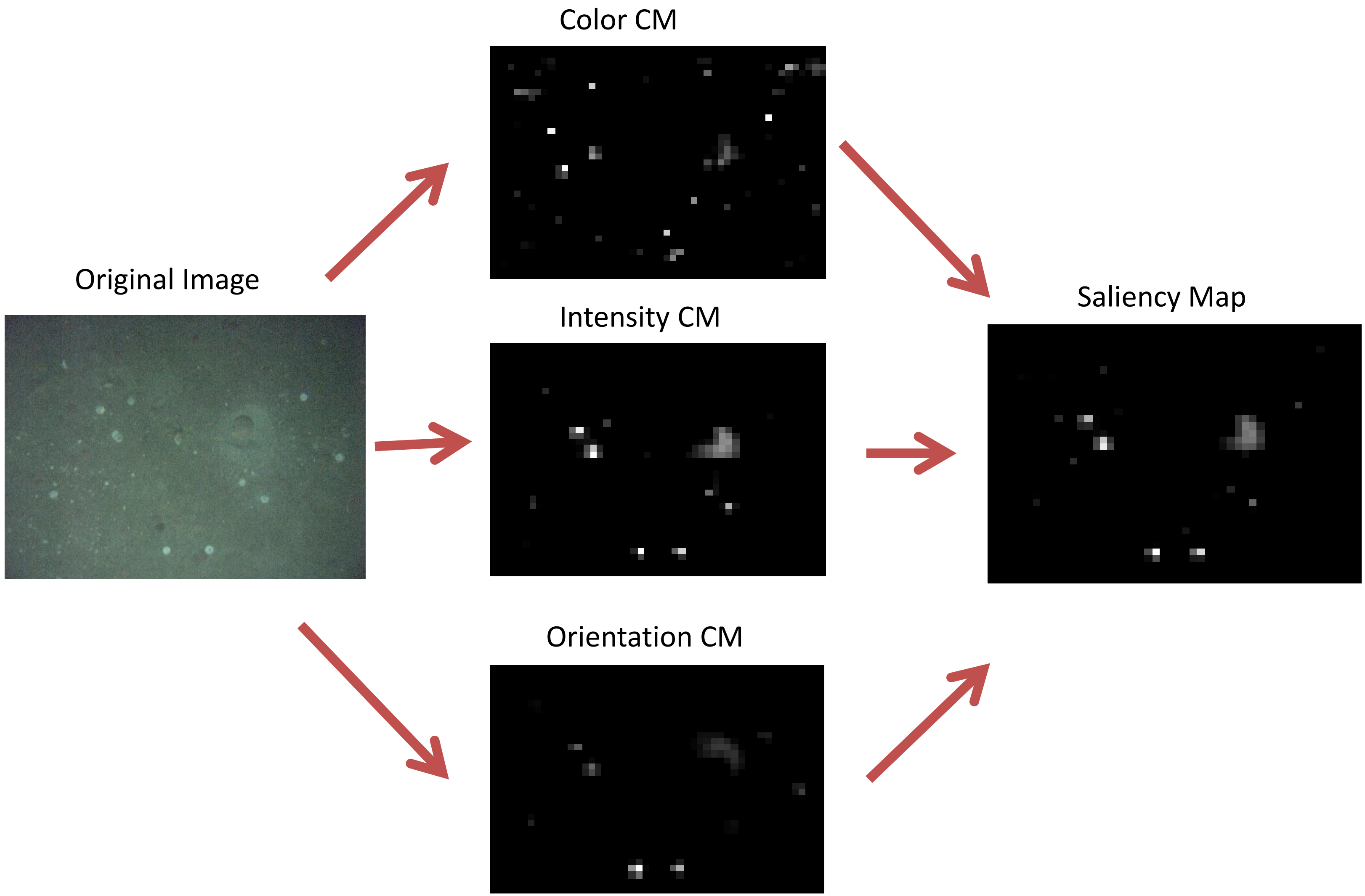
Where $\bigoplus$ is the cross-scale addition operator and N is the map normalization operator.

- Saliency Map

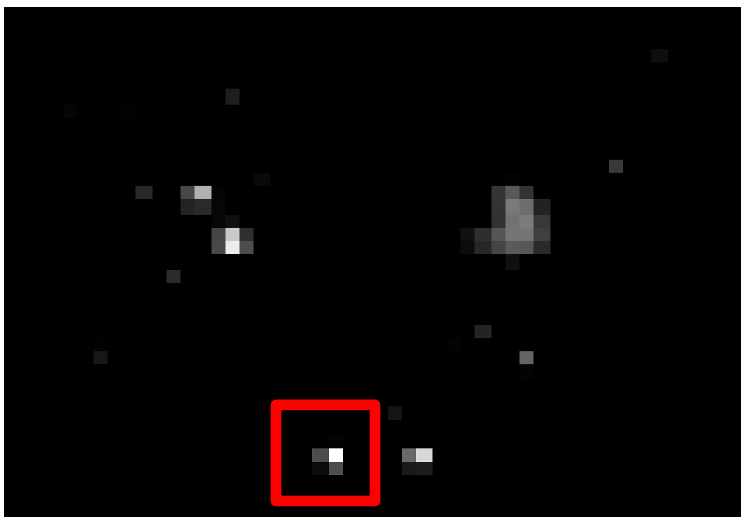
$$S = \frac{1}{3}[w_1\bar{I} + w_2\bar{C} + w_3\bar{O}]$$

w_1, w_2 and w_3 are the top-down weights.

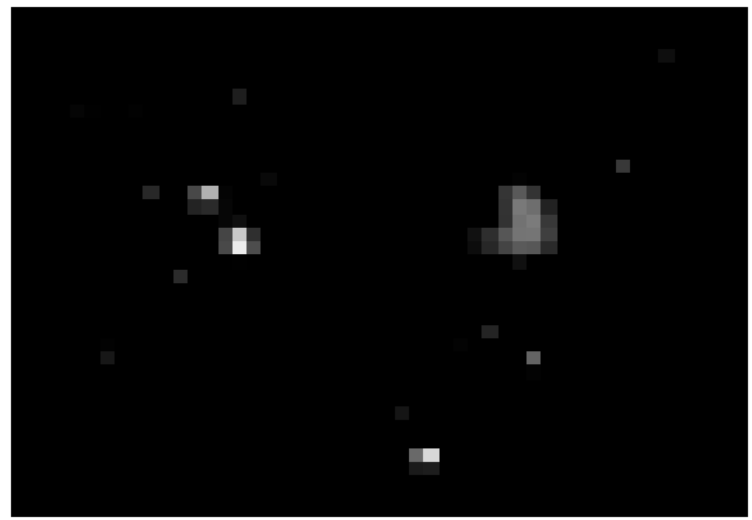
Example Saliency Computation



Winner Takes All Neural Network(WTA) and Inhibition of Return

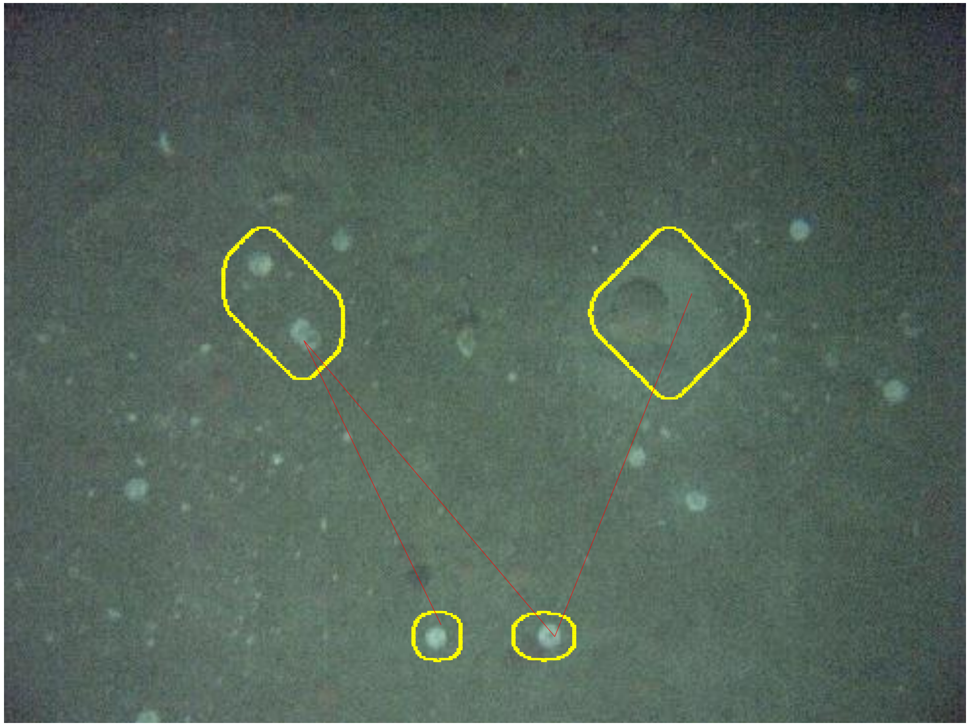


WTA identifies the most salient region

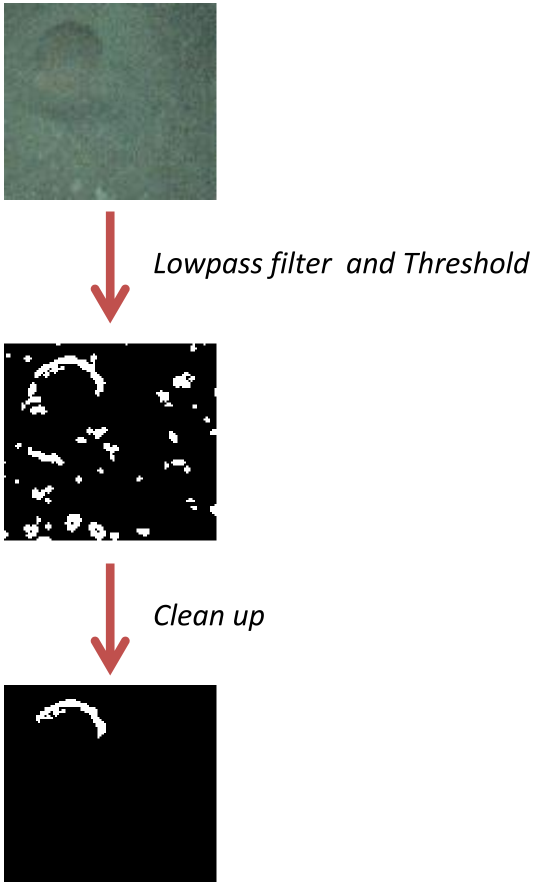


Inhibition of return suppresses the recently attended fixation

Example: Filtering



Original image with fixations



Eigen Value Based Shape Descriptors

- Can one hear the shape of the drum? -Kac, 1966
- In other words, can we determine the shape of a drum membrane just by hearing the sound of the drum(i.e. by knowing the principle modes of vibration)
- Wave equation

$$\Delta w(x, y, z, t) - \frac{1}{v^2}\frac{dw(x, y, z, t)}{dt} = 0$$

- Helmholtz equation

$$\Delta u(x, y, z) - \lambda u(x, y, z) = 0$$

Eigen Value Based Shape Descriptors

- By numerically solving the eigen value problem, we compute λ*s*

$$0 < \lambda_1 \leq \lambda_2 \leq \lambda_3 \leq \cdots \leq \lambda_\infty$$

- Eigen value based descriptor,

$$F(\tau) = \left[\frac{\lambda_1}{\lambda_2}, \frac{\lambda_1}{\lambda_3}, \ldots \frac{\lambda_1}{\lambda_n}\right]$$

These descriptors are RST invariant

Best and Worst Features (compared to a rectangle)

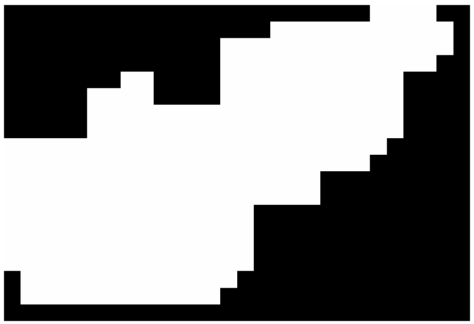


Fig 1

Fig 2

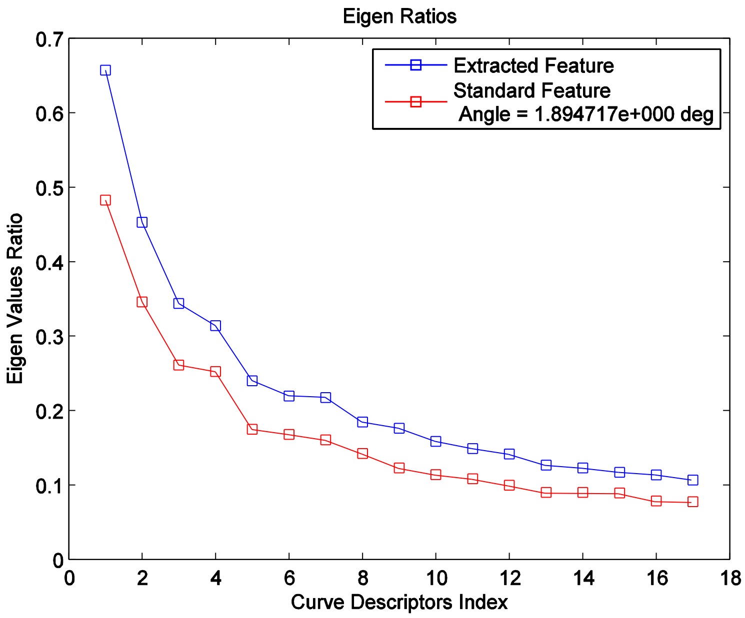


Fig 3

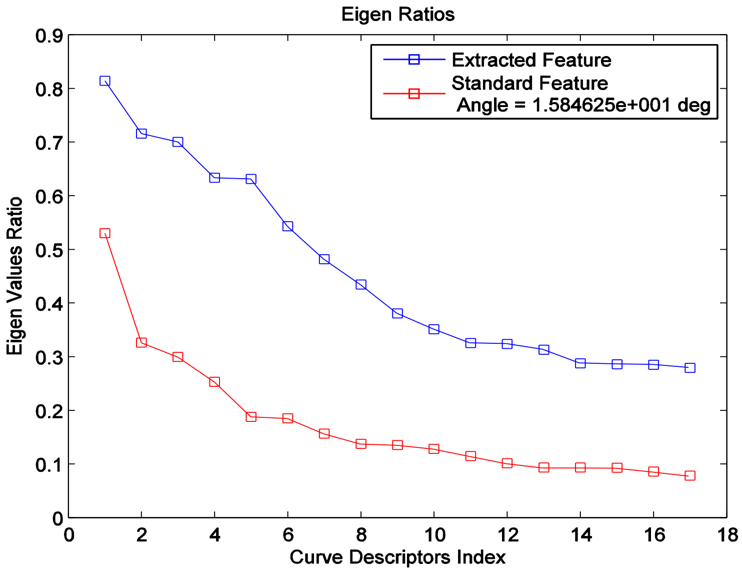


Fig 4

Fig 1. *Best match feature*

Fig 2. *Worst match feature*

Plot of eigen ratios:-

Fig 3. *best feature and standard shape*

Fig 4. *worst feature and standard shape*

Note: Closer the curves, better the match.

Conclusions and Future Work

- Visual attention helps in identifying 90% of the scallop locations.
- We are improving the algorithm to reduce the number of false positives which is 50%.
- We are working to improve the efficiency of the eigen value shape descriptors.

References

- A Demonstration Sea Scallop Survey of the Federal Inshore Areas of the New York, Bight using a Camera Mounted Autonomous Underwater Vehicle, Trembanis et. al.
- A model of saliency-based visual attention for rapid scene analysis, Itti et. al., 1998.
- Shape Recognition using eigen values of the Dirichlet Laplacian, Khabou et. al., 2007.
- Drums and Curve Descriptors, Zuliani et. al., 2004.

- All scallop and subway car data was provided by Dr. Trembanis, Univ of Delaware.