Identifying sea scallops from benthic camera images

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Introduction

US Scallop fishery
58 million pounds, >$500 Million

Background on Scallop Survey Efforts

- NEFC scallop survey conducted annually since 1979.
- Dredges are on the order of 30-45% efficient (NOAA NMFS, 2010)
- Dredges impact the seabed and integrate over the entire tow area.
- Utilizing images has a theoretical 100% efficiency.
- However performing manual scallop counts on hundreds of thousands of images is a time consuming process.

Autonomous Underwater Vehicle
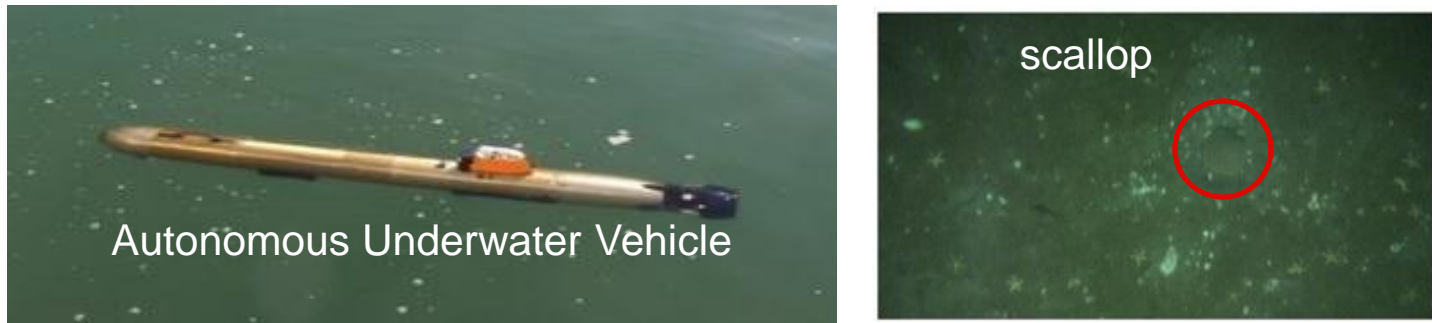
scallop

Automated counting of scallops

- AUVs mounted with cameras provide a non-invasive alternative to dredge surveys.
- We developed an automated scallop detection framework using computer vision tools.

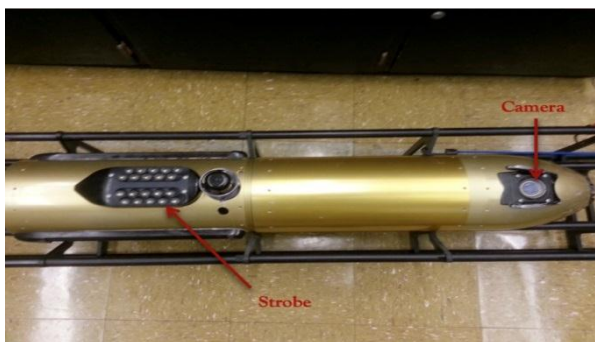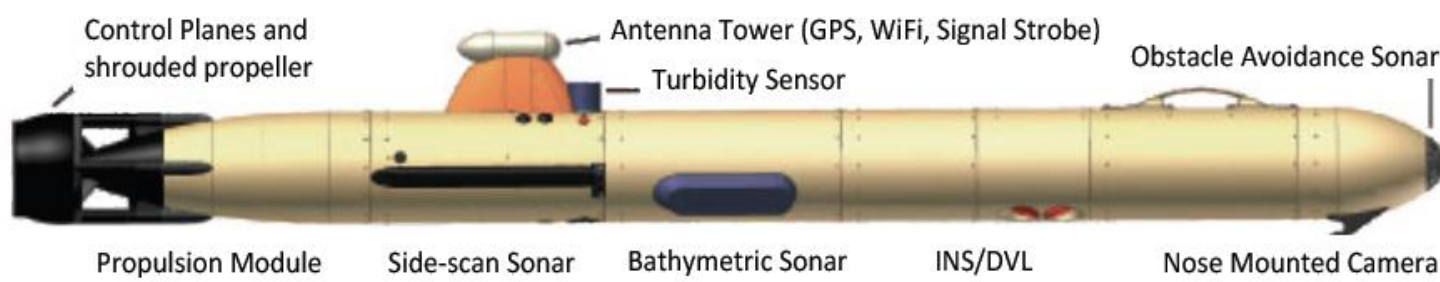## Purpose & Research Question

Scallops shown in red circles

Original   Thresholded   Edge Filtered

Scallop appearance cues: Yellowish color, dark crescent at top, bright crescent at lower rim and sometimes no crescent features.
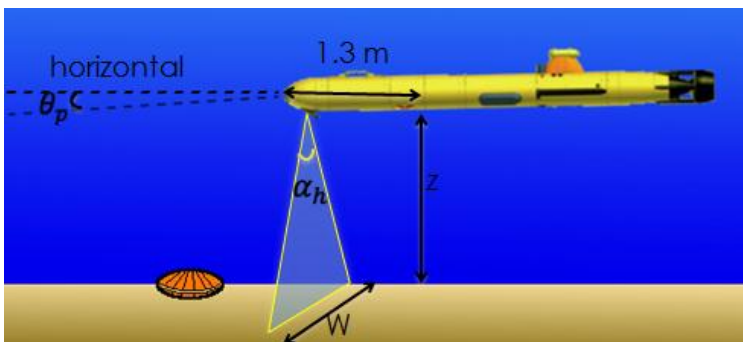
Conventional image processing tools are ineffective.

Subjects, Methods & Analysis

AUV Schematics

Control Planes and shrouded propeller — Antenna Tower (GPS, WiFi, Signal Strobe) — Obstacle Avoidance Sonar — Turbidity Sensor

Propulsion Module   Side-scan Sonar   Bathymetric Sonar   INS/DVL   Nose Mounted Camera
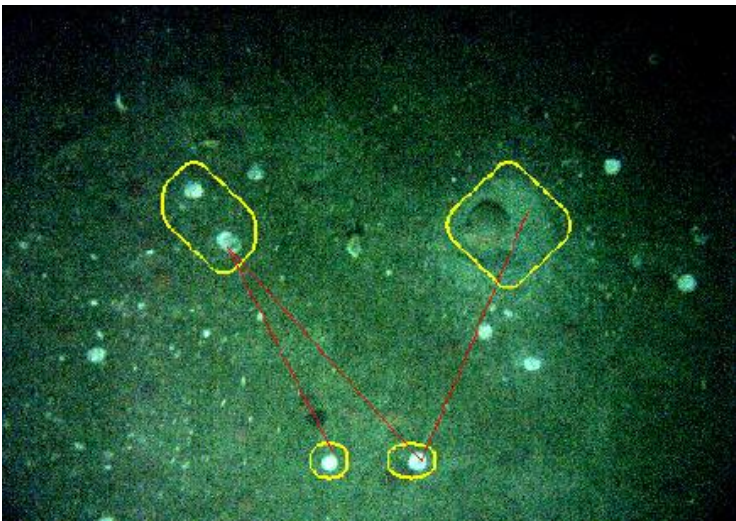
Point Grey Scorpion 20SO Camera
2.11 MP, 1600 X 1200 resolution

Horizontal FOV = 44.65 deg
Vertical FOV = 34.91 deg
Image Dim: 1.64 X 1.23 m

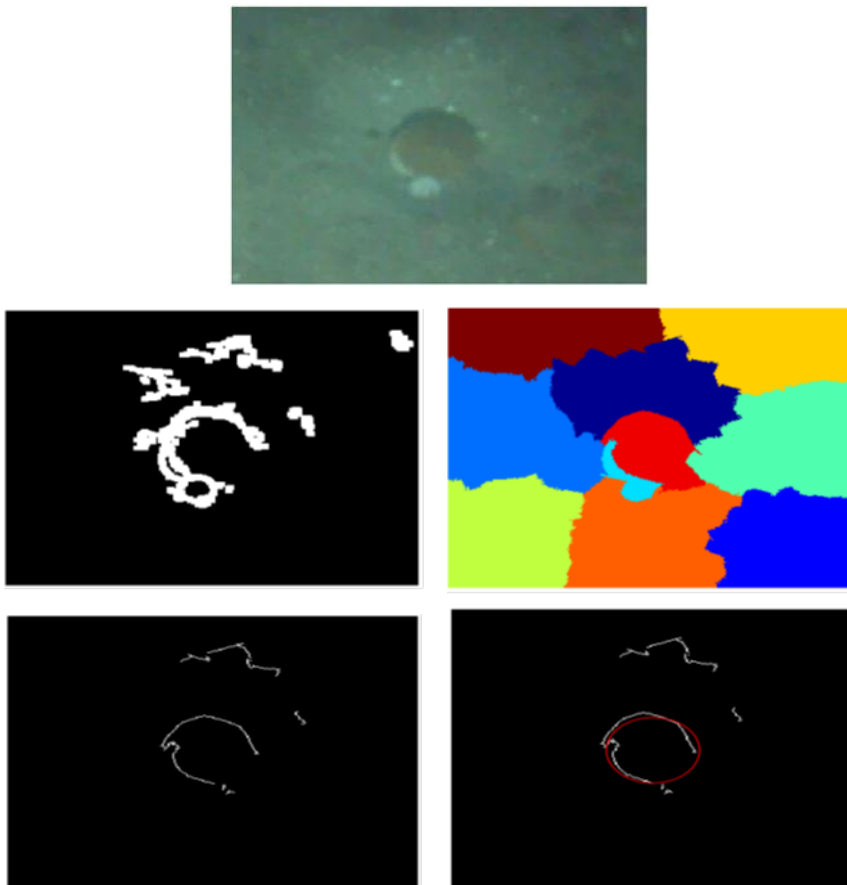### Automated Scallop Counting Framework

Visual Attention
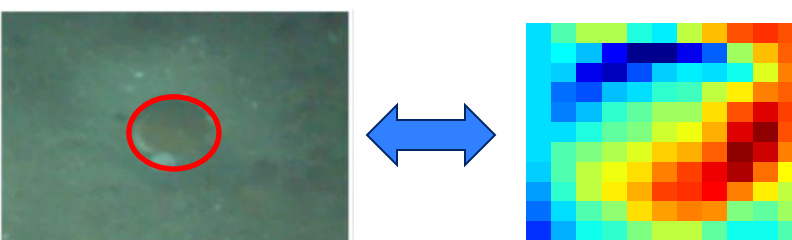Finds 'interesting' points in images

Segmentation
Distinguishing foreground from background.
- Edge Detection
- Graph-cut
- Circle fitting

Classification
Is this a scallop? Template matching gives a numeric similarity measure

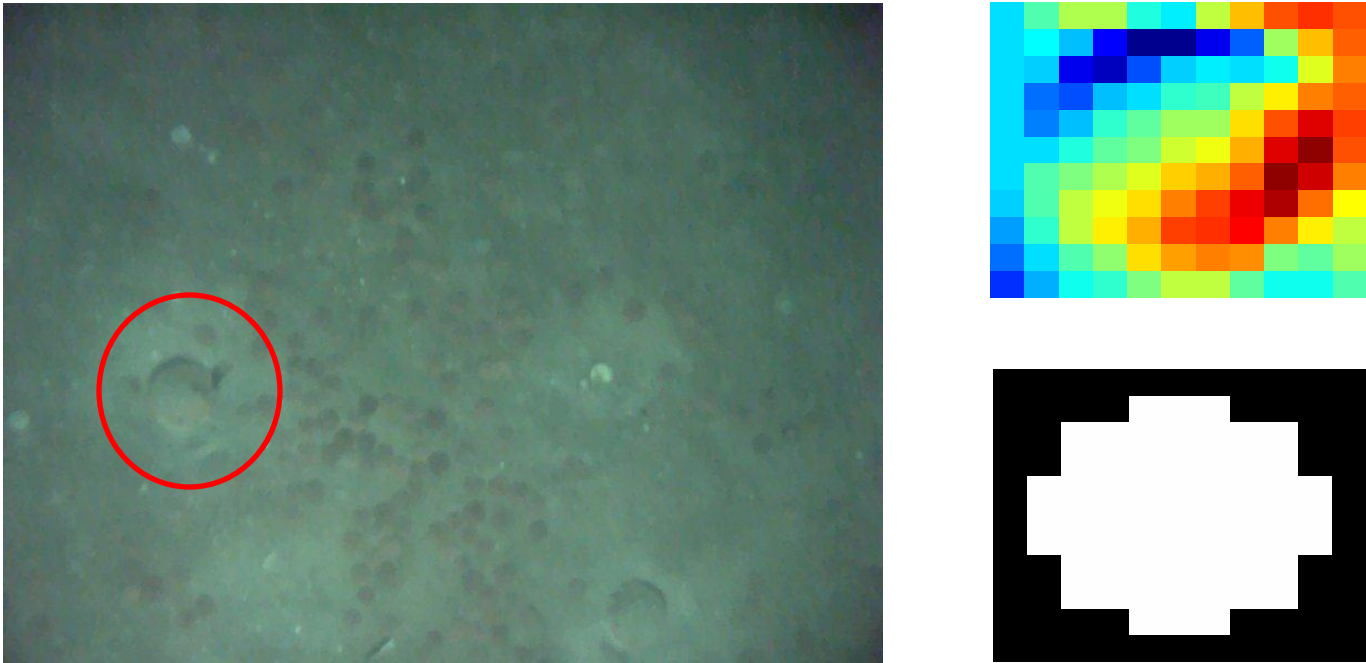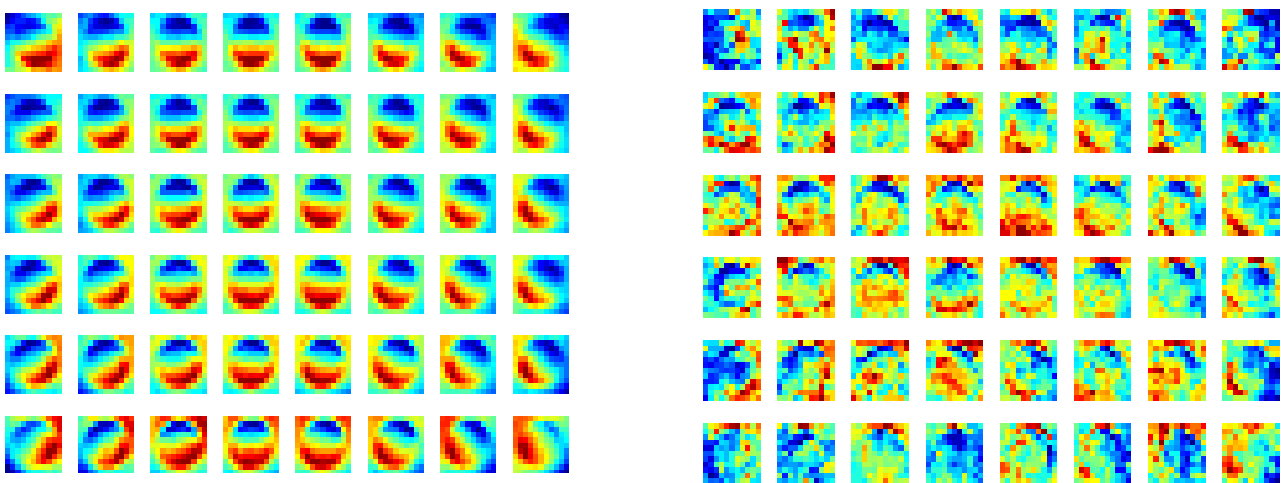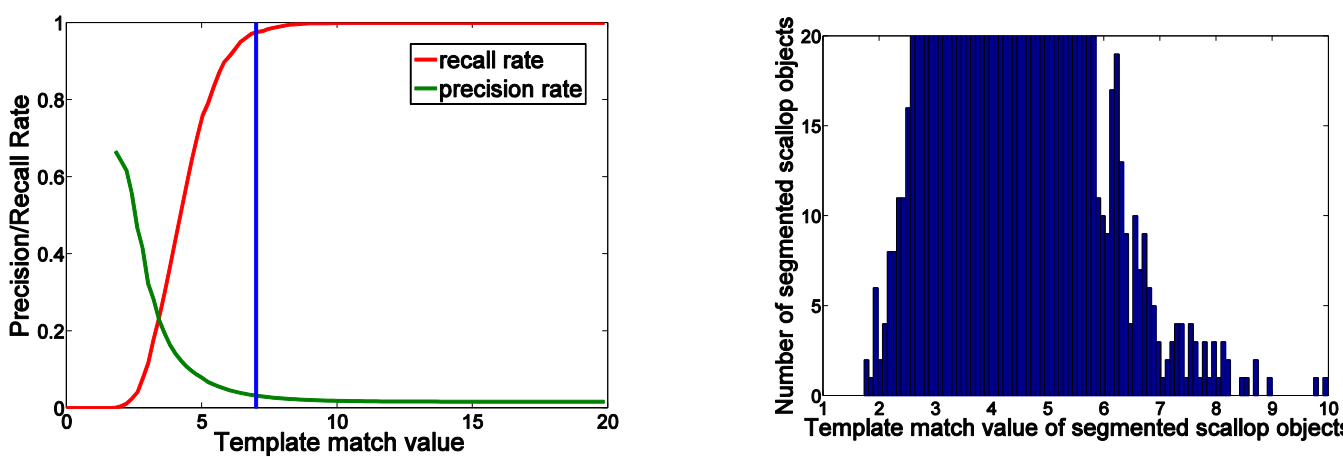## Subjects, Methods & Analysis

Image with scallop (left), corresponding template (right top) and template mask (right bottom).

Mean maps (left) and standard deviation maps (right) of scallop templates. Red implies high and blue implies low values.
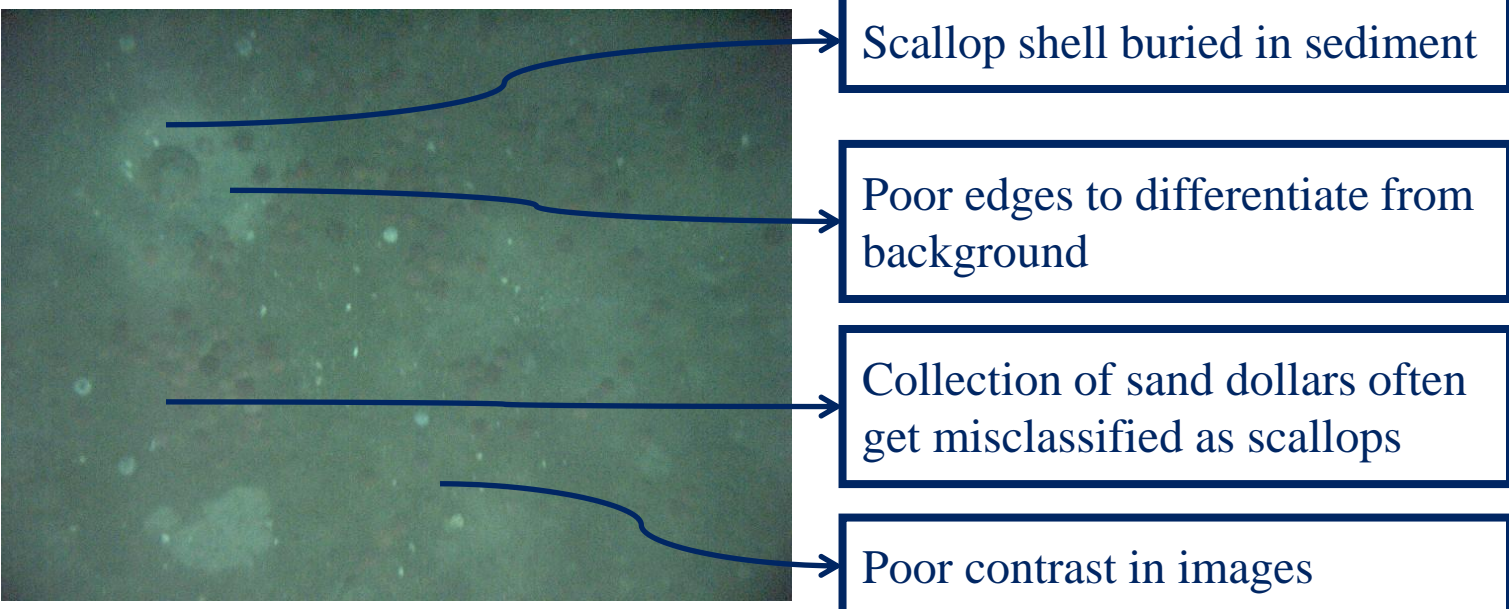

A template matching threshold value of 7 is chosen as it is capable of classifying 97% of the scallops correctly. Any object with a template matching value <7 is classified as scallop.

Results

	Dataset 1	Dataset 2
Number of Images	1,299	8,049
Ground Truth Scallops	363	3,698
Valid Ground Truth Scallops	250	2,781
After Visual Attention Layer	231 (92.4%)	2,397 (86.2%)
After Segmentation Layer	185 (74%)	1,807 (64%)
After Classification Layer	183 (73%)	1,759 (63.2%)
False positives	17,785	52,456

Conclusions

- Scallop shell buried in sediment
- Poor edges to differentiate from background
- Collection of sand dollars often get misclassified as scallops
- Poor contrast in images

- Implementing color and light correction before image compression can improve results.
- There is a tradeoff between detection rate and false positives. Template matching threshold can be tuned to obtain application specific performance.

Directions for Future Research
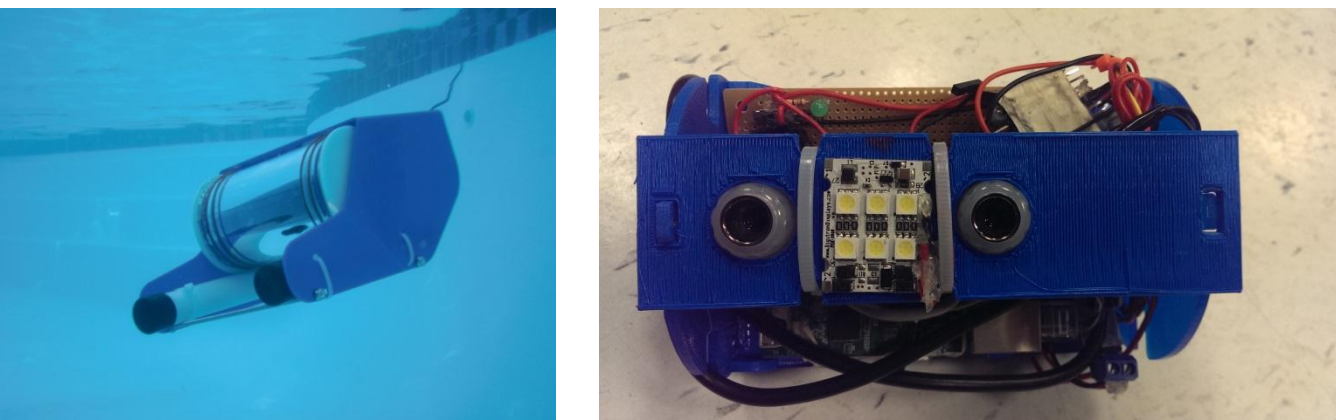
Development of an underwater platform based on OpenROV to conduct further experiments.
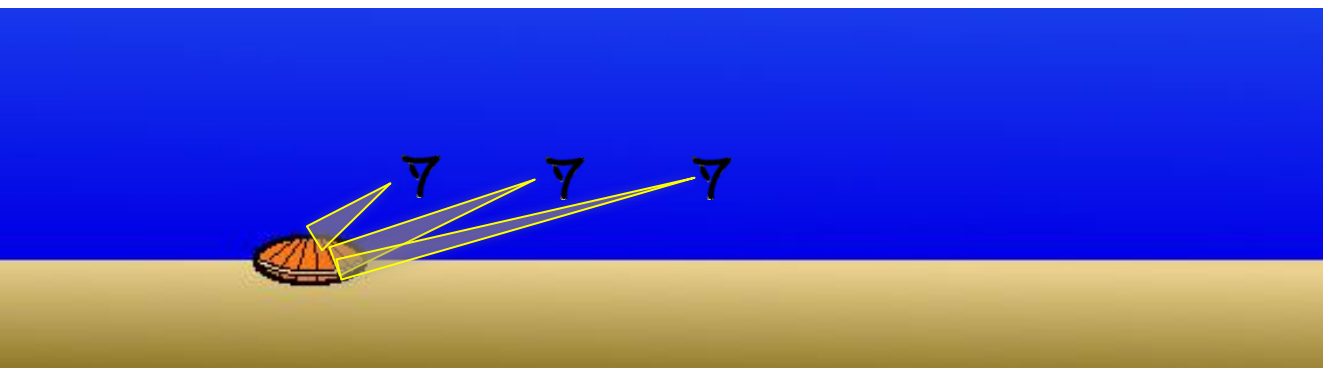
Development of feature descriptors that link vehicle dynamics and camera motion into mechanisms of detection and classification.

References and Acknowledgements

- Itti et. al. (2004) "A model of saliency based visual attention for rapid scene analysis", IEEE PAMI 20(11):1254-1259.
- Kannappan et. al. (2013) "Automated detection of scallops in their natural environment", IEEE MED pp.1350-1355.
- Kannappan et. al. (2014) "Identifying sea scallops from benthic camera images", ASLO: Methods (in review).

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