Application of USVs in Littoral Environments

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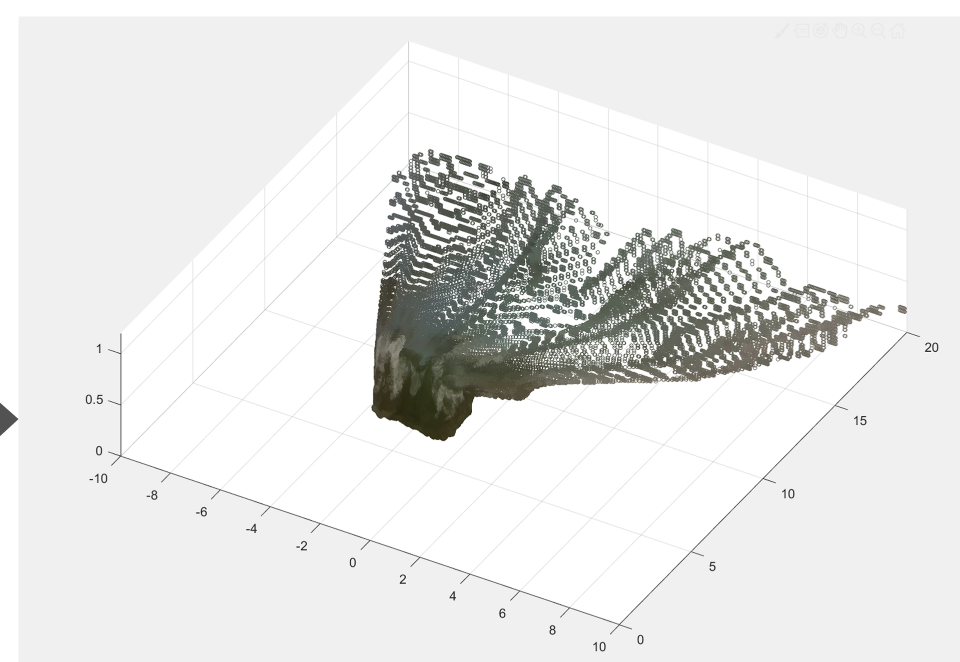
Ocean Wave Model

Motivation

To efficiently plan the motion of small USVs in the surf zone requires real-time mapping of the sea surface. To achieve this, we investigated a computer vision solution to segmenting waves to estimate their height, velocity, and heading.

Data Acquisition

We used Intel ReslSense D435 stereo camera to generate a 3D point cloud for every frame.



This figure shows the point cloud that the stereo camera captures.

Wave Tracking Approach

Step 1: Wave Segmentation

a. Use horizon detection to estimate the camera roll angle and transform all points based on the gravity vector
b. Select points whose height (z-coordinate) is above a threshold of 0.8 meters

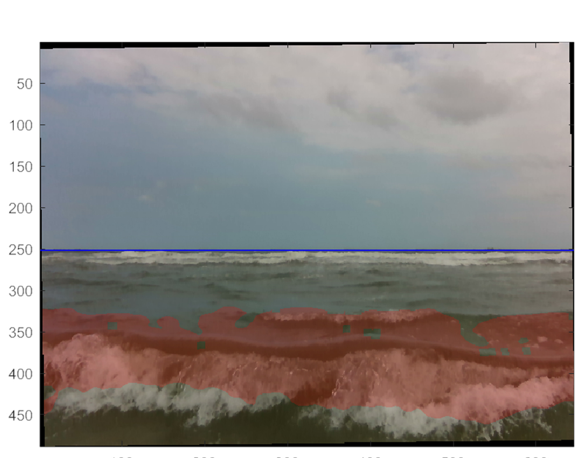
Step 2: Heading Estimation

a. Calculate the positional covariance of the wave segmented in step 1
b. Estimate the orientation from the eigenvector of the largest principal component
c. Visualize with an uncertainty ellipse at a 95% confidence interval

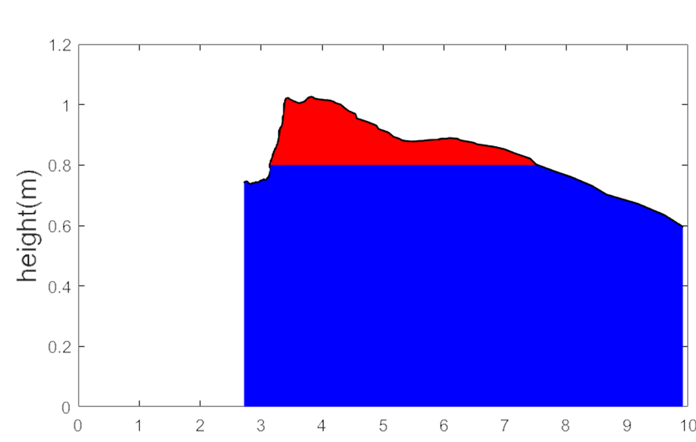
Step 3: Velocity Estimation

a. Identify the peak and tail of each wave within a working distance of 3-4 meters and track their depths shwon in y-coordinates
b. Estimate the velocity by differentiating the peak/tail depth in time

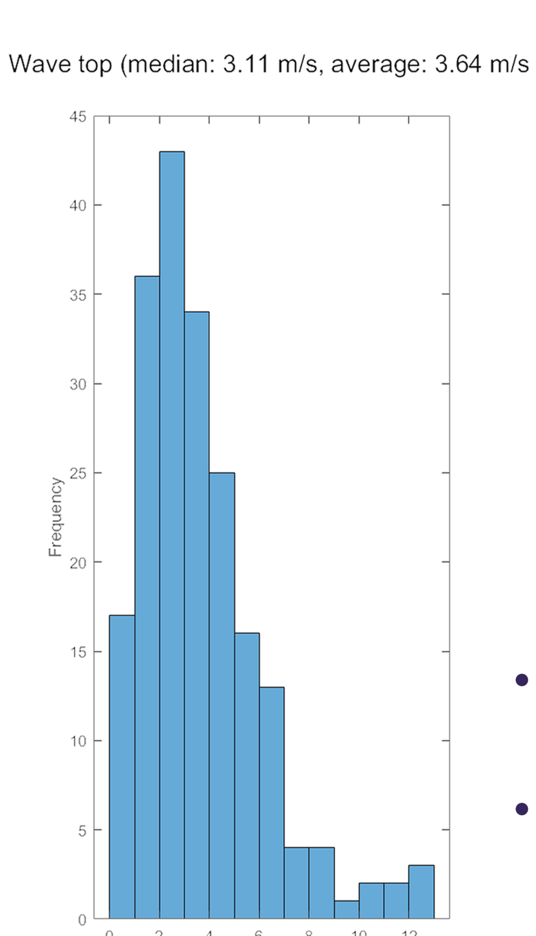
Results & Future Work

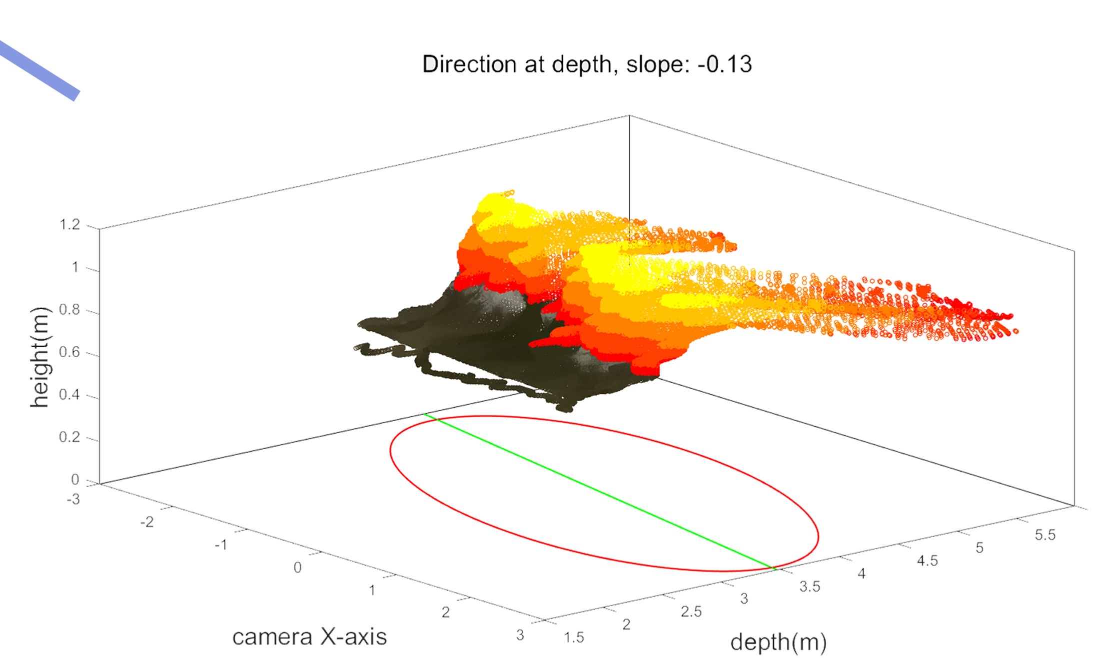


Segmented Wave



Wave View From Side





- We were able to reliably detect and track waves with a mean detection range of 6.5m.
- In the future, we would like to model the periodicity of the wave field to predict waves before they are visible.

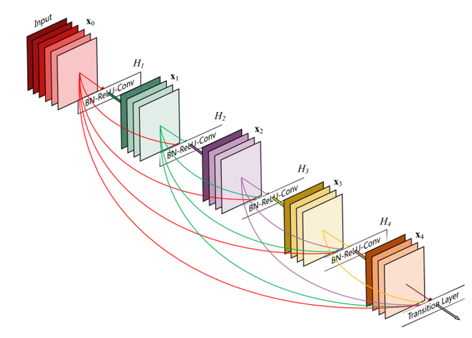
Coral Reef Recognition

Motivation

Based on neural networks, develop a model that is able to effectively recognize and classify different coral reefs for biodiversity research and environment monitoring.

Neural Networks

- VGG-16: Takes less time to train than ResNet50 because it has fewer layers. Has more parameters, so its weight has larger size (1.50GB).
- ResNet50: Takes longer time to train because it has more layers. ResNet50 has much smaller weight (0.18GB). More accurate than VGG-16



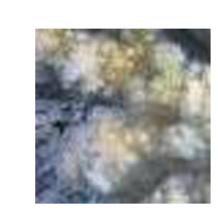
ResNet50 makes use of residual blocks to link details to deeper layers to improve accuracy. We will focus on ResNet50 in our project because of this feature.

Training Techniques

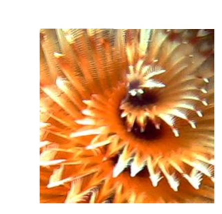
- Loss Function: Categorical Cross Entropy
- Optimizer: Stochastic Gradient Descent
- Pretrained weights: ImageNet
- Data augmentation, Adjust input shape, Balance classes
- Adjust the learning rate and the epoch count to ensure validation loss and validation accuracy converge

Data

MLC2008
9 classes
312x312



EILAT
8 classes
64x64



RSMAS
14 classes
256x256

- MLC2008 has the most abundancy (over 30000 images).
- RSMAS has least amount of images in each classification. MALC class only has 22 images.

Distracting features in MLC2008

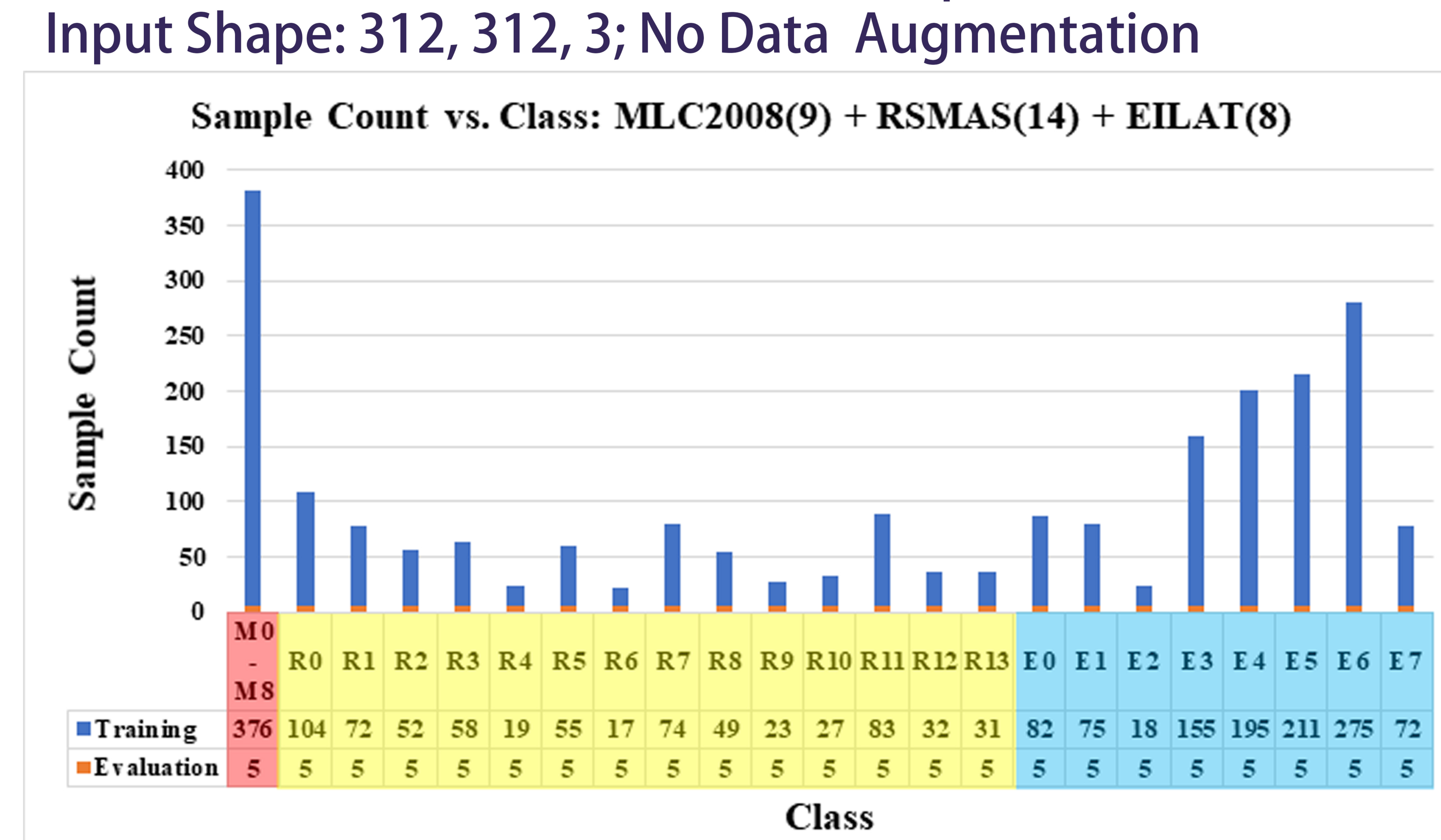
Images in the same class in MLC2008 are distinct

Challenges and Results

a. Challenges of analyzing MLC2008
   - Balanced MLC2008 Subset: 471 Samples/Class
   - Balanced Training Set: 80% Balanced Evaluation Set: 20%

MLC2008-Only Models				
Neural Network	Data Augmentation	Input Shape	Initial Weights	Accuracy
VGG 16	Height/Width Shift 0.2	312*312*3	ImageNet	83.63%
ResNet 50	Zooming 0.4	312*312*3	ImageNet	85.73%

b. Challenges of analyzing union of MLC2008 & RSMAS & EILAT
   Balanced Union Evaluation Set: 5 Samples/Class
   Input Shape: 312, 312, 3; No Data Augmentation



	M0-M8	R0	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	E0	E1	E2	E3	E4	E5	E6	E7
Training	376	104	72	52	58	19	55	17	74	49	23	27	83	32	31	82	75	18	155	195	211	275	72
Evaluation	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5

Overall Accuracy Breakdown	
Dataset	Accuracy
MLC2008	84.44%
RSMAS	98.57%
EILAT	95.00%
Overall	93.55%

Accuracy Per Class		
Range	Class Count	Percentage
⩾90%	23	74%
⩾80%	29	94%
⩾60%	31	100%

Larger MLC2008-Only Evaluation Set (95 Samples/Class)		
Best MLC2008-Only Model	Best Union Model	Accuracy Loss
85.73%	80.82%	-4.91%

References

Gomez-Rios, A., *et. al., Towards Highly Accurate Coral Texture Images Classification Using Deep Convolutional Neural Networks and Data Augmentation*, (2018).