Reduction of False Positives in Vessel Detection using HSV-based Thresholding

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INTRODUCTION

Maritime Surveillance is essential because it protects several elements of a country such as its security and its economy. If this does not exist, illegal activities will be on the rise.

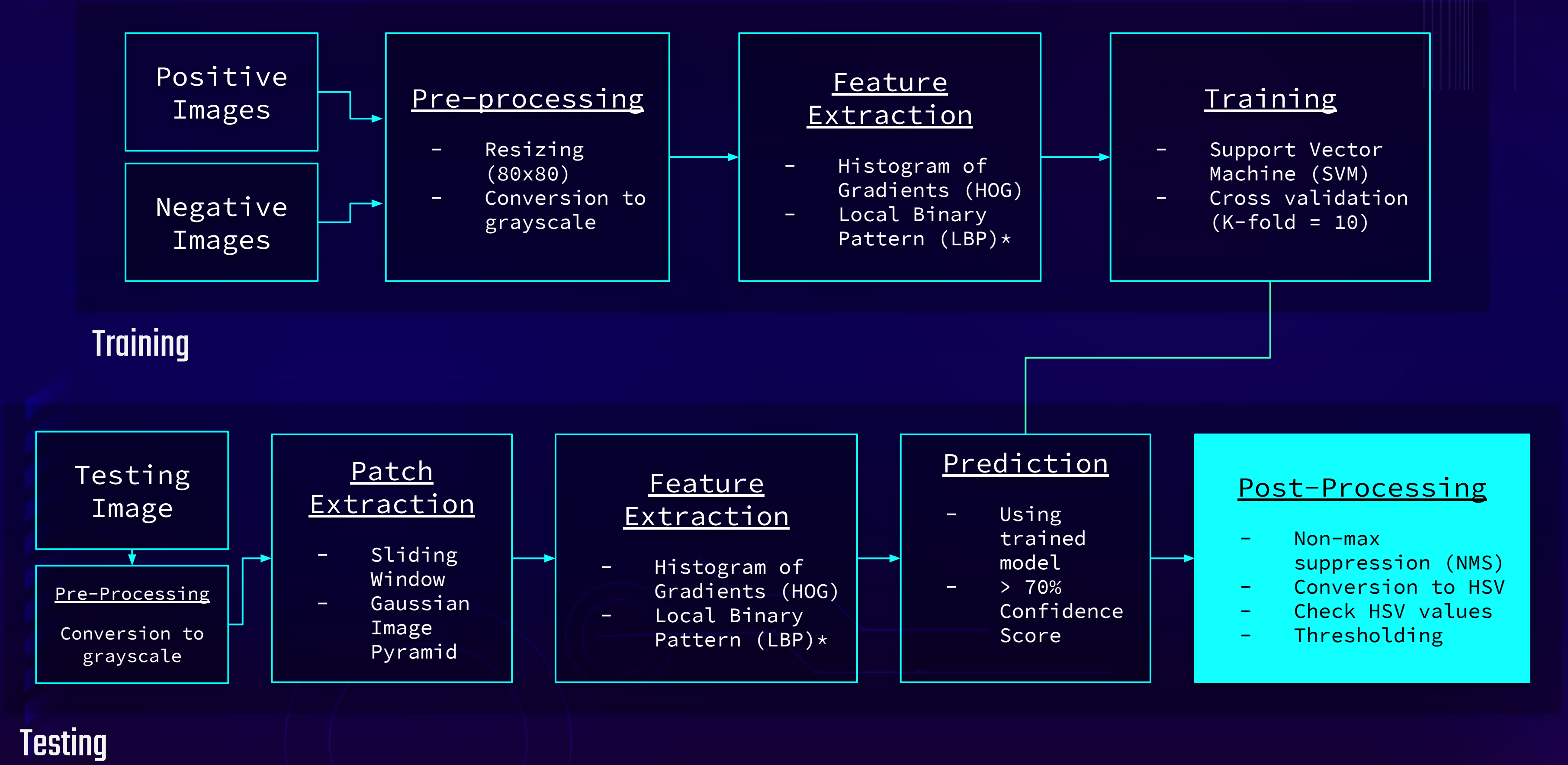
A good amount of researches have been made with regards to ship detection through various combinations of pre-processing, feature extraction, classification, etc. We realized that a combination of Histogram of Gradients (HOG) and Local Binary Patterns (LBP) as feature descriptors hasn't been tested yet. The HOG + LBP combination has been done to both human and plant detection/recognition and it gave a promising result. We now want to implement this to ship detection to see if can also give a good result.

Furthermore, we want to find a way to decrease the false positives detected by the said model. Our goal is to find a model that can give a good amount of initial detections that we can use for post-processing later on.

THE TWO RESEARCHES

1. Model Selection for Vessel Detection (HOG vs LBP vs HOG+LBP)
2. Reduction of False Positives in Vessel Detection by HSV Thresholding

Methodology



MODEL SELECTION

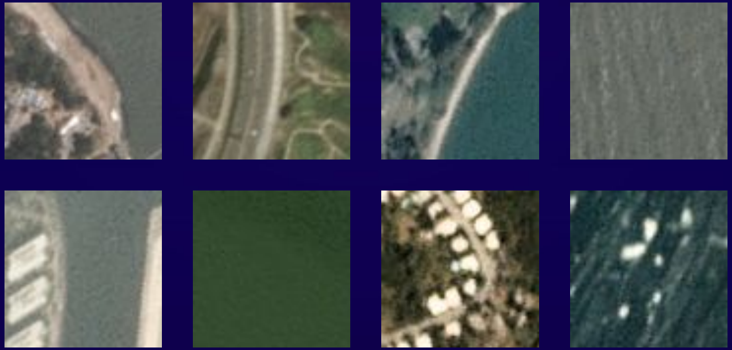
The initial detection is highly dependent of the trained model. Therefore, we should choose the model that will give us the best initial detection.

MODEL SELECTION: Training Dataset

Dataset from: https://www.kaggle.com/rhammell/ships-in-satellite-imagery

Positive Images

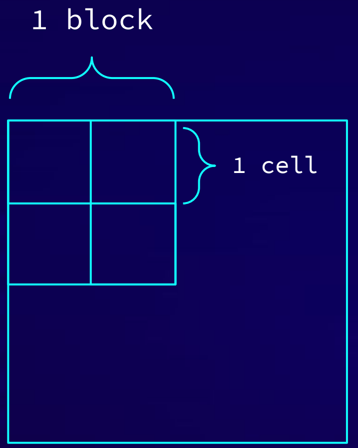
Negative Images



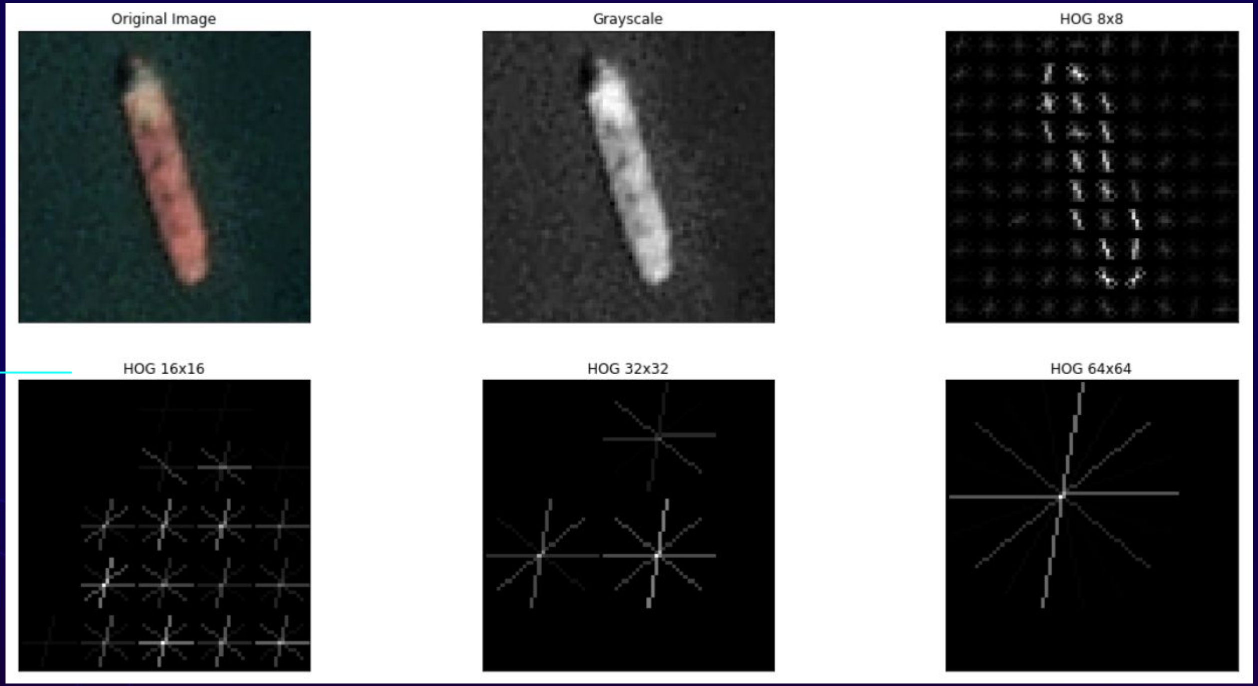
Images removed from dataset:

MODEL SELECTION: Feature Extraction (HOG)

Histogram of Oriented Gradients (HOG) was proposed by Dalal and Triggs [1] as a feature descriptor to represent objects by the distribution of gradient intensities and orientations in spatially distributed regions, this has been widely acknowledged as one of the best features to capture the edge or local shape information of the objects. [2]

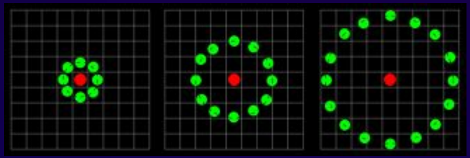


- 16x16 pixels per cell
- 2x2 cells per block
- 9 orientations



MODEL SELECTION: Feature Extraction (LBP)

Local Binary Pattern (LBP) by Ojala et al. [3] is a feature descriptor typically used for texture classification problems.



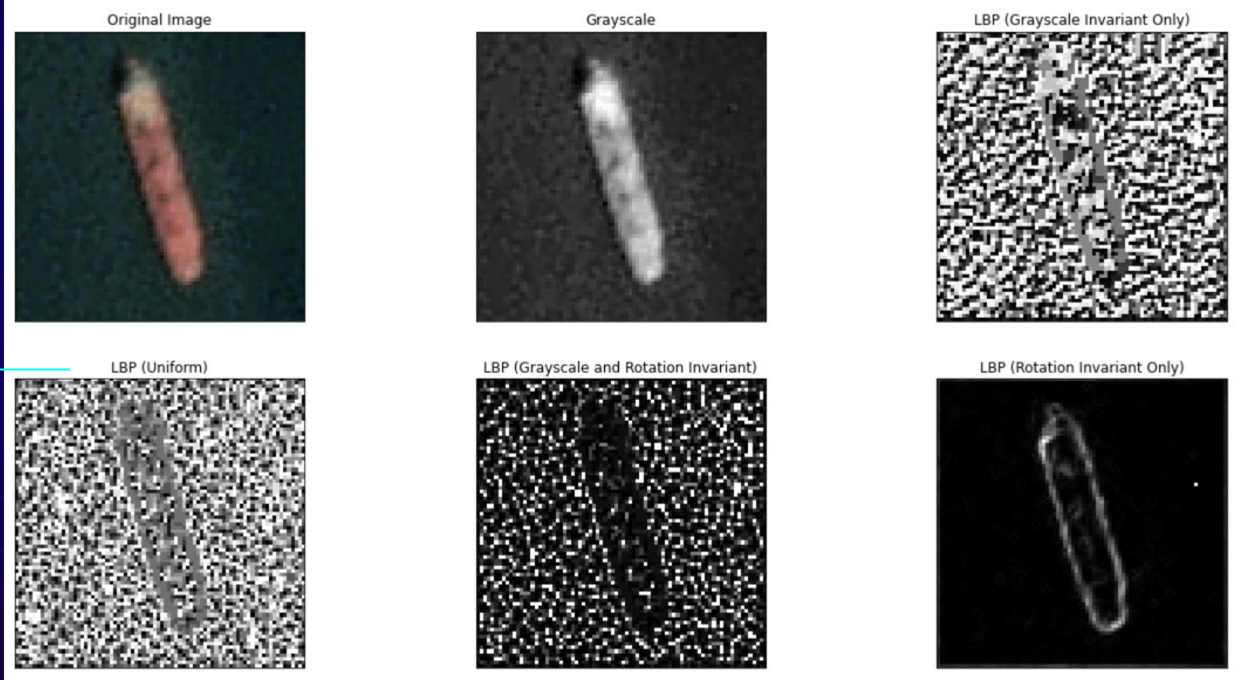
Source: Wikipedia
* Green circles = circle points

20	66	80
79	56	13
41	55	28

Binary:
1000110
Decimal:
70

0	1	1
1		0
0	0	0

- Radius = 1
- Circle Points = (radius*8) = 8



MODEL SELECTION: Training (SVM)

Number of Positive Images: 1520 | Number of Negative Images: 1951 | SVM using Polynomial (d=7) kernel

	HOG (8x8)	HOG (16x16)	HOG (32x32)	HOG (64x64)	LBP (Default)	LBP (Uniform)	LBP (RoR)
Precision	96%	**96%**	87%	80%	83%	76%	76%
Recall	82%	94%	92%	83%	93%	94%	93%
F1-Score	88%	**95%**	89%	82%	88%	84%	84%
Support	289	289	289	289	289	289	289

* Precision = calculates the proportion of predicted ships over the number of actual ships. [2]. Prefers false negatives than false positives.
* Recall = calculates the proportion of actual ships that are correctly classified as ships [2]. Prefers false positives than false negatives.
* F1-Score = calculates the weighted average of precision and recall [2]. Balance of both.
** LBP (Var) takes too long to test
** HOG and LBP features are normalized

MODEL SELECTION: Feature Fusion

According to [4] and [5], HOG + LBP is a good combination for feature extraction especially in plant texture detection and face recognition respectively. In [4], the HOG + LBP was able to achieve a 91.25% accuracy as compared to HOG only (85.31%) or LBP only (40.6%) for plant texture detection.

MODEL SELECTION: Training (SVM)

using HOG (16x16) + Grayscale Invariant Only (Default) LBP. Cost = 2

	Linear SVM	Radial Basis (RBF) SVM	Polynomial SVM (d=7)	Sigmoid SVM
Precision	93%	92%	94%	78%
Recall	91%	95%	**96%**	74%
F1-Score	92%	94%	**95%**	76%
Support	289	289	289	289

CONCLUSION: It can be seen that the polynomial SVM (degree = 7) gave the highest F1-score. In general, when using the F1-score as a basis, the HOG+LBP combination did not give an improvement, however, it was able to increase the recall from 94% to 96%. The precision, on the other hand, gave a lower score.

TESTING

We will now test our model using 32 images taken from various websites (Planet.com, NASA, Asia Maritime Transparency Initiative)

TESTING: Method

Sliding Window Method

Window is the same size as the resized training image (80px x 80px)

TESTING: Method

Sliding Window Method

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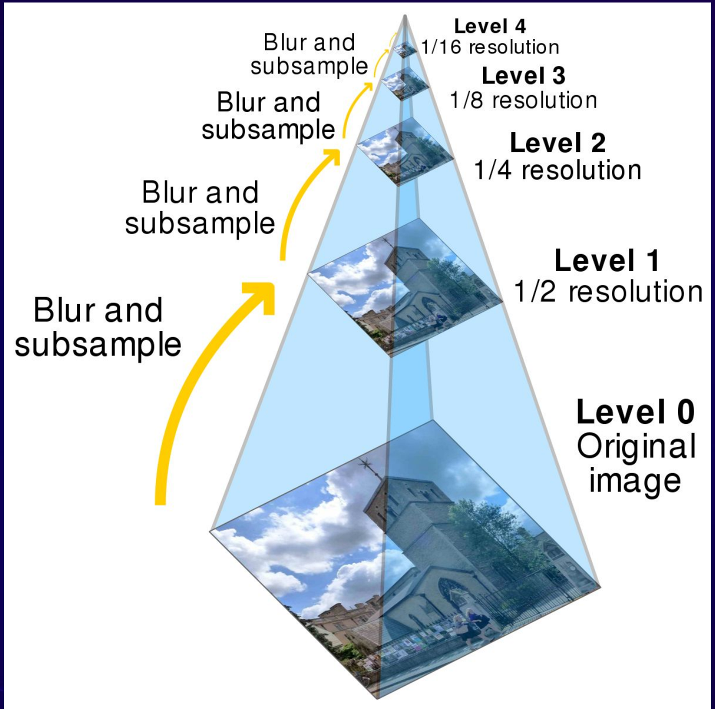
TESTING: Method

Sliding Window Method

Window is the same size as the resized training image (80px x 80px)

TESTING: Method

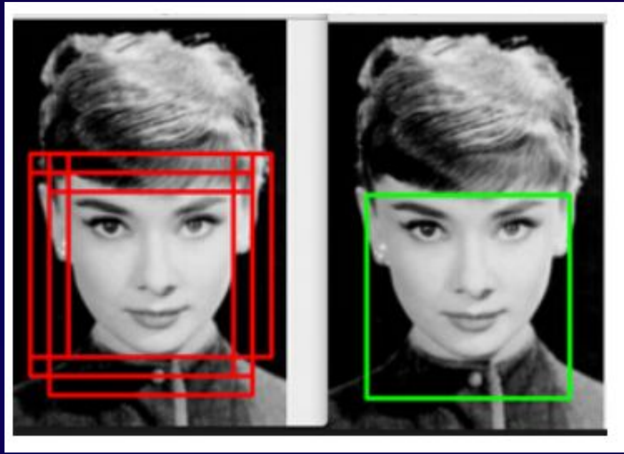


Gaussian Image Pyramid

TESTING: Method

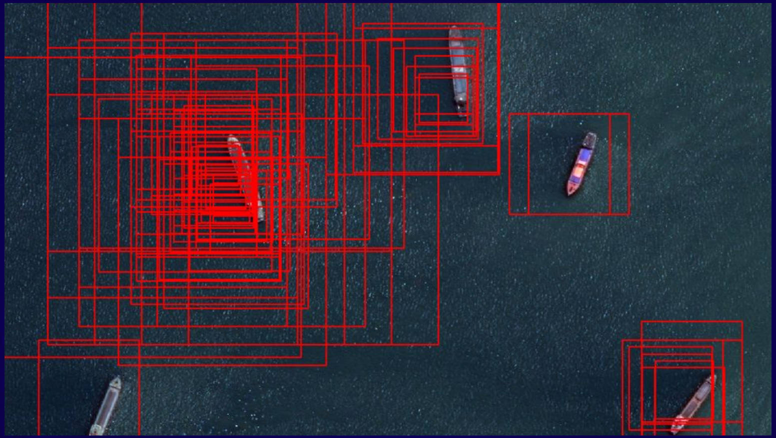
Gaussian Image Pyramid

TESTING: Method



Non-Maximum Suppression

TESTING: Method



NMS

Non-Maximum Suppression

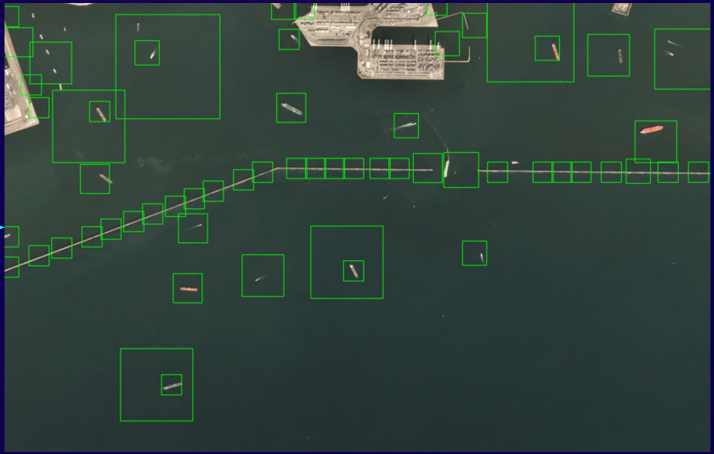
TESTING: Prediction

Image to detect ship/vessel in

Trained SVM Model

> 70% Confidence Score

- NMS



Result

TESTING: Prediction

- Although the model has predicted a handful of ships/vessels, it can be seen that it has also predicted a lot of false positives.
- A possible solution to this is train the model with more images or increase the threshold of the confidence level (currently at > 70%)
- Increasing the threshold however can also decrease the number of “right” detections.

Our approach

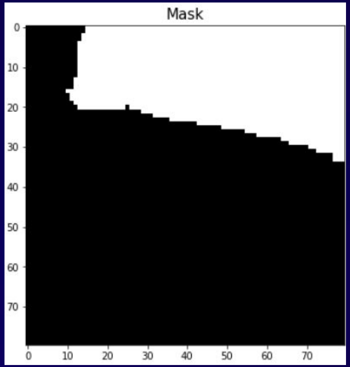
- Our method is to do post-processing to reduce false positives
- The image on the right shows a detection with less false positives.

CONCEPT

The main idea is to segregate objects such as ships/vessels and land to water. This method assumes that land-to-water ratio (aka “not vessel”) is greater than vessel-to-water ratio. Therefore, anything higher than a certain threshold shall be tagged as “not vessel” and will be disregarded.

To further improve the segregation, we have to take account the variety of images (shown in the next slide). Using the HSV values of the images, we can determine how to properly mask them and calculate the ratio.

Our approach: Concept



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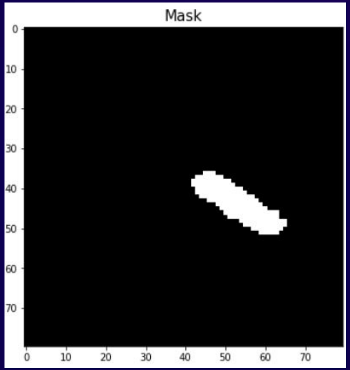


land-to-water ratio

vessel-to-water ratio

Our approach: Why HSV?





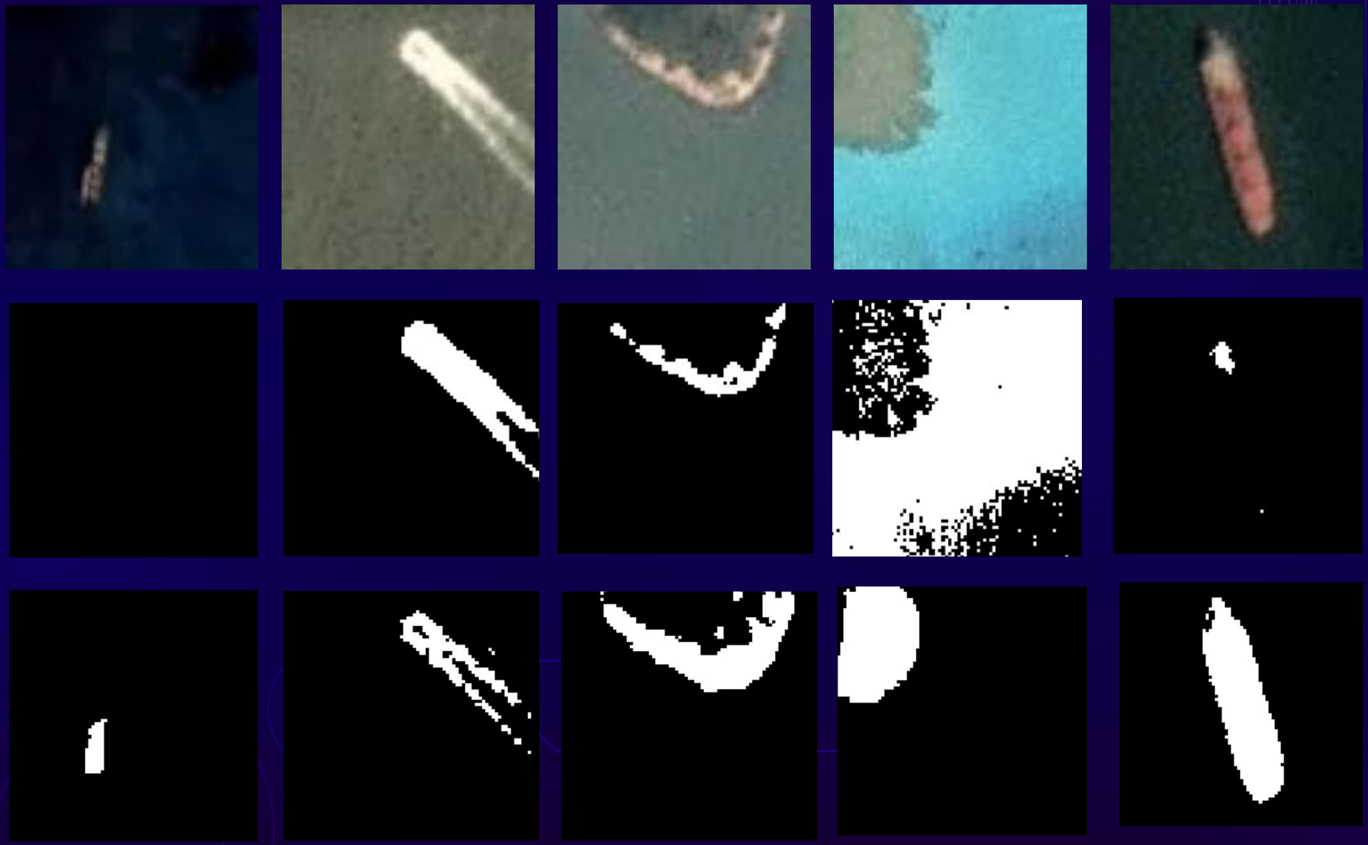
* Water color variation (blue, green, blue-green, gray, olive green, royal blue, sky blue)
* Water texture variation (wavy, clear water, blurry)
* Vessel shape variation
* Vessel color variation
* Vessel size variation
* Objects and locations that can pass as vessels (bridges, shoreline, sand, rock, small island, barriers, etc.)

Our approach: Why HSV?

Original Image

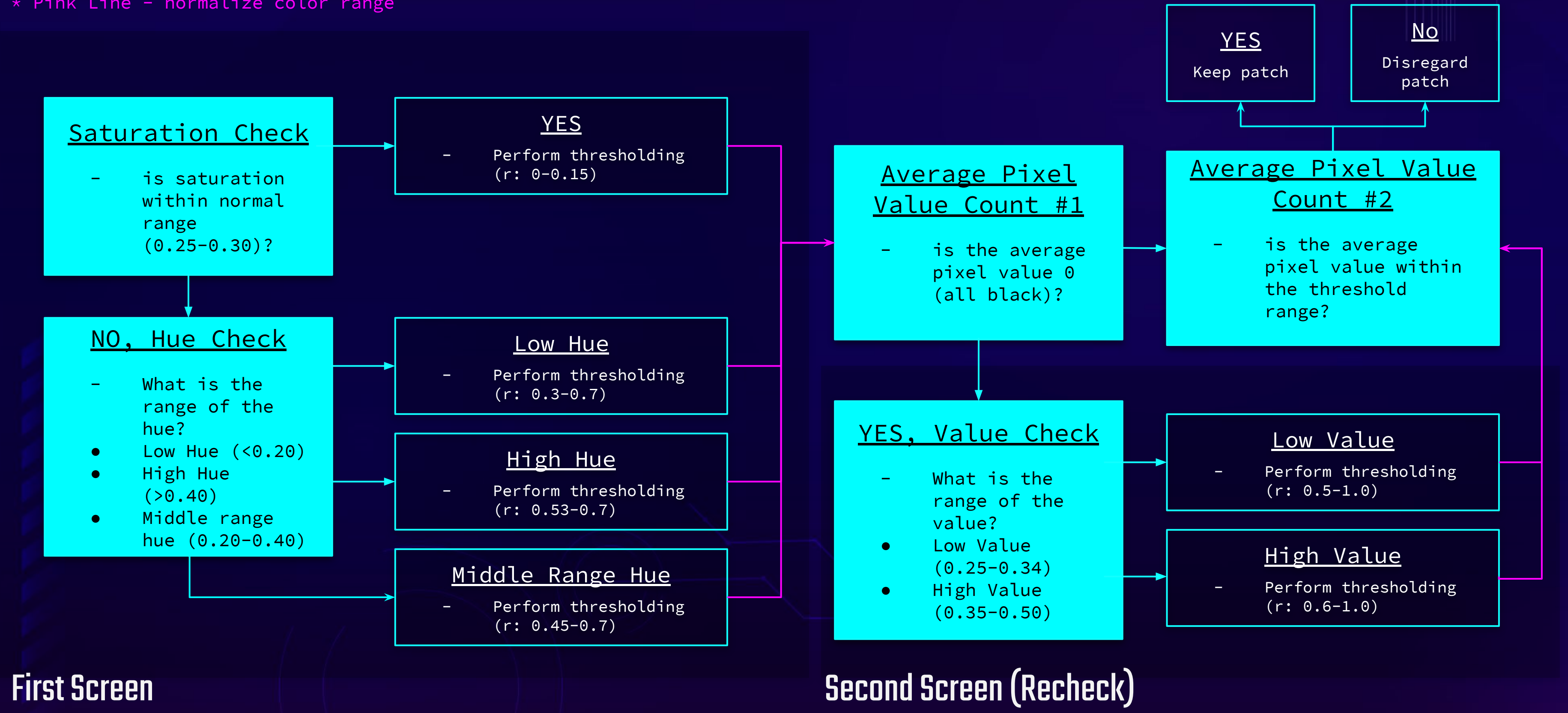
Binary Thresholding

HSV-dependent Thresholding (our method)

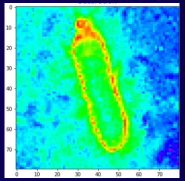


Our approach: Method

⋆ Pink Line - normalize color range

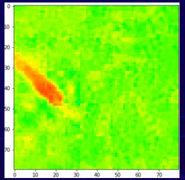


Our approach: Saturation



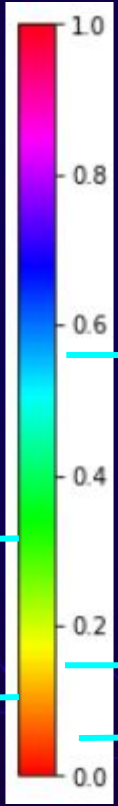
High Saturation (0.45-0.60)

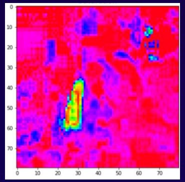
- sky blue to dark blue background
- red to green mask (0-0.35)
- noisy/not coherent



Medium 1 Saturation (0.25-0.30)

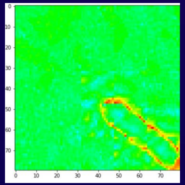
- yellow to green background
- red to orange mask (0-0.15)
- coherent
- just the right range!





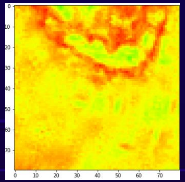
Extremely High Saturation (>0.60)

- dark blue to red background
- red to sky blue mask (0-0.5)
- overlapping red (since red is both 0 and 1)



Medium 2 Saturation (0.30-0.45)

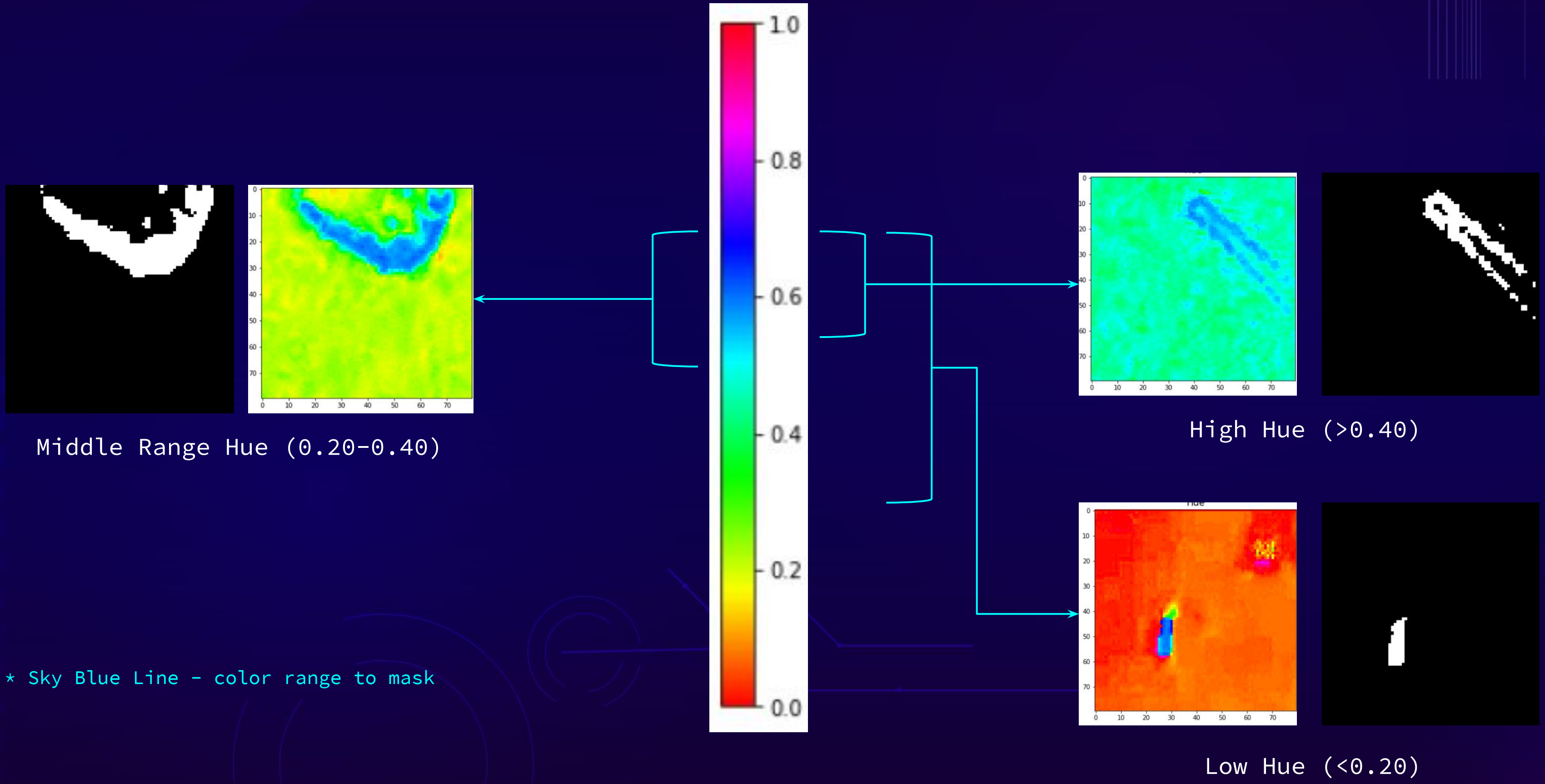
- green to sky blue background
- red to yellow mask (0-0.2)
- noisy/not coherent



Low Saturation (<0.25)

- orange to yellow background
- red to dark orange mask (0-0.05)
- small range for mask

Our approach: Hue

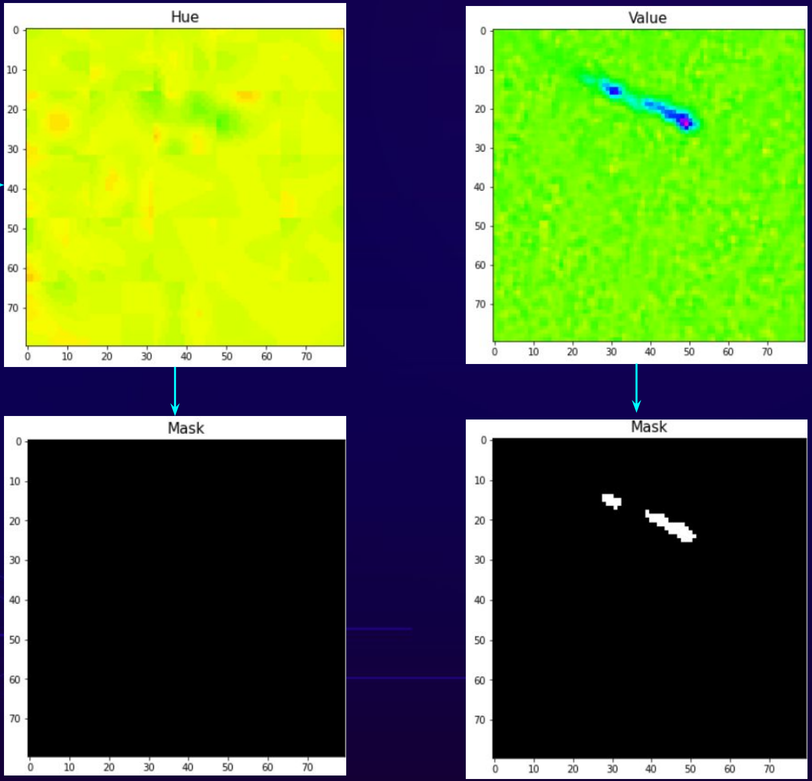


* Sky Blue Line - color range to mask

Our approach: Value

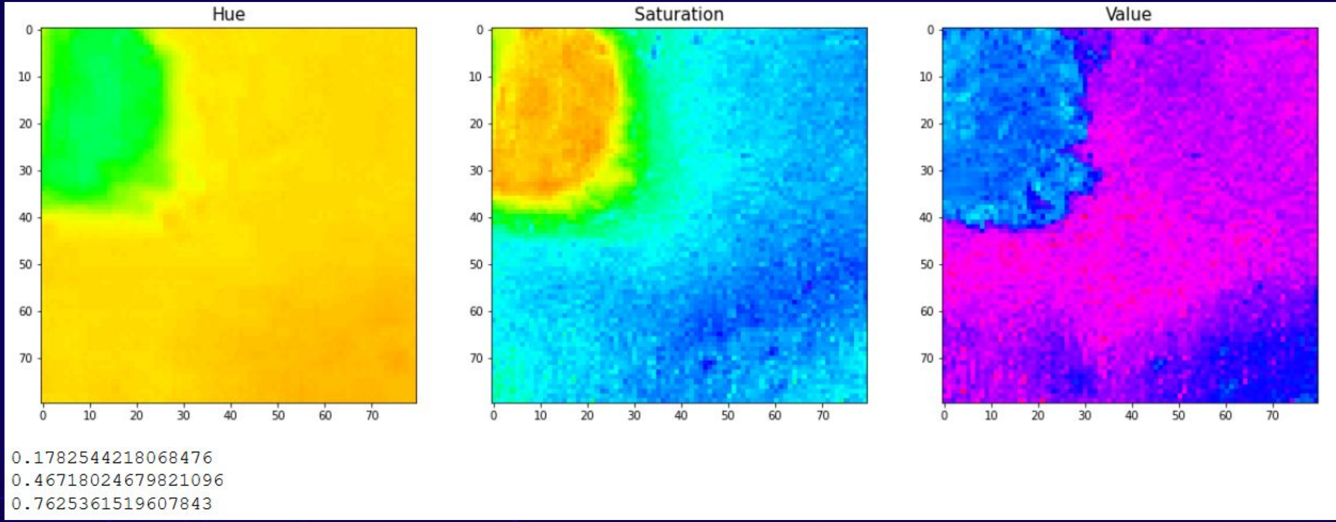
* Using only saturation and hue, sometimes, small or light objects cannot anymore be detected.

- low saturation
- middle range hue



Our approach: Why not straight up use value?

* Value is not that coherent at certain ranges



Our approach: Side by Side Comparison

San Francisco Bay, USA
(Planet.com)

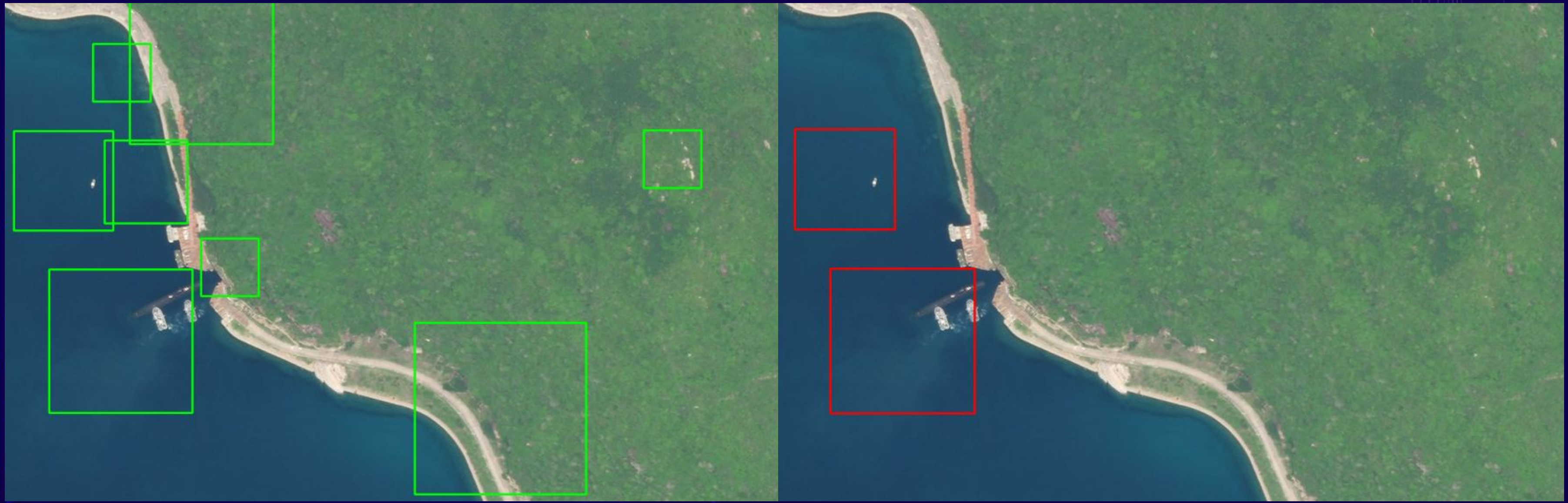
Our approach: Side by Side Comparison

Whitsun Reef/ Julian Felipe Reef
(Google Images)

Our approach: Side by Side Comparison

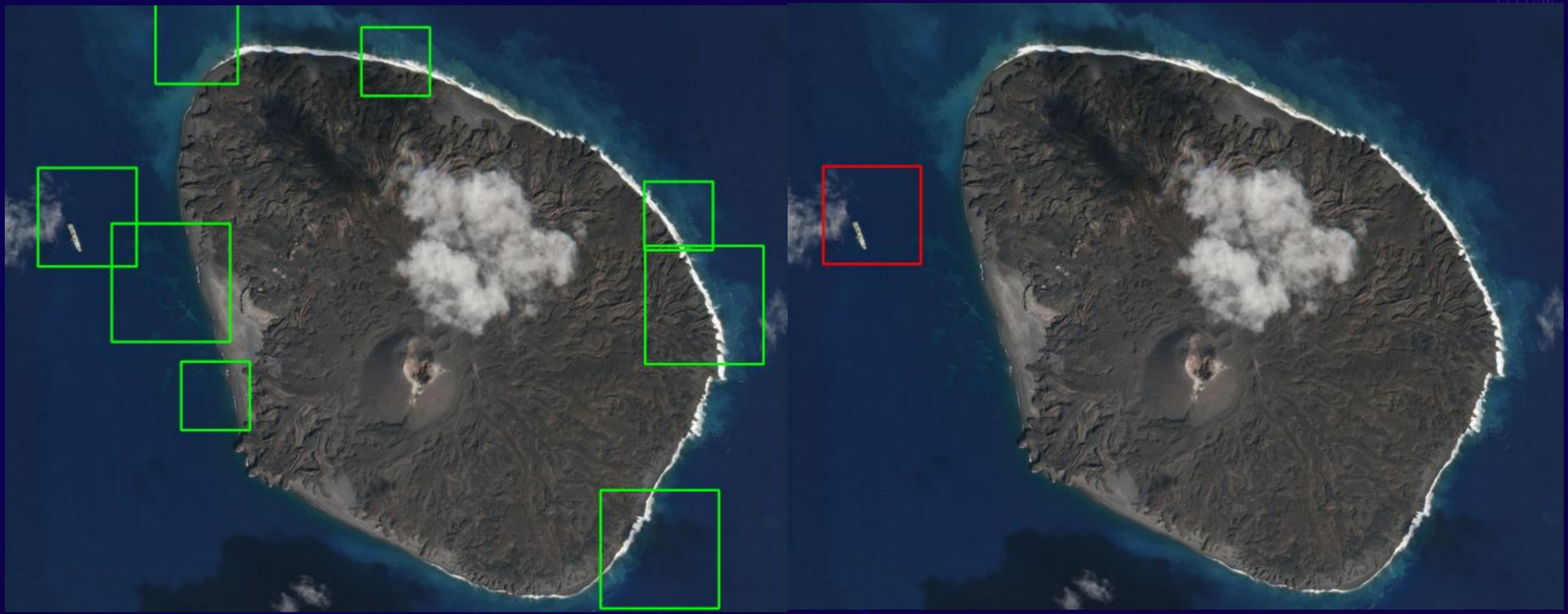
San Francisco Bay, USA
(Planet.com)

Our approach: Side by Side Comparison



Hainan Island, China (Planet.com)

Our approach: Side by Side Comparison

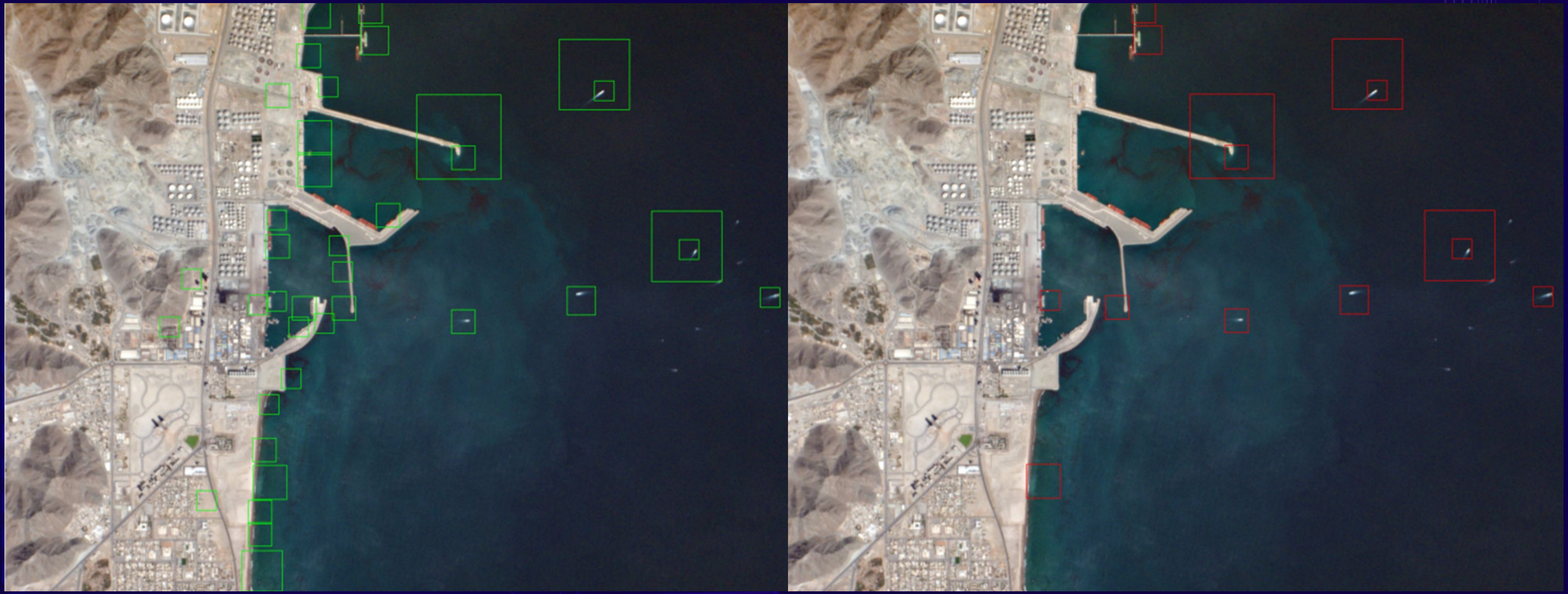


Nishinoshima Island, Japan
(Planet.com)

Our approach: Side by Side Comparison

Hong Kong (Planet.com)

Our approach: Side by Side Comparison

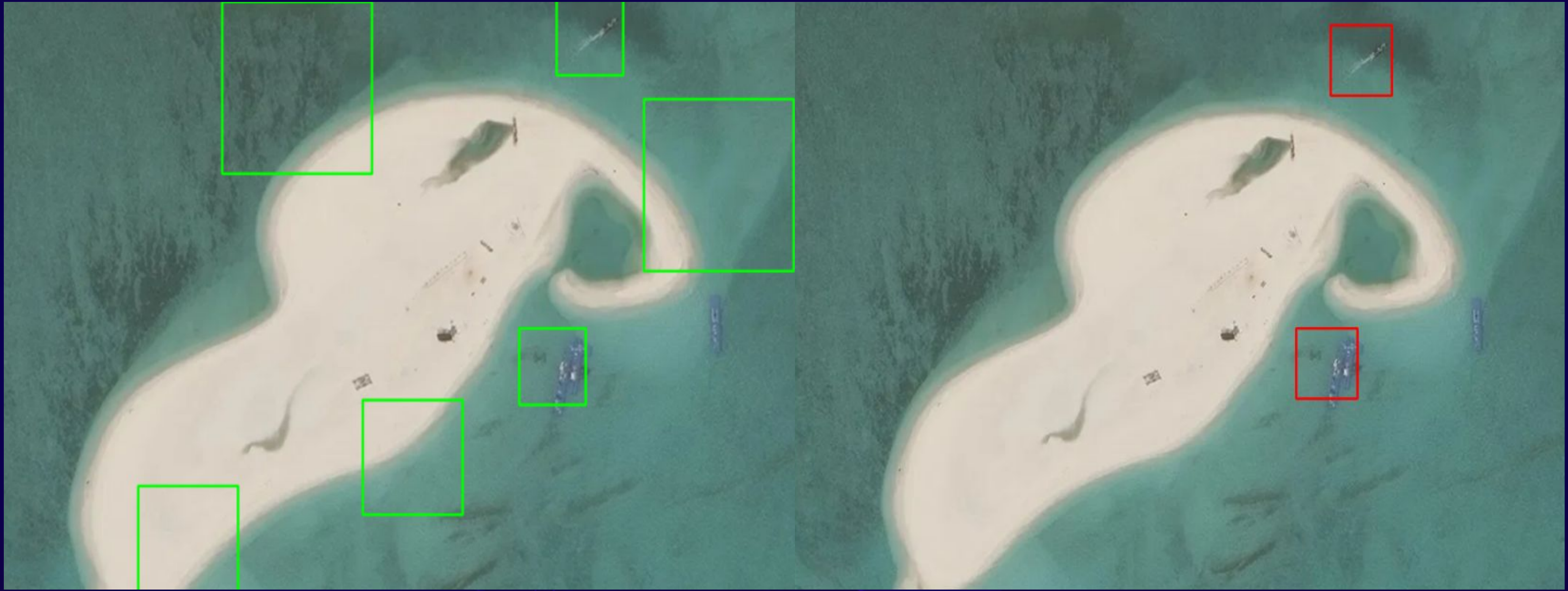


Fujairah Oil Industry Zone, UAE
(Planet.com)

Our approach: Side by Side Comparison

(Google Images)

Our approach: Side by Side Comparison



Quanfu Island, China (AMTI)

Our approach: Side by Side Comparison

Sydney, Australia (Planet.com)

Our approach: Side by Side Comparison

Bay Bridge, USA (Planet.com)

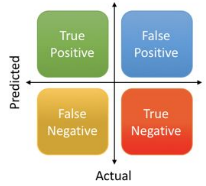
Our approach: Results

Image #	Total Detected	True Positives	False Positive (original)	False Positive (post-processed)	False Negative (post-processed)	Precision (original)	Precision (post-processed)	Recall (post-processed)
1	86	67	19	3	9	0.78	0.96	0.88
2	35	24	11	5	1	0.69	0.83	0.96
3	6	2	4	0	0	0.33	1.00	1.00
4	5	5	0	0	0	1.00	1.00	1.00
5	3	1	2	0	0	0.33	1.00	1.00
6	8	2	6	0	0	0.25	1.00	1.00
7	8	1	7	0	0	0.13	1.00	1.00
8	15	11	4	1	1	0.73	0.92	0.92
9	25	14	11	2	2	0.56	0.88	0.88
10	4	4	0	0	0	1.00	1.00	1.00
11	38	16	22	0	4	0.42	1.00	0.80
12	6	6	0	0	0	1.00	1.00	1.00
13	60	23	37	7	4	0.38	0.77	0.85
14	15	7	8	1	0	0.47	0.88	1.00
15	20	9	11	3	0	0.45	0.75	1.00
16	19	17	2	0	0	0.89	1.00	1.00
17	26	14	12	2	0	0.54	0.88	1.00
18	23	13	10	1	3	0.57	0.93	0.81
19	37	10	27	3	1	0.27	0.77	0.91
20	8	2	6	0	0	0.25	1.00	1.00
21	7	1	6	0	0	0.14	1.00	1.00
22	5	4	1	0	0	0.80	1.00	1.00
23	6	3	3	1	2	0.50	0.75	0.60
24	15	3	12	2	0	0.20	0.60	1.00
25	38	5	33	1	2	0.13	0.83	0.71
26	95	49	46	5	16	0.52	0.91	0.75
27	100	54	46	3	18	0.54	0.95	0.75
28	23	4	19	5	1	0.17	0.44	0.80
29	20	20	0	0	0	1.00	1.00	1.00
30	6	6	0	0	0	1.00	1.00	1.00
31	61	22	39	2	2	0.36	0.92	0.92
32	33	9	24	6	3	0.27	0.60	0.75
					Average	**0.52**	**0.89**	**0.92**

$$\textbf{Precision} = \frac{\text{True Positive}}{\text{Actual Results}} \text{ or } \frac{\text{True Positive}}{\text{True Positive + False Positive}}$$

$$\textbf{Recall} = \frac{\text{True Positive}}{\text{Predicted Results}} \text{ or } \frac{\text{True Positive}}{\text{True Positive + False Negative}}$$

$$\textbf{Accuracy} = \frac{\text{True Positive + True Negative}}{\text{Total}}$$



We tested this method on 32 images and got an average of 89% precision, which is a 71.15% increase as compared to the raw precision which is only 52% (did not undergo post-processing). We also got a recall score of 92%, this means the "loss" (the actual vessels that were initially detected and later disregarded) is low.

CONCLUSION

The research shows that combining HOG (16x16) + LBP (Default) gives the same F1-score as HOG (16x16) alone. However, the recall increased from the previous highest of 94% to 96%. This is not the case for precision, which is lower than the highest one attained by the HOG (16x16) alone.

The proposed post-processing method, on the other hand, was able to notably decrease the false positives detected by the initial detection, specifically, it was able to increase the precision by 71.15% of the 32 images tested with only a small loss. This post-processing method can be useful for vessel detection systems based on classical machine learning methods such as SVM, which feature extraction step is manually done and carefully parameterized to get a more precise detection.

Moreover, the research was able to present a novel thresholding method using the relationship between HSV values and color ranges of the background and objects. This can be useful not only as a post-processing method for reduction of false positives in vessel detection but also for general segmentation of vessels in varying image conditions.

Our approach: Drawbacks

It’s a post-processing step so it is highly reliant on the initial detection. If initial detection was not able to detect a specific object, this process can’t do anything about it.

Taiping Island / Ligao Island (AMTI)

Our approach: Drawbacks

We also lose some of our initial detections.

San Francisco Bay, USA (Planet.com)

Our approach: Drawbacks

Not 100% accurate. Vulnerable to false detection of wave barriers and bridges as vessels.

Kashima Industrial Zone, Japan (Planet.com)

Our approach: Method (Shortcut)

Post-Processing

- Conversion to HSV Colormap
- Conversion to Grayscale
- Binary Thresholding
- Count average pixel value
- Set threshold

Our approach: Method (Shortcut)

Original Method

Shortcut Method

References

[1] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, 2005, pp. 886-893 vol. 1, doi: 10.1109/CVPR.2005.177.

[2] S. Charchut (2020), *Ship Detection Feature Analysis in Optical Satellite Imagery through Machine Learning Applications through Machine Learning Application.* University of New Orleans.

[3] T. Ojala, M. Pietikäinen, and D. Harwood (1994), "Performance evaluation of texture measures with classification based on Kullback discrimination of distributions", *Proceedings of the 12th IAPR International Conference on Pattern Recognition (ICPR 1994)*, vol. 1, pp. 582 - 585.

[4] Islam, Mohammad & Billah, Mustagis & Yousuf, Md. (2019). Automatic Plant Detection Using HOG and LBP Features With SVM. *International Journal of Computer (IJC)*. 33. 26-38.

[5] V. F. Arguedas, "Texture-based vessel classifier for electro-optical satellite imagery," in 2015 IEEE International Conference on Image Processing (ICIP), 2015, pp. 3866–3870

THANK YOU!