Improved Supervised Classification of Underwater Military Munitions Using Height Features Derived from Optical Imagery

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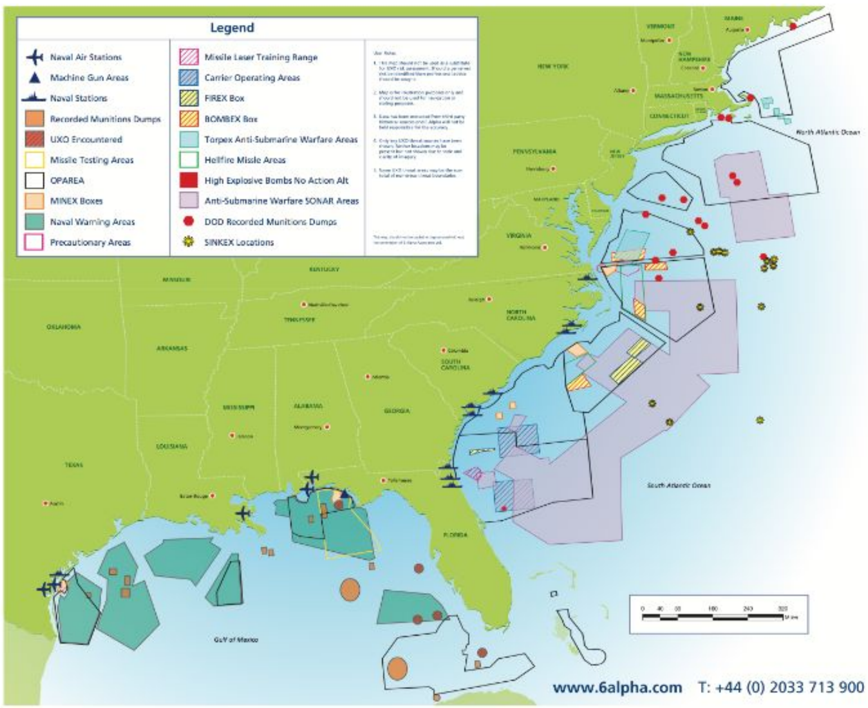
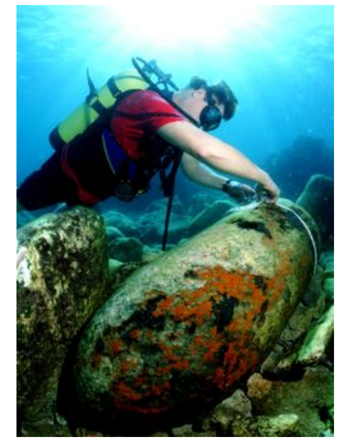
Outline

- Motivation and Objectives
- Approach
- Testing methodology
- Results
- Conclusions

Motivation

After World War II, the United States and other European nations dumped 300,000 tonnes of chemical and conventional munitions into the ocean

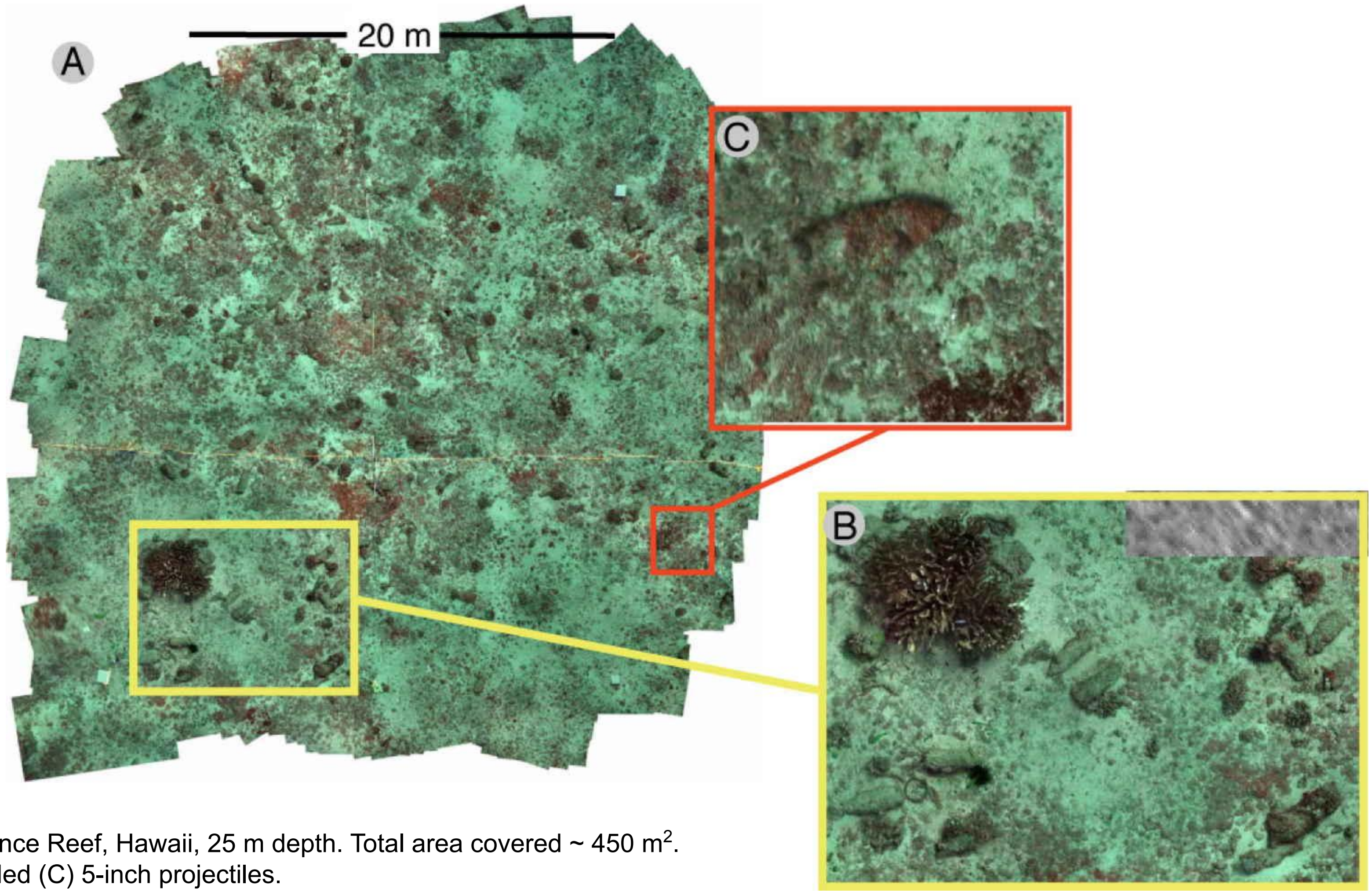




- Underwater Military Munitions (UWMM) are a safety and environmental hazard.
- Methods for ***detection, identification and mapping*** are needed, to assess remediation feasibility.

Motivation

- Underwater Military Munitions (UWMM) are a safety and environmental hazard.
- Methods for detection, identification and mapping are needed, to assess remediation potential.



Example from Ordnance Reef, Hawaii, 25 m depth. Total area covered ~ 450 m^2.
Intact (B) and degraded (C) 5-inch projectiles.

Why use optical images?

- **Acoustic, metal detection and chemical sensing** are the current methods of choice for wide-area mapping for UWMM
- **No single technology works best in all situations**. A multi-modal approach with different technologies provides the most robust solution.

- **Optical images have much higher spatial resolution** and can supplement existing approaches.
- **However optical images have limitations** :
  a) Not useful everywhere. Yes, but *very* useful in some important places.
  b) Hard to map large areas. Largely overcome within last 15 years.
  c) Manual analysis for quantitative data extraction. **Bottleneck we address**!

Bomb, projectiles, and M47A2 chemical munitions imaged in ~500 m depth off Pearl Harbor, HI.

Why use optical sensing?

- Wide-area search and detailed mapping for UWMM currently rely on acoustic and/or metal detection methods.
- No single technology works best in all situations. A multi-modal approach using several different technologies provides the most robust solution. (True on land also.)
- Optical images of the seabed could be a valuable supplement to existing approaches due do high spatial resolution.
(1-2 or more orders of magnitude better than alternatives).

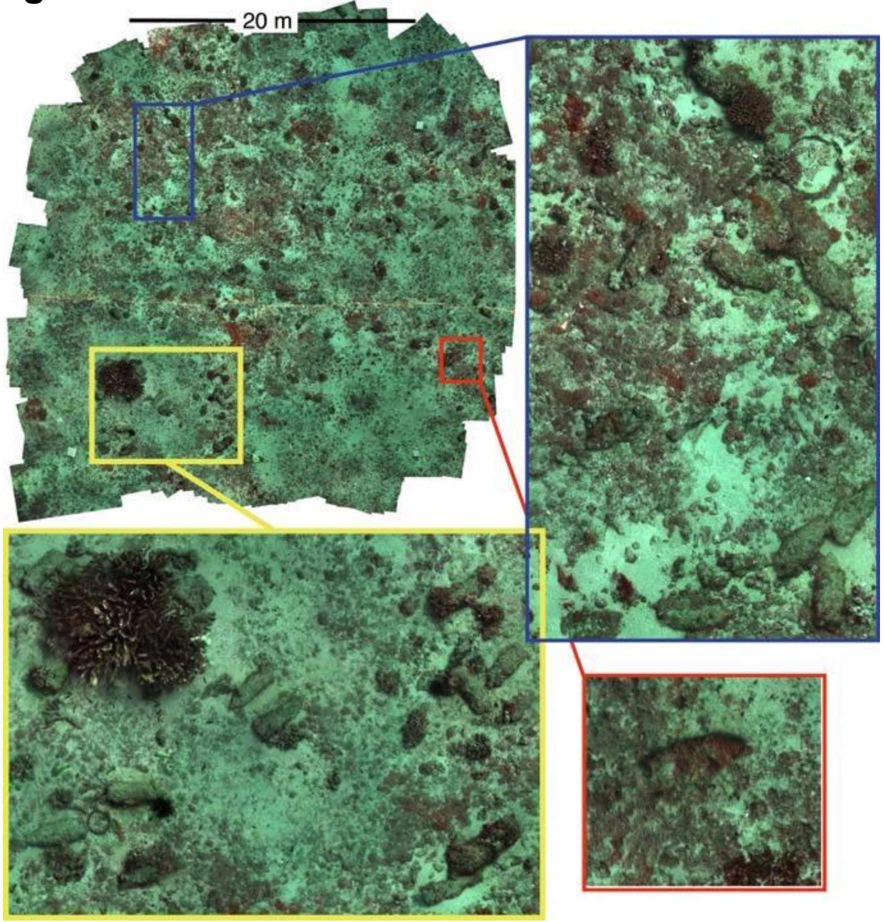
- Obstacles for quantitative analysis of optical images of the seabed:
a) Not useful everywhere. Yes, but *very* useful in some important places.
b) Hard to map large areas. Largely overcome within last 15 years.
c) Manual analysis for quantitative data extraction. **Bottleneck we address**!

More Examples:
Bomb, projectiles, and M47A2 chemical munitions imaged in ~500 m depth off Pearl Harbor, HI.

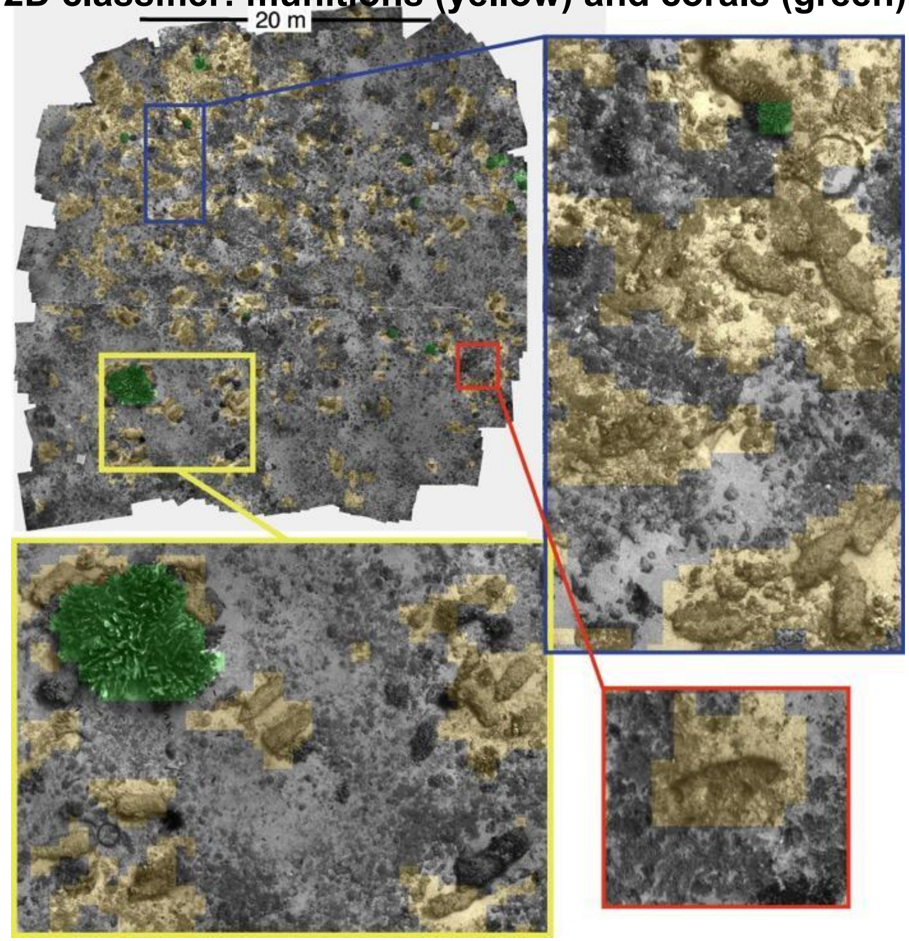
Previous work

- Combined color/texture image classification algorithm works fairly well (2-D)

Original mosaic and details

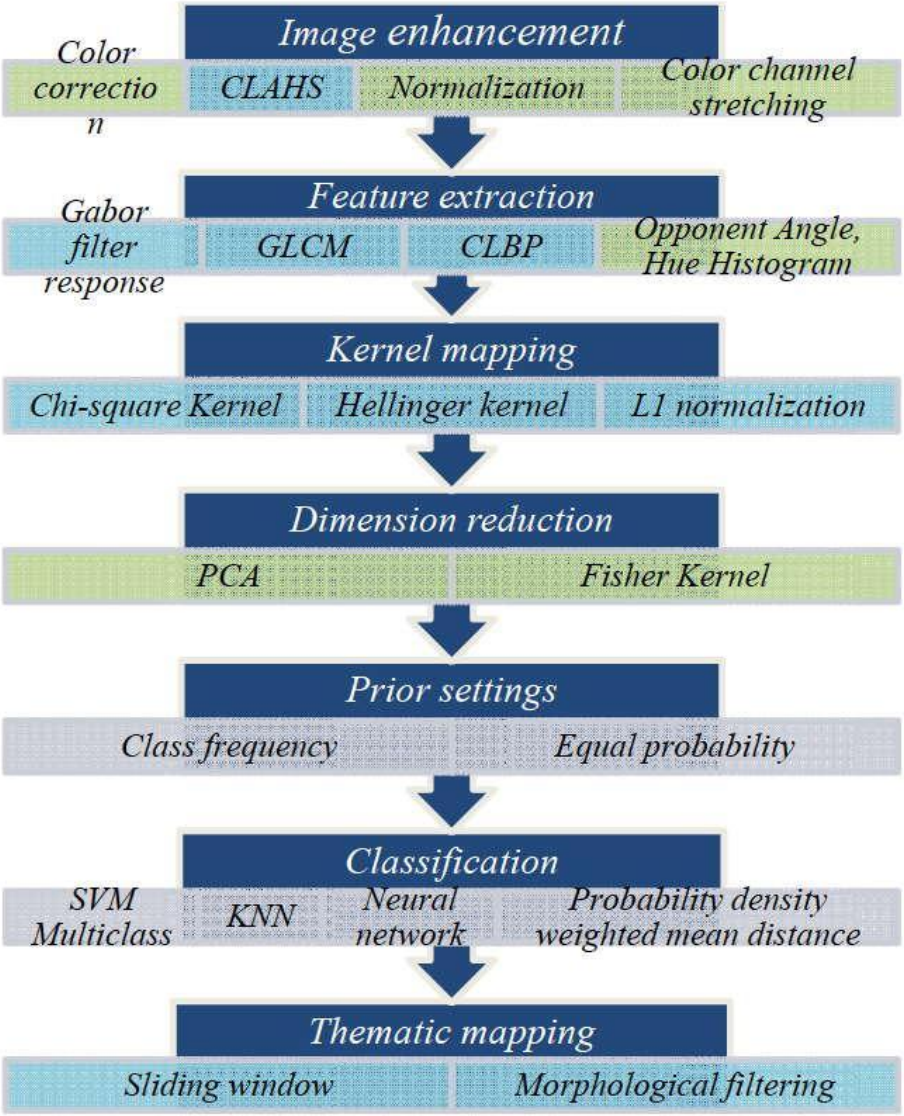


2D classifier: munitions (yellow) and corals (green)



How much does the addition of height information improve accuracy?

2-D Classifier



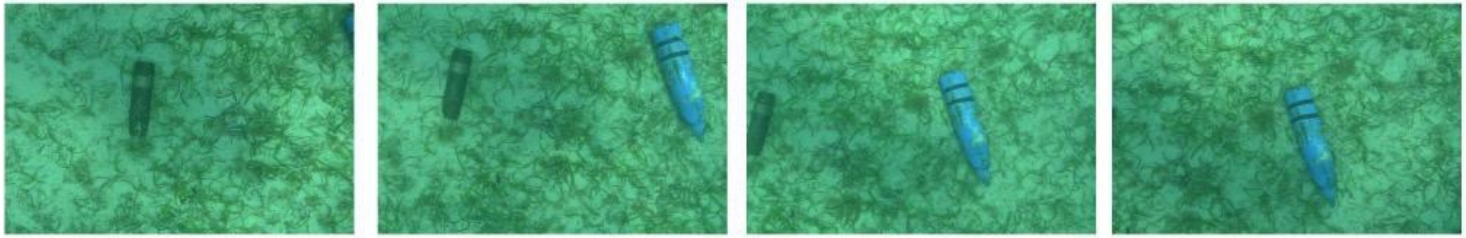
- 7 Steps (green optional, blue mandatory, grey mutually exclusive)
- Not really a single method; the mutually exclusive (grey) steps tend to be fixed, but here they can vary
- Very supervised method; requires good training data

Shihavuddin, A. S. M., N. Gracias, R. Garcia, A. Gleason and B. Gintert (2013). **Image-Based Coral Reef Classification and Thematic Mapping**. *Remote Sensing* **5**(4): 1809-1841

Computing height features

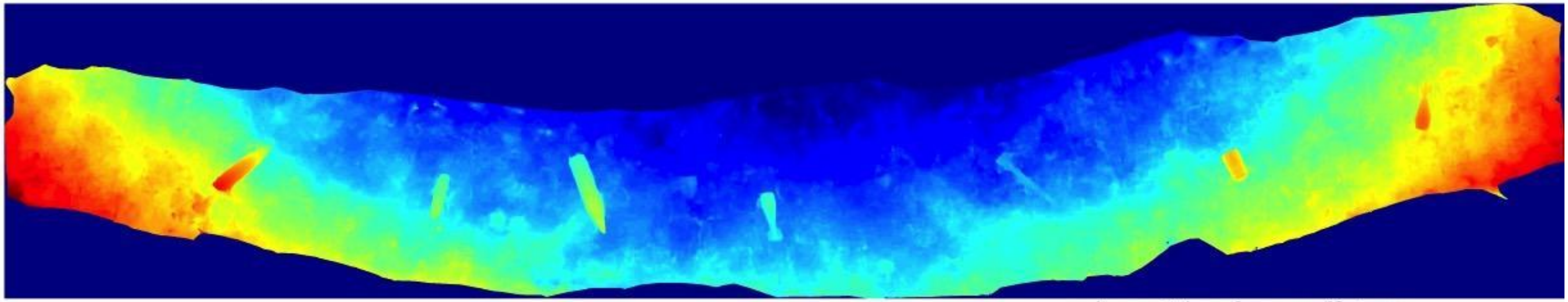
Many overlapping images

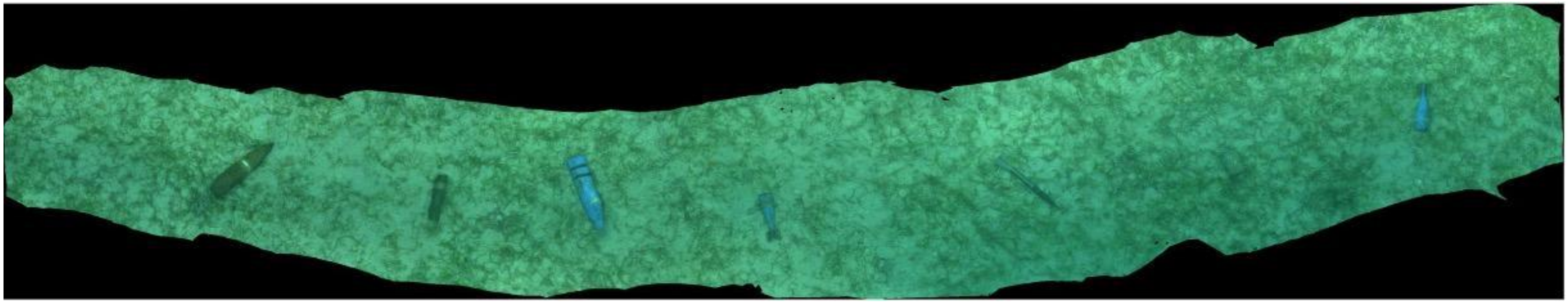
...etc



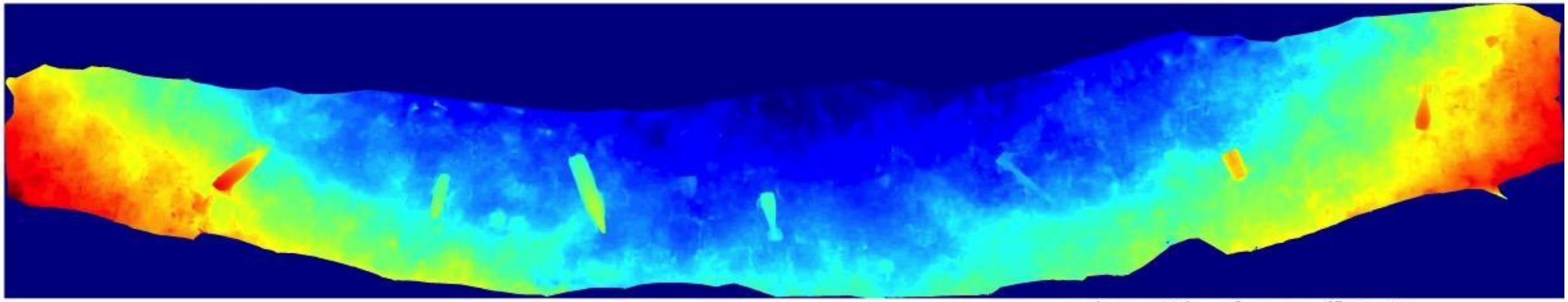
etc...

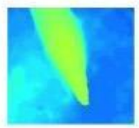
Create a height map





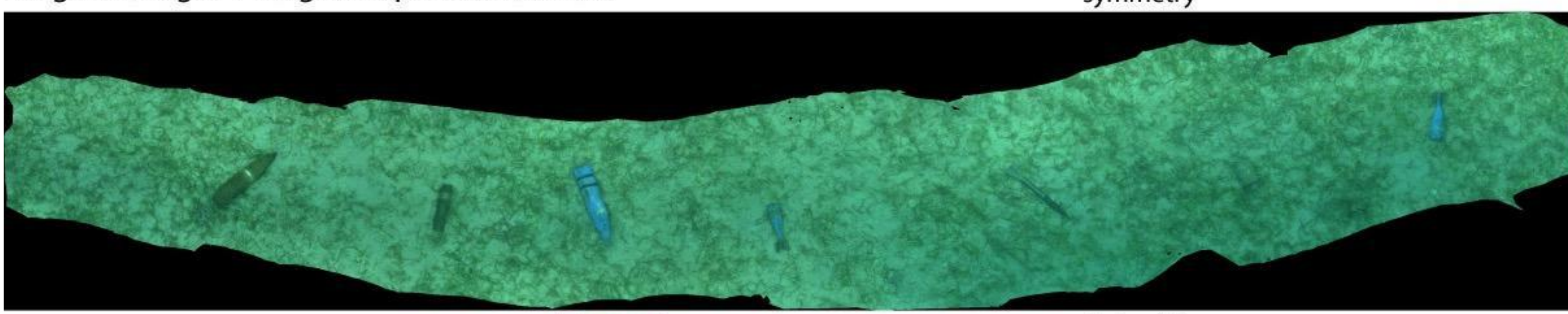
Computing height features



For every patch  generate the 2.5-D features

- polynomial surface coefficients
- elevation statistics
- slope of surface
- curvature
- surface normal
- rugosity
- symmetry

Original images + height map = orthomosaic

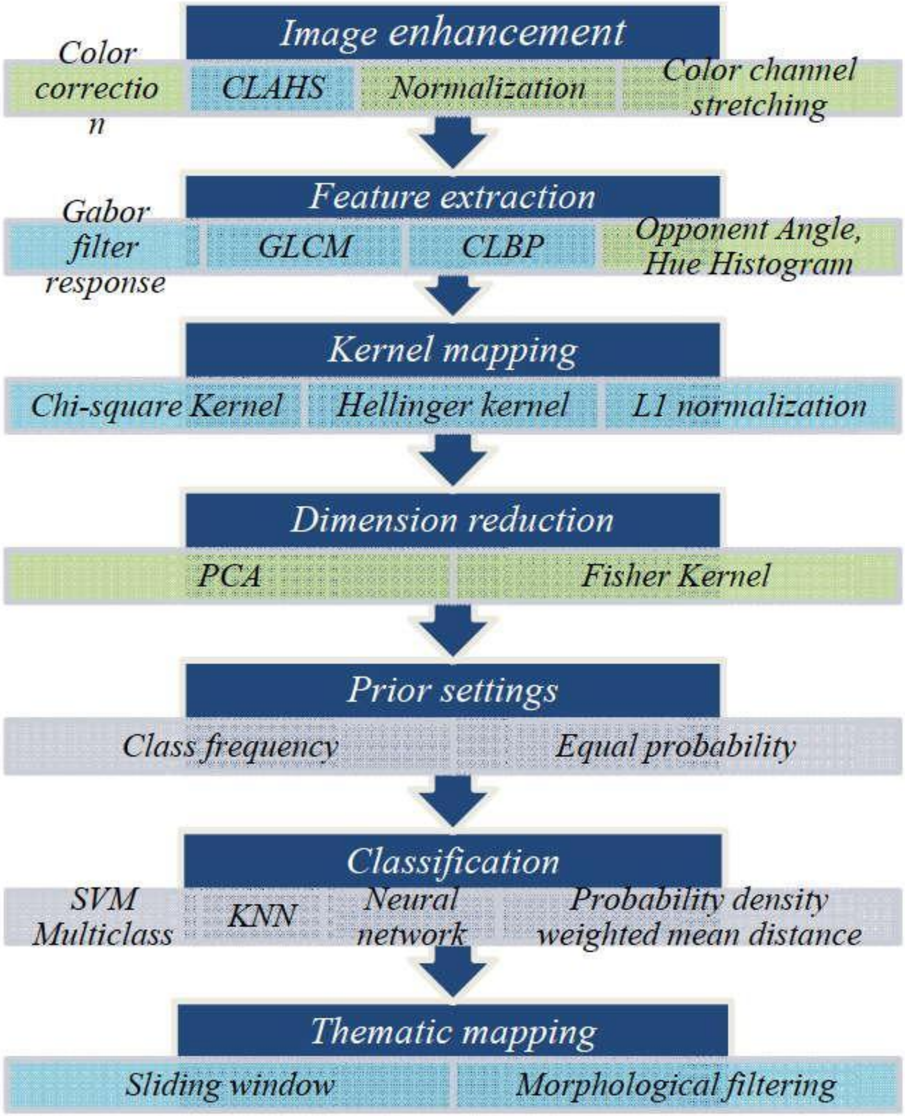


For every patch  generate the 2-D features

- Gabor filter response
- grey level co-occurance matrix
- computed local binary pattern
- opponent angle histogram
- hue color histogram

Combined 2-D and 2.5-D features are used in classifier. Other steps of classifier remain the same as 2-D only case.

2.5-D Classifier



+ all height features

Shihavuddin, A. S. M., N. Gracias, R. Garcia, A. Gleason and B. Gintert (2013). **Image-Based Coral Reef Classification and Thematic Mapping**. *Remote Sensing* **5**(4): 1809-1841

Dataset collected near Miami, FL

16 types of Inert / training rounds used:
A - BDU-28 Submunition
B - 60mm Mortar (without fuze)
C - 60mm Mortar (with fuze)
D1 - 81mm M43A1/M49A2 Mortar (fuze)
D2 - 81mm M43A1/M49A2 Mortar (no fuze)
E - 81mm Mortar (with fuze)
F - 81mm M821A1/M889A1
G - 2" Rocket APFSDS-T M735
H - 76mm Projectile (no fuse)
I - 3" Armor Piercing Projectile MK28
J - 90mm Projectile (no widscreen)
K - 90mm Projectile M71
L - APDS Adapter with Cap and Cartridge
M - 105mm Projectile
N - 105mm Projectile (with solid tip)
Z - 155 mm Howitzer Projectile

Images collected as HD video and manually annotated by an expert

Accuracy Assessment

Error matrix approach: hypothetical example with N = 400 reference points

A) Raw counts

Reference	Predicted C1	Predicted C2
C1	100	25
C2		275

OA = 94%

B) Producer's Accuracy

Reference	Predicted C1	Predicted C2
C1	80%	20%
C2		100%

B) Users' Accuracy

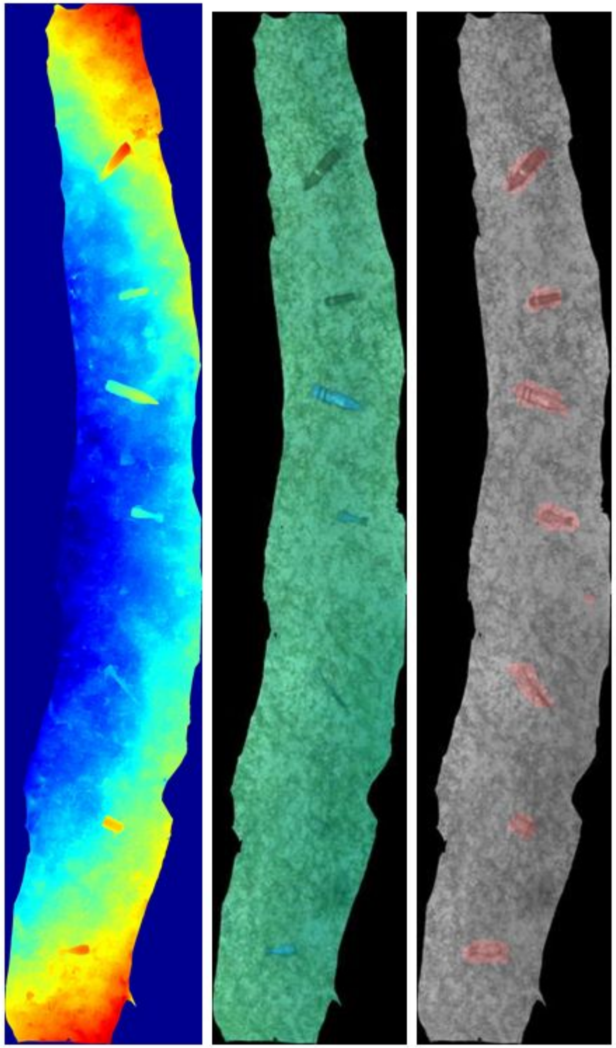
Reference	Predicted C1	Predicted C2
C1	100%	8%
C2		92%

(A) Overall accuracy = % of points correctly classified: 0.94 = (100+275)/400

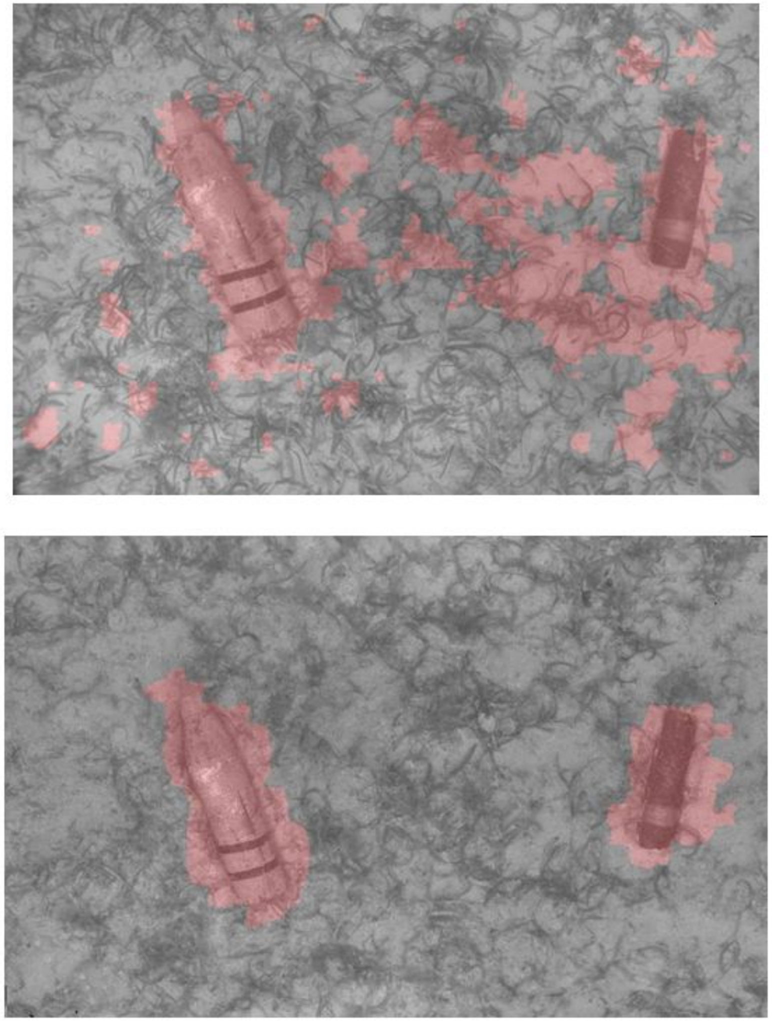
(B) Producers accuracy = (A) normalized by row sums
Indicates false negatives (high producer’s accuracy = few false negatives)

(C) Users accuracy = (A) normalized by column sums
Indicates false positives (high user’s accuracy = few false positives)

Improvement with 2.5-D: One Seagrass Site



2.5-D products for the Seagrass 1 site. Left: DEM with low (blue) to high (red) colormap. Center: Mosaic of the site. Right: Greayscale of mosaic with pixels classified as munitons colored red.



One of the frames used for the Seagrass 1 mosaic presented in grayscale. Pixels have been colored red where they were classified as munitions by the 2-D algorithm (top) and the 2.5-D algorithm (bottom). Note fewer false posistives in the 2.5-D results.

Results: Overall Accuracy

Dataset	MTypes	Binary
Reef 1 2-D	76	80
Reef 1 2.5-D	94	94
Reef 2 2-D	71	75
Reef 2 2.5-D	95	95
Seagrass 1 2-D	67	72
Seagrass 1 2.5-D	95	95
Seagrass 2 2-D	53	60
Seagrass 2 2.5-D	89	89

Mtypes = 13 classes
12 munitions types
1 class for everything else

Binary = 2 classes
munitions
not munitions

OA higher for Binary than MTypes (as expected, due to fewer # of classes).
OA using 2.5-D features greater than OA using only the 2-D features (!)

Results: Binary Classification Scheme

Users Accuracy (%): Main Diagonals with Binary Class Scheme

	Reef 1		Reef 2		Seagrass 1		Seagrass 2	
Class	2-D	2.5-D	2-D	2.5-D	2-D	2.5-D	2-D	2.5-D
Seabed	94	98	97	98	98	97	98	98
Munitions	25	73	28	76	25	86	18	54

Producers Accuracy (%): Main Diagonals with Binary Class Scheme

	Reef 1		Reef 2		Seagrass 1		Seagrass 2	
Class	2-D	2.5-D	2-D	2.5-D	2-D	2.5-D	2-D	2.5-D
Seabed	83	94	74	97	70	97	57	89
Munitions	54	91	80	84	86	86	89	90

- Users and producers accuracy ***2.5-D > 2-D*** for all 4 sites.
- ***False positive matches for munitions***. The evidence for this was high producer's accuracy (all munitions were classified as munitions) but low user's accuracy (many pixels classified as munitions were actually something else).
- ***2.5-D processing gave fewer false positive*** matches for munitions.

Results: Munitions Types Scheme

Users Accuracy (%): Main Diagonals

	Reef 1		Reef 2		Seagrass 1		Seagrass 2	
Class	2-D	2.5-D	2-D	2.5-D	2-D	2.5-D	2-D	2.5-D
Seabed	94	98	97	98	98	97	98	98
MA							0	80
MB							6	25
MC	7	63	71	70	49	88		
MD							0	71
ME	0	78						
MF	0	93	22	79	2	91		
MG	0	88	14	69	0	80		
MH	84	68	0	86			52	88
MI							0	67
MJ					7	71		
MK			87	86	29	80		
ML					26	92		

Producers Accuracy (%): Main Diagonals

Reef 1		Reef 2		Seagrass 1		Seagrass 2	
2-D	2.5-D	2-D	2.5-D	2-D	2.5-D	2-D	2.5-D
83	94	74	97	70	97	57	89
						0	89
						3	95
45	96	60	92	27	95		
						0	90
0	88						
0	84	62	74	5	76		
0	89	64	79	0	84		
26	92	0	85			55	73
						2	95
				17	81		
		54	83	45	86		
				75	86		

Same general patterns as for the binary munitions / not-munitions class scheme:

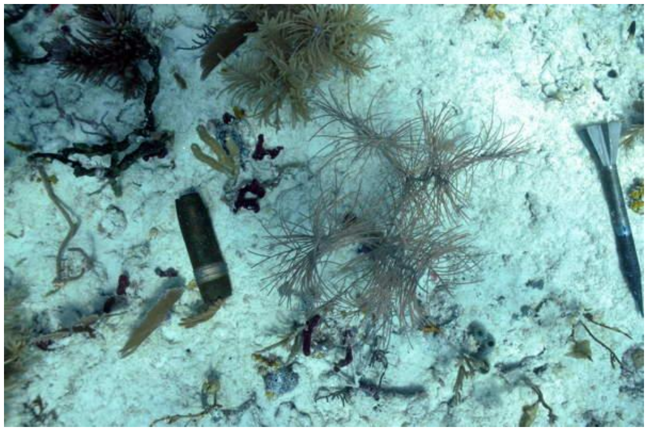
- Users and producers accuracy *2.5-D > 2-D* for all 4 sites.
- *False positive matches for munitions*. The evidence for this was high producer's accuracy (all munitions were classified as munitions) but low user's accuracy (many pixels classified as munitions were actually something else).
- *2.5-D processing gave fewer false positive* matches for munitions.

Also: **2.5-D gave dramatic improvement in classifying individual munitions types**!

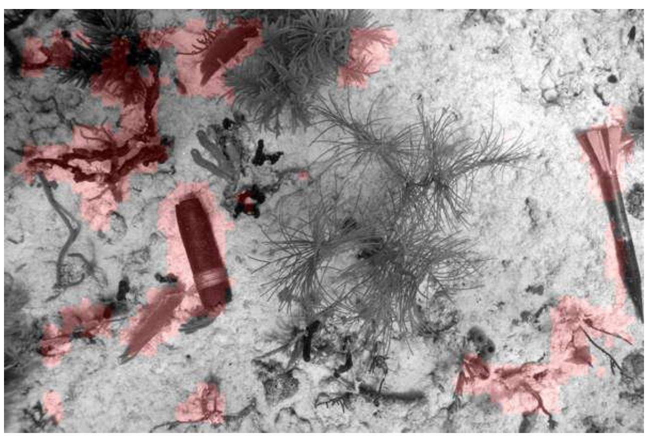
- Accuracy of munitions ID increased from < 50% to > 80% in many cases.

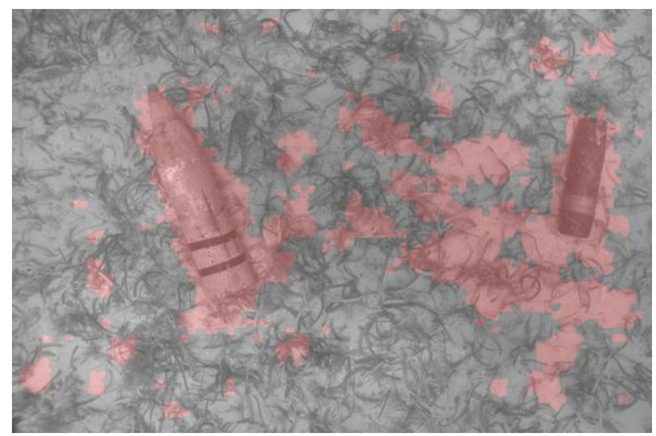
Results: Examples with 2-D only

Original images over reef and seagrass



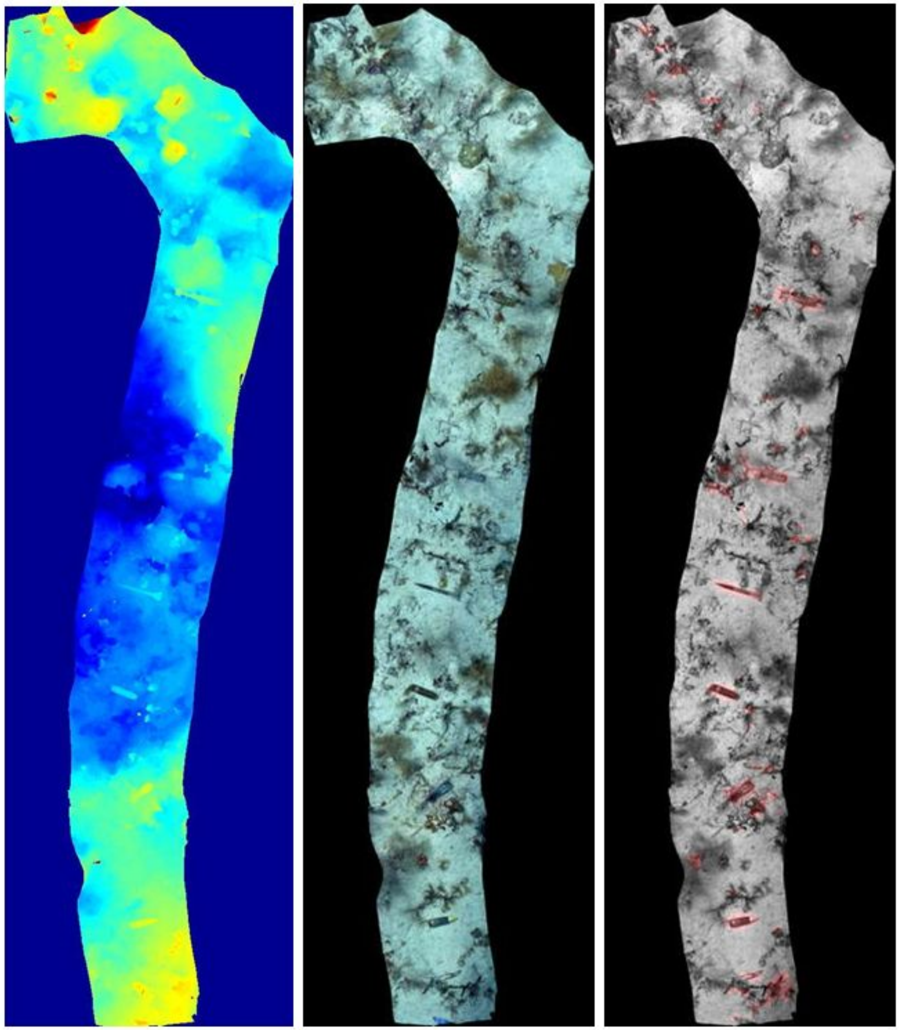
Areas classified as munitions



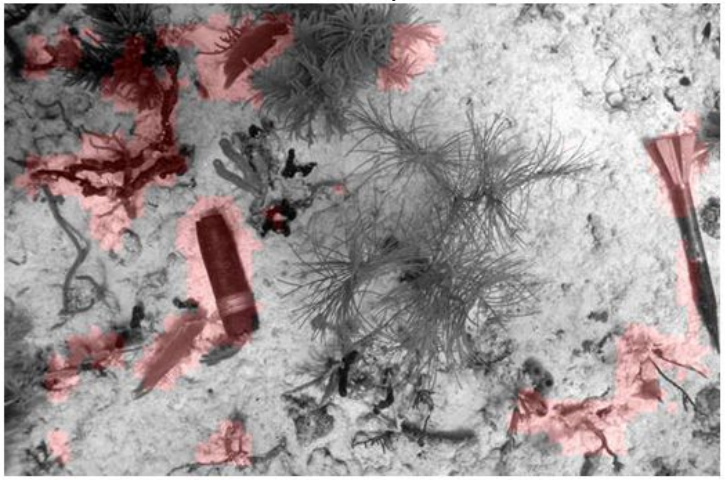


Images show qualitatively what the error matrix has quantified:
false positive matches for munitions

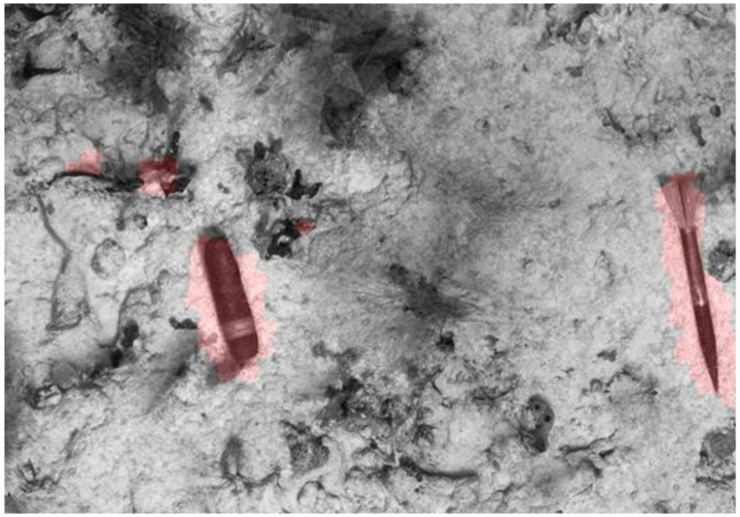
Improvement with 2.5-D: One Reef Site



2D only



2.5D



Summary

- Incorporating height information greatly improved classification results.
  - Reduced false positives for munitions in the Miami dataset, increasing accuracy from the 0-80% range to the 50-100% range.

- Improvement not only on the basic, binary munitions / non-munitions classes
  - 2.5-D information improved the capability to discriminate different types of munitions from one another.

Conclusions

- Automated classification of optical imagery can improve *wide-area high-resolution* surveys by both **identifying munitions** and **characterizing the surrounding environments**.

- Automated classification at detailed levels (*e.g.* munitions types) was much more robust when using height information, compared to a texture-only approach.

- Further testing is due with partly proud munitions

- Based on the results, we expect that further improvements to the algorithms will allow joint classification of several classes of munitions and natural benthic objects (e.g. corals and sponges).

Backup Slides

Consistency of analysts

- Measured as Cohen's Kappa: $\kappa = \dfrac{Pr(a) - Pr(e)}{1 - Pr(e)}$
- Corals vs. other accuracy was good
  - Self-consistency: 86-92%
  - Inter-operator: 79-86%
- Coral genera accuracy were also good
  - Self-consistency: ~80%
  - Inter-operator: 59%
- Algal groups accuracy were lower
  - Macro [self: 71%, inter:59%]
  - CCA [self: 51%, inter: 35%]
  - Turf algae [self: 62%, inter 43%]

Moorea, inter-operator:

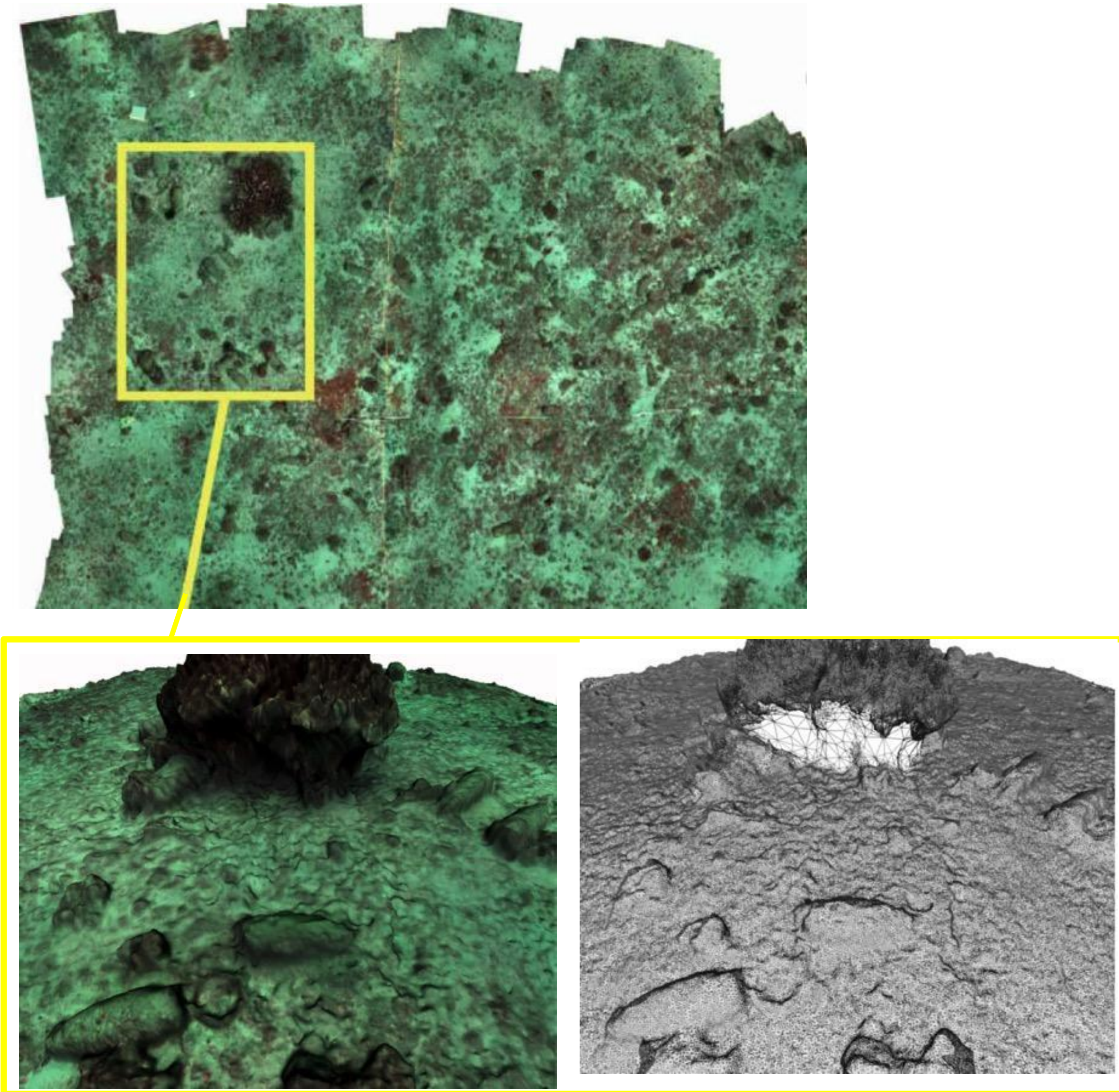
	Acropora	Favia	Montipora	Pavona	Pocillopor.	Porites	Other scle.	CCA	Turf	Macroalgae	Sand	Transect h.	Unclear	
Acropora	.63			.01	.24		.01	.02	.07				.02	100
Favia		.50					.25	.25						4
Montipora		.01	.49			.12	.09	.09	.14		.05		.02	238
Pavona			.02	.63			.19	.02	.04	.02	.05	.01	.02	124
Pocillopor.	.01			.15	.77			.01	.04	.01			.01	435
Porites	.01		.14	.01		.75	.02	.03	.03		.01		.01	1185
Other scle.		.17	.10			.02	.36	.17	.14	.01	.02		.01	132
CCA			.01		.01	.01	.01	.46	.44	.03	.01		.03	4285
Turf	.01		.01		.01	.02		.11	.72	.06	.05	.01	.02	1125
Macroalgae				.01	.01	.01	.01	.10	.20	.60	.01		.04	622
Sand			.01					.09	.12		.76		.01	1000
Transect h.												1.0		700
Unclear														0

Beijbom et al. compared self-consistency (same person doing repeat IDs) and inter-operator consistency (agreement among multiple people) for typical benthic classes in coral reef environments.

"Good" agreement *by humans* was 80-90%; algae were lower; hard to expect computer to do better.

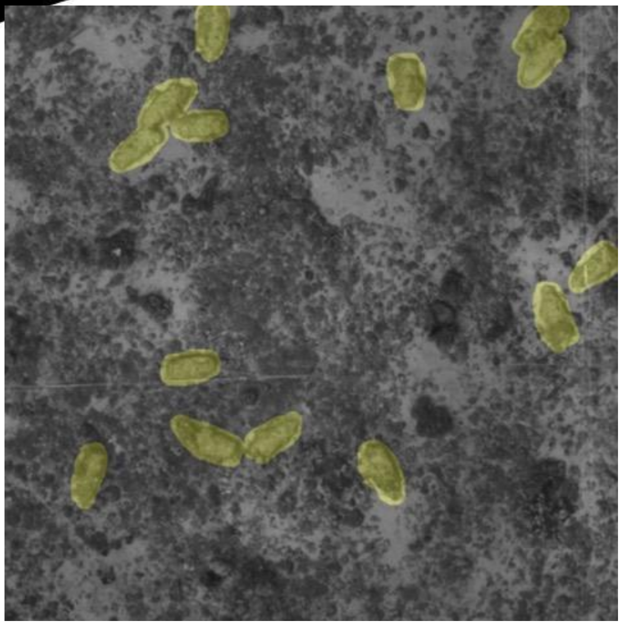
Beijbom, O., P. J. Edmunds, C. M. Roelfsema, J. Smith, D. I. Kline, B. Neal, M. J. Dunlap, V. Moriarty, T.-Y. Fan, C.-J. Tan, S. Chan, T. Treibitz, A. Gamst, B. G. Mitchell and D. Kriegman (in review). Towards automated annotation of benthic survey images: variability of human experts and operational modes of automation. *PLoS ONE.*

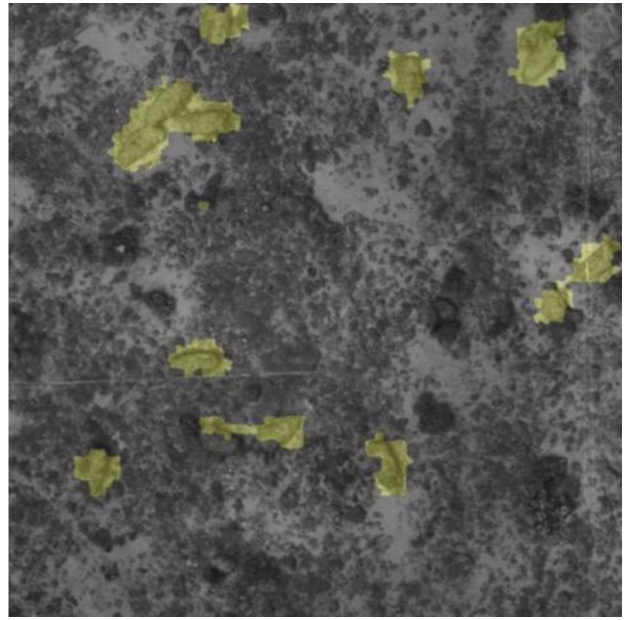
2.5-D Features



For objectives

Results: Ordnance Reef





Background shows a portion of the mosaic in grayscale.
Left: hand-drawn regions around munitions shown in yellow.
Right: munitions identified by the 2.5-D classifier in yellow.

Overall accuracy = 96% with 2-D data, 97% with 2.5-D data.
Small increase because good already!
High OA partially due to chance (large background class) but Kappa and AMI also increase with 2.5-D data.

	2D	2.5D	2D + 2.5D
Accuracy	96.01%	94.59%	96.95%
Kappa	66.51%	57.58%	71.82%
AMI	0.146	0.107	0.165

Miami Classes

ALL CLASSES (36 classes)	MUNITIONS TYPES (16 classes)	BINARY (2 classes)
coral (1)	**Background (1)**	**Background (1)**
macroalgae (2)	coral	coral
turf algae (3)	macroalgae	macroalgae
seagrass (4)	turf algae	turf algae
sand (5)	seagrass	seagrass
sand and seagrass (6)	sand	sand
sponge (7)	sand and seagrass	sand and seagrass
octocoral (8)	sponge	sponge
bare (9)	octocoral	octocoral
unknown (10)	bare	bare
crustose, turf & bare (11)	unknown	unknown
Acropora palmata (12)	crustose, turf & bare	crustose, turf & bare
Acropora cervicornis (13)	Acropora palmata	Acropora palmata
Acropora prolifera (14)	Acropora cervicornis	Acropora cervicornis
Dichocoenia stokesii (15)	Acropora prolifera	Acropora prolifera
Montastrea cavernosa (16)	Dichocoenia stokesii	Dichocoenia stokesii
Solenastrea bournoni (17)	Montastrea cavernosa	Montastrea cavernosa
Meandrina meandrites (18)	Solenastrea bournoni	Solenastrea bournoni
Porites astreoides (19)	Meandrina meandrites	Meandrina meandrites
Sideratrea siderea (20)	Porites astreoides	Porites astreoides
Palythoa (21)	Sideratrea siderea	Sideratrea siderea
BDU-28 Submunition (22)	Palythoa	Palythoa
60mm Mortar (without fuze) (23)	**BDU-28 Submunition (2)**	**Munitions (2)**
60mm Mortar (with fuze) (24)	**60mm Mortar (without fuze) ()**	BDU-28 Submunition
81mm M43A1/M49A2 Mortar (25)	**60mm Mortar (with fuze) (4)**	60mm Mortar (without fuze)
81mm Mortar (with fuze) (26)	**81mm M43A1/M49A2 Mortar (5)**	60mm Mortar (with fuze)
81mm M821A1/M889A1 (27)	**81mm Mortar (with fuze) (6)**	81mm M43A1/M49A2 Mortar
2" Rocket APFSDS-T M735 (28)	**81mm M821A1/M889A1 (7)**	81mm Mortar (with fuze)
76mm Projectile (no fuse) (29)	**2" Rocket APFSDS-T M735 (8)**	81mm M821A1/M889A1
3" Armor Piercing Projectile MK28 Type A (30)	**76mm Projectile (no fuse) (9)**	2" Rocket APFSDS-T M735
90mm Projectile (no widscreen) (31)	**3" Armor Piercing Projectile MK28 Type A (10)**	76mm Projectile (no fuse)
90mm High Explosive (HE) Projectile M71 (32)	**90mm Projectile (no widscreen) (11)**	3" Armor Piercing Projectile MK28 Type A
APDS Adapter with End Cap and Cartridge (33)	**90mm High Explosive (HE) Projectile M71 (12)**	90mm Projectile (no widscreen)
105mm Projectile (Blue Training Round) (34)	**APDS Adapter with End Cap and Cartridge (13)**	90mm High Explosive (HE) Projectile M71
105mm Projectile (with band and solid tip) (35)	**105mm Projectile (Blue Training Round) (14)**	APDS Adapter with End Cap and Cartridge
155 mm Howitzer Projectile (36)	**105mm Projectile (with band and solid tip) (15)**	105mm Projectile (Blue Training Round)
	155 mm Howitzer Projectile (16)	105mm Projectile (with band and solid tip)
		155 mm Howitzer Projectile