Hyperspectral Imaging Analysis for Remote Sensing of Marine Litter

Sara Freitas

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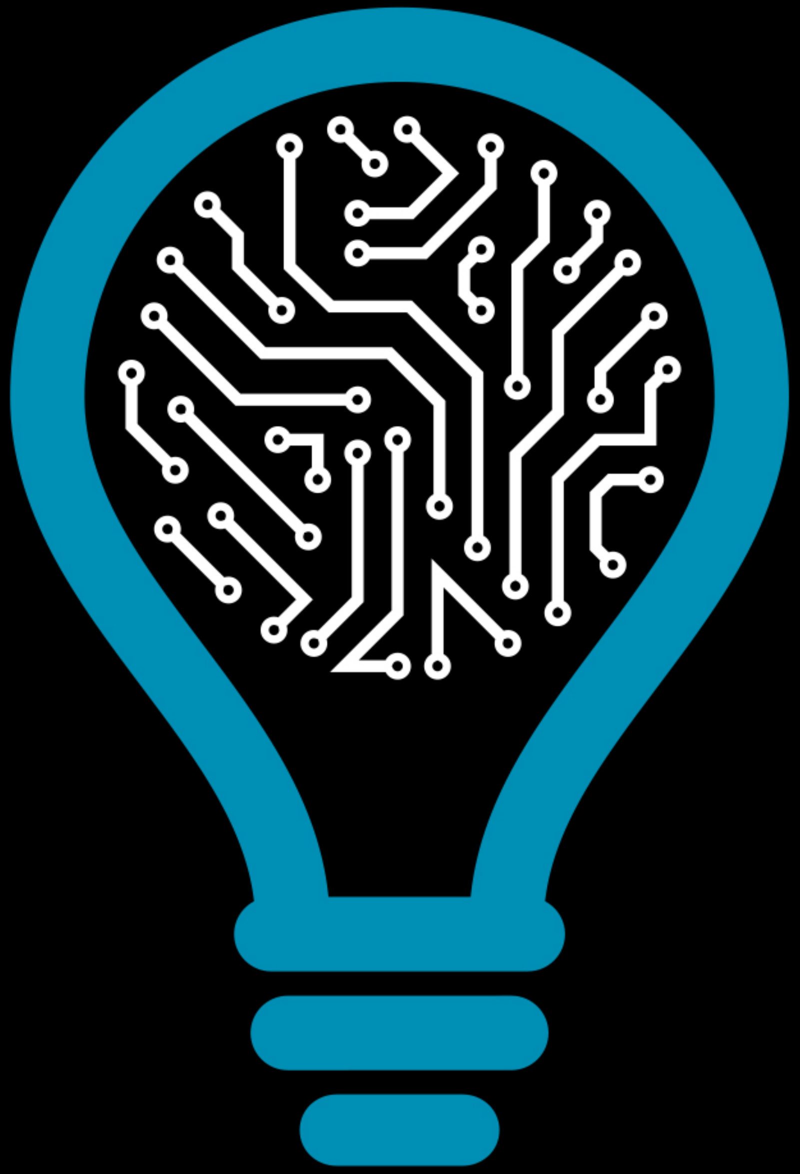
Remote Sensing of Marine Litter Workshop 2023



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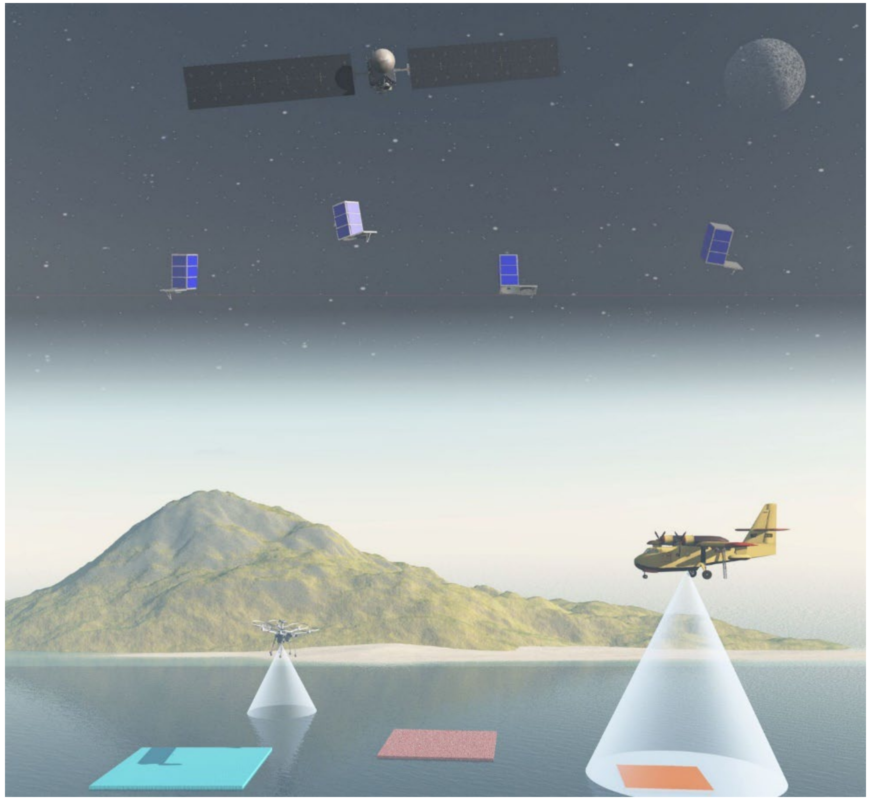
Problem Definition



1. Perform the study and implementation of a novel hyperspectral imaging system;
2. Create a digital hyperspectral imaging database (build a dataset) using manned and unmanned aerial vehicles, in a marine litter hotspot, for marine litter detection;
3. Study, develop and implement supervised and unsupervised methods to perform hyperspectral image classification;
4. Development of a novel semi-supervised technique to perform hyperspectral imaging classification of unknown data;
5. Apply the developed methods in a real demonstration scenario and carefully evaluate the obtained results.

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ESAPlastics Project

ESA is looking and fostering the development of spaceborne solutions and campaigns for detecting and classifying marine litter in the oceans, such as ESAPlastics project:

- Evaluate the state-of-the-art;
- Develop and assemble a remote hyperspectral imaging payload;
- Perform extensive data acquisition using satellite, UAV and manned aircraft in a marine litter hotspot using artificial (marine litter-based) targets;
- Develop and test post-processing marine litter detection and classification algorithms;
- Perform in-situ analysis with different techniques (FTIR, Raman Spectroscopy, X-Ray Fluorescence, LIBS);
- Evaluate compressive sensing techniques for developing a single-pixel hyperspectral camera.

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In-situ Marine Litter Samples Characterisation

- Batch of 34 catalogued marine litter samples;
- Structure developed to perform in-situ tests (morning and afternoon, dry vs samples submerged in seawater);
- Creation of a ground-truth spectral response database.

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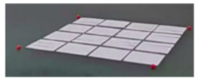
Flight Data Acquisition

- Three artificial targets (10 x 10 m – due to the Sentinel 2 MS resolution)




Orange Plastic Target (Orange)	White Plastic Target (White)	Ropes Target (Ropes)	Water	Concrete pier	Trees	Boats
						

Polyethylene Polypropylene

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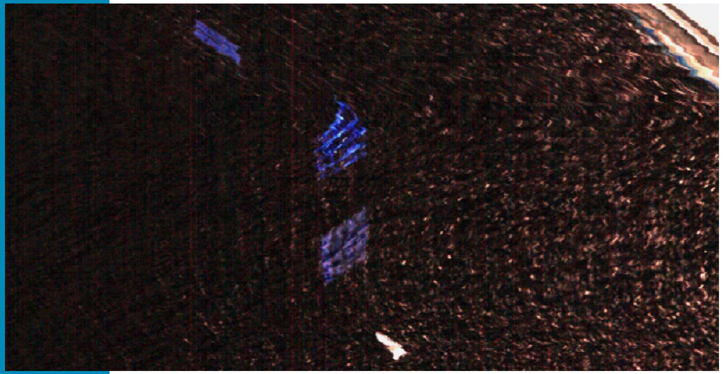
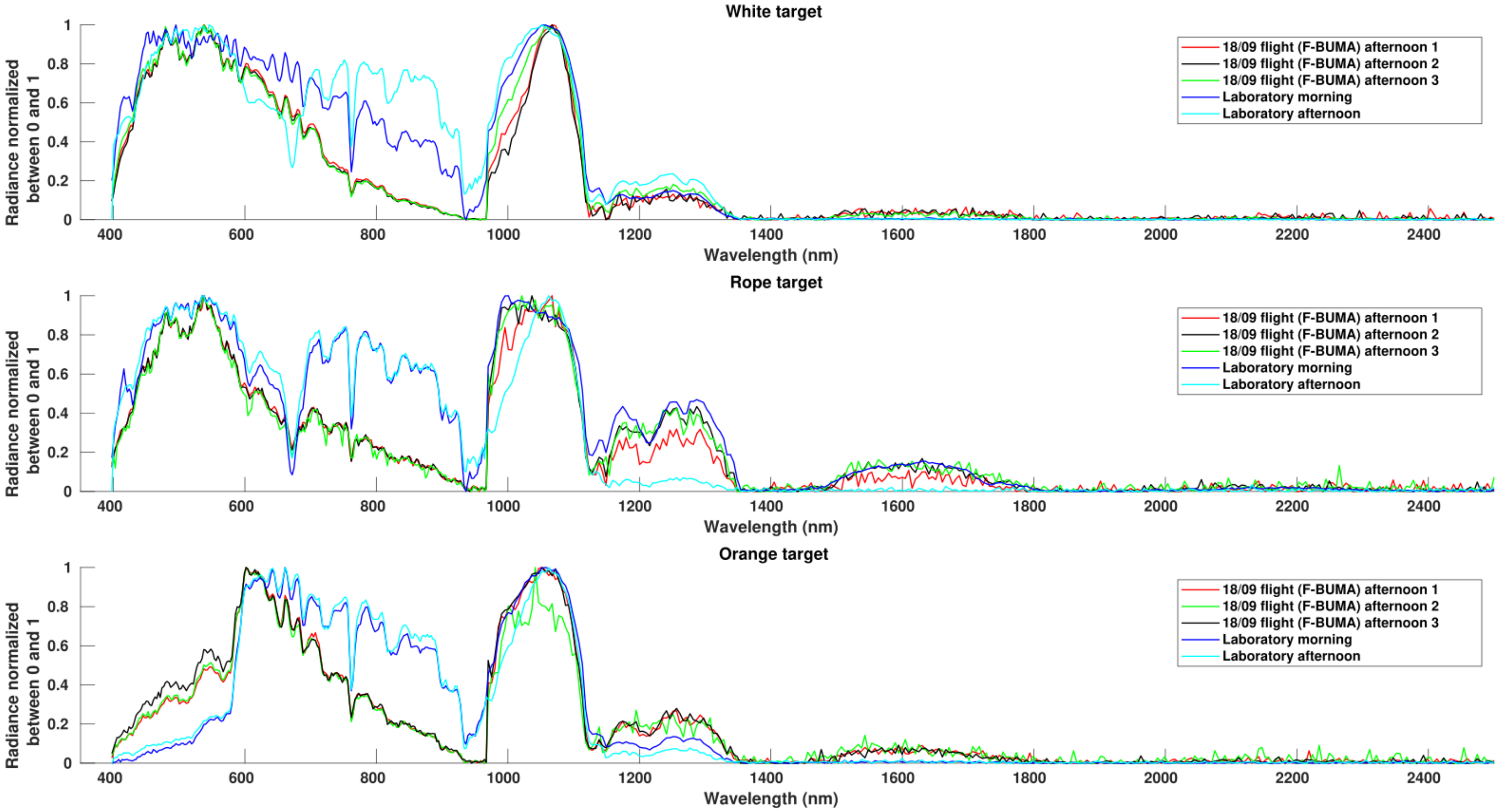
Dataset Campaign Spectral Characterization Results – F-BUMA

- Normalized radiance
- Absorption peaks are the same
- Signal attenuation:
  - Altitude
  - Weather differences between in-situ and airborne tests





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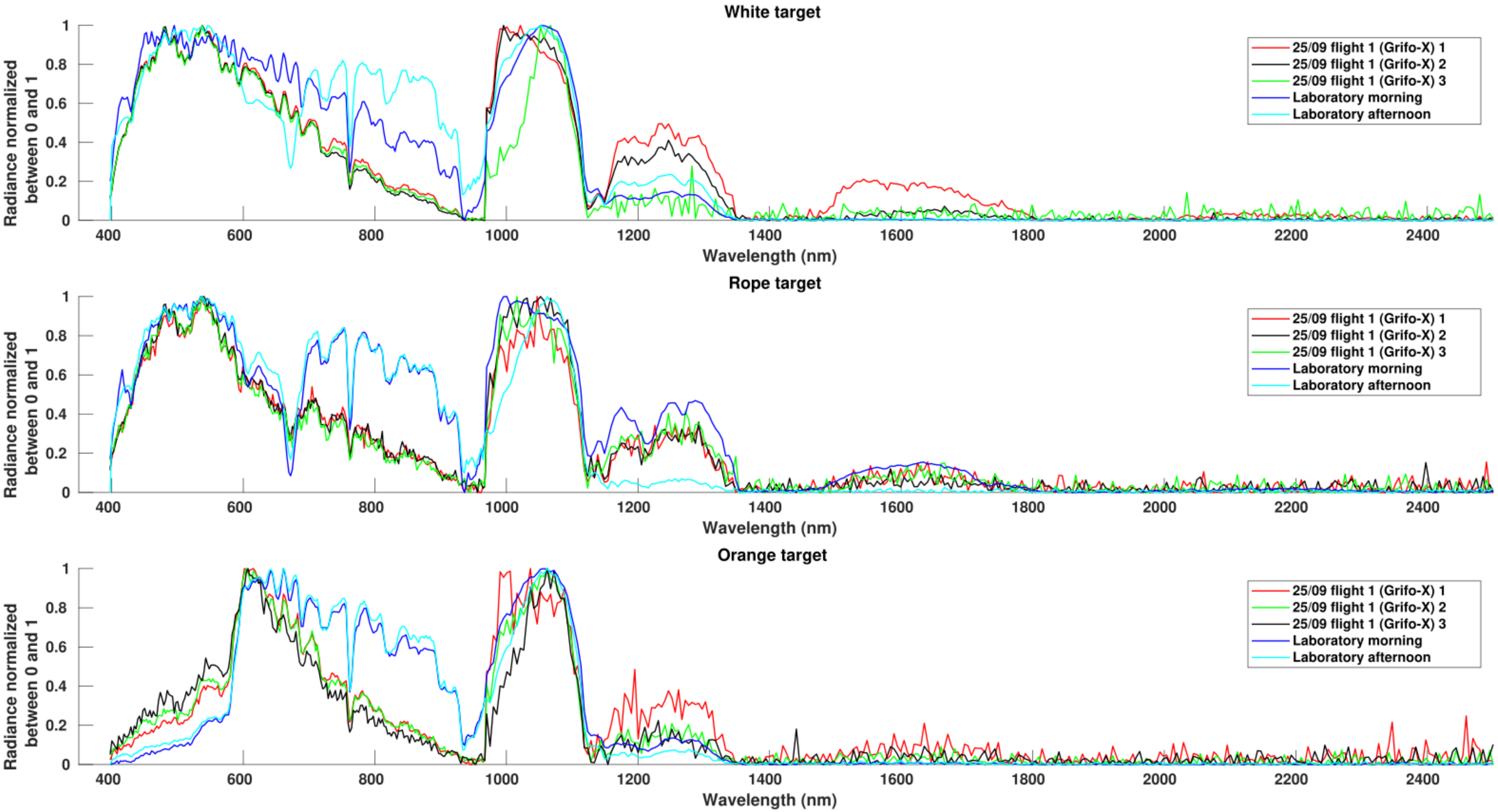
Dataset Campaign Spectral Characterization Results – Grifo-X



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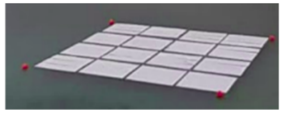
Supervised Approaches for Hyperspectral Imaging Classification

Support Vector Machines (SVM) and Random Forests (RF)

- Class imbalance: we randomly selected some pixels in order to have an identical number of points for each class (Class 0: 170773; Class 1: 4119 (all); Class 2: 4119; Class 3: 7000
- Feature normalisation: unit variance and zero mean
- Grid search method to fine-tuning both RF and SVM
    - SVM: C = 100, kernel RBF, gamma = 0.0001
    - RF: Number of trees = 3500, maximum features = log2, maximum depth = 10, minimum number of samples in a leaf node = 1, minimum samples required to split an internal node = 5

Class 0	Class 1	Class 2	Class 3
Water and Land (Houses, Trees, Streets, Cars, and Others Materials)	Orange Plastic Target	White Plastic Target	Ropes Target
			

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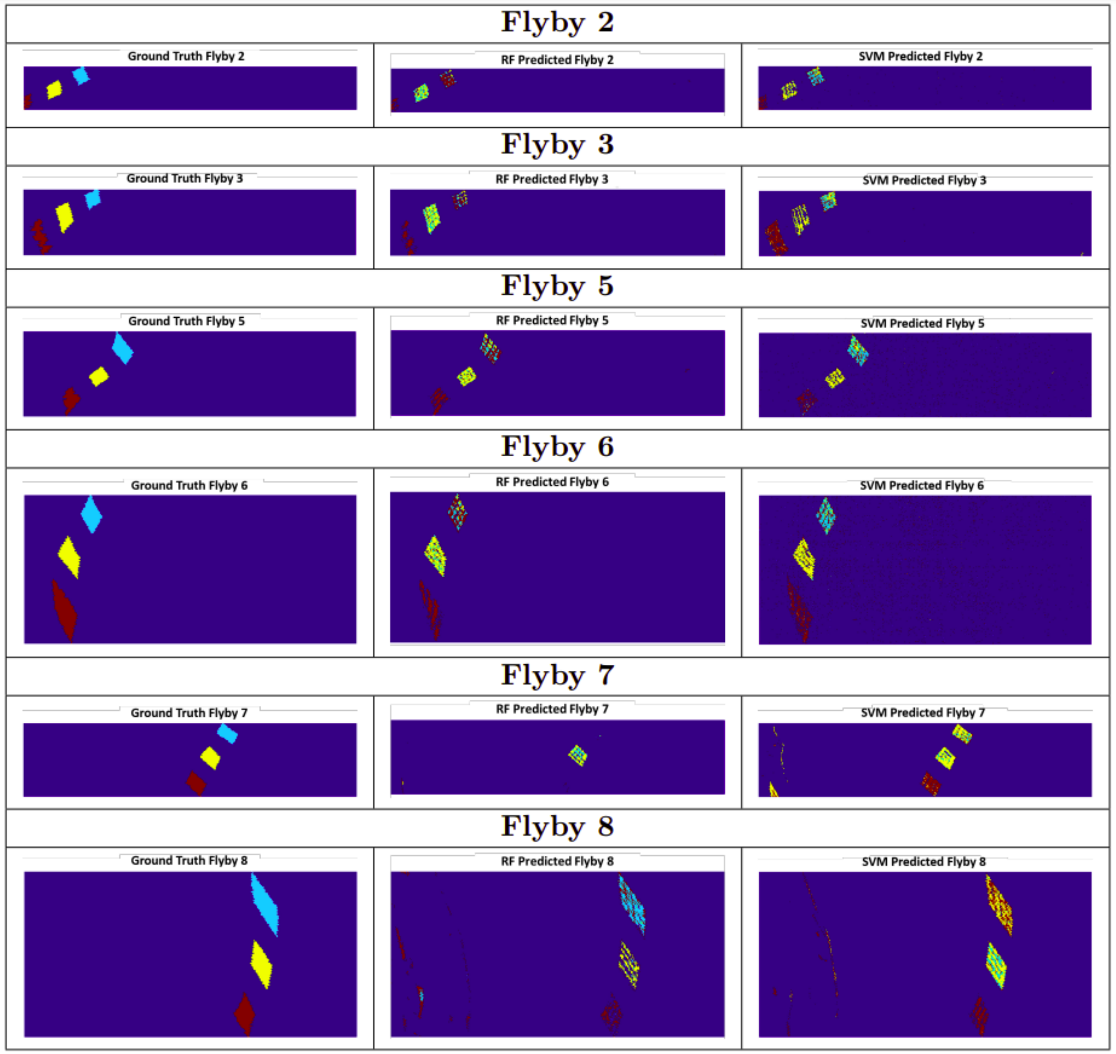
Supervised Approaches for Hyperspectral Imaging Classification

SVM and RF Results



Flyby 2 - F-BUMA

	RF				SVM			
Class	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy
0	0.99	1	0.99	97.35%	0.99	0.99	0.99	97.47%
1	0.24	0.12	0.16		0.75	0.42	0.54	
2	0.85	0.42	0.56		0.66	0.47	0.55	
3	0.18	0.44	0.26		0.22	0.50	0.31	

Flyby 3 - F-BUMA

	RF				SVM			
Class	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy
0	0.99	1	0.99	97.34%	0.99	0.99	0.99	97.27%
1	0.20	0.13	0.16		0.75	0.38	0.51	
2	0.85	0.53	0.65		0.56	0.43	0.49	
3	0.45	0.38	0.41		0.52	0.74	0.61	

Flyby 5 - F-BUMA

	RF				SVM			
Class	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy
0	0.99	1	0.99	98.09%	0.99	0.99	0.99	97.06%
1	0.71	0.25	0.37		0.77	0.46	0.58	
2	0.74	0.62	0.67		0.57	0.59	0.58	
3	0.38	0.56	0.45		0.21	0.47	0.29	

Flyby 6 - F-BUMA

	RF				SVM			
Class	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy
0	0.99	1	0.99	97.92%	0.99	0.98	0.98	96.56%
1	0.52	0.22	0.31		0.71	0.48	0.57	
2	0.85	0.59	0.70		0.78	0.67	0.72	
3	0.50	0.42	0.46		0.27	0.51	0.35	

Flyby 7 - F-BUMA

	RF				SVM			
Class	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy
0	0.98	1	0.99	97.32%	1	0.99	0.99	98.01%
1	0.01	0	0.01		0.50	0.16	0.24	
2	0.95	0.45	0.61		0.44	0.72	0.54	
3	0.17	0.01	0.02		0.64	0.76	0.70	

Flyby 8 - F-BUMA

	RF				SVM			
Class	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy
0	0.99	0.99	0.99	97.44%	0.99	0.99	0.99	97.28%
1	0.85	0.55	0.66		0.10	0.02	0.04	
2	0.94	0.36	0.52		0.46	0.55	0.50	
3	0.21	0.35	0.26		0.30	0.51	0.38	

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Supervised Approaches for Hyperspectral Imaging Classification
SVM and RF Results Discussion

- The 600 m altitude makes it challenging to annotate ground-truth pixels as “pure” manually. It is also important to consideer the submerged pixels;

- SVM: able to detect the targets in all flybys, variable values of precision and recall. RF: don’t detect the three targets in all flybys, precision and recall values more stable;

- Presence of “land” in the targets/presence of the targets in the “land”: class 0 (“land”) represents a “non-marine litter” class, which suggests the appearance of unknown artefacts of class 0 that were wrongly classified as class 2 or class 1;

- SVM and RF show potential to be able to detect marine litter, with 0.70 – 0.80 precision values and few false positives;

Would it be beneficial for the classifier to introduce the spatial information?

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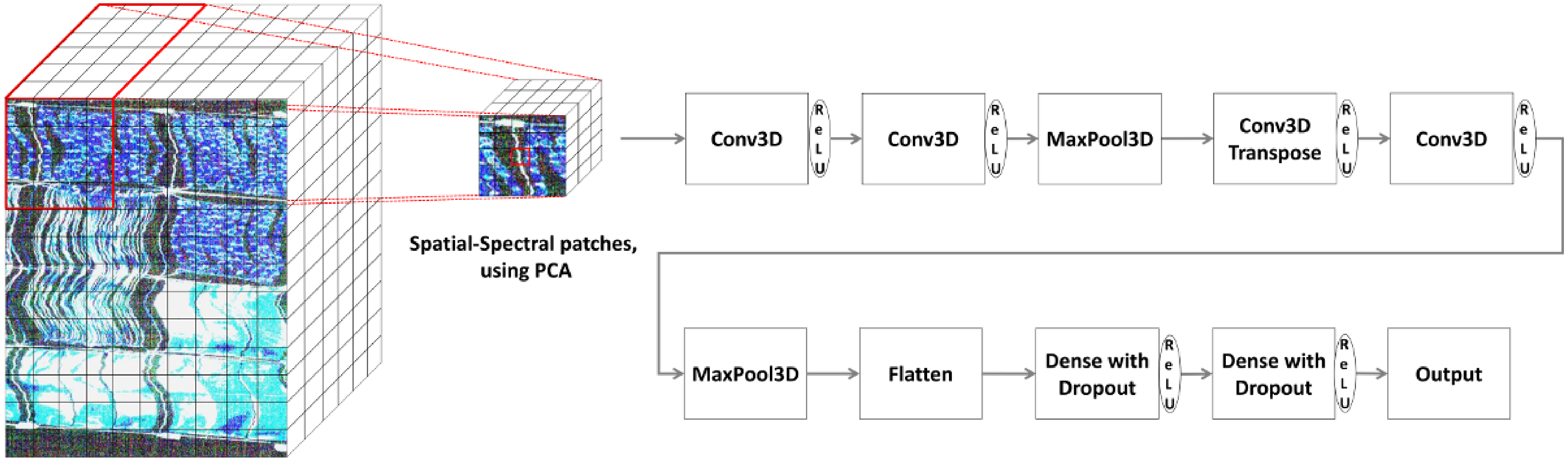
Supervised Approaches for Hyperspectral Imaging Classification

CNN-3D Spectral/Spatial Marine Litter Detection and Classification

- Input patch: 11 x 11 pixels
- Learning rate: 1^{-6}, decay: 1^{-6}, batch size: 64, epochs: 200
- The first four flybys are used for training, while the last two are used for classification



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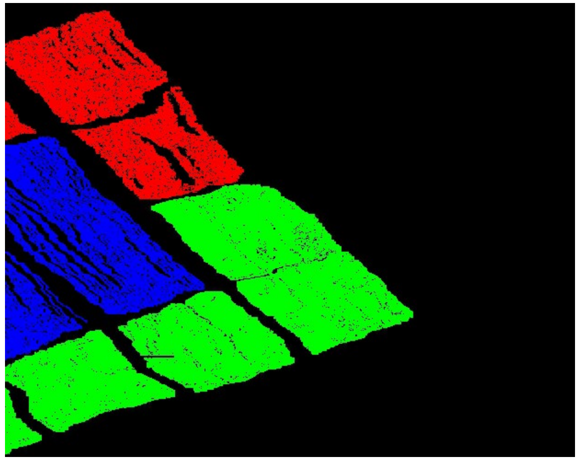
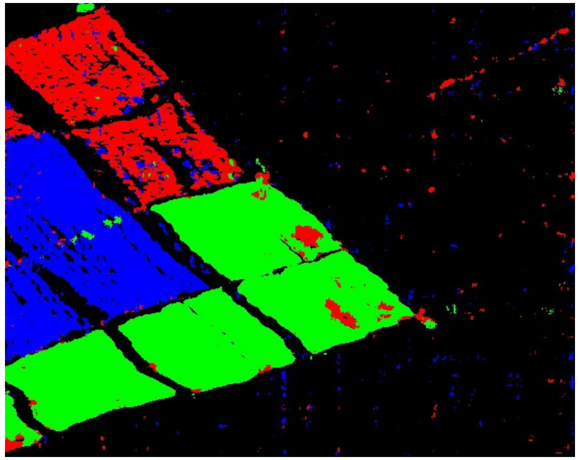
Supervised Approaches for Hyperspectral Imaging Classification

CNN-3D Results

Flyby 4



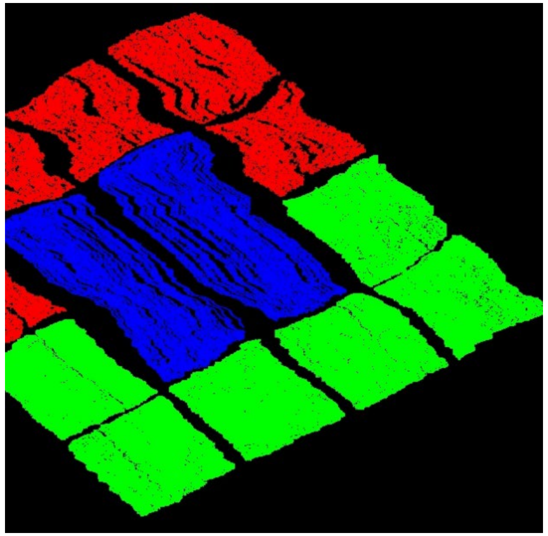
Ground-truth

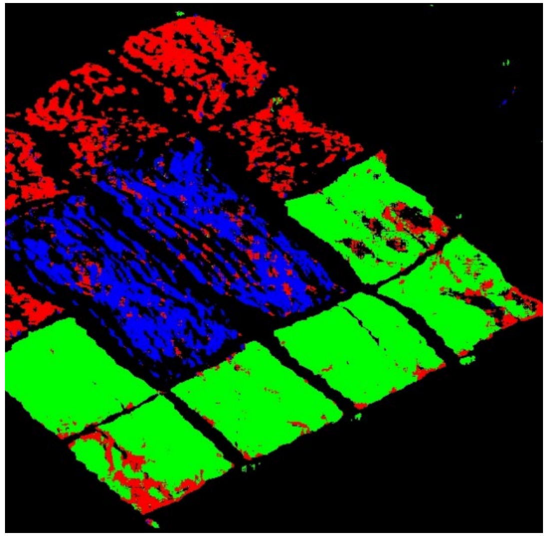


Predictions

	Precision	Recall	F1-Score	Number of pixels
Class 0	0.98	0.93	0.95	214882
Class 1	0.75	0.78	0.77	21852
Class 2	0.94	0.95	0.94	48505
Class 3	0.69	0.96	0.80	20421
OA	91.67%			

Flyby 5





	Precision	Recall	F1-Score	Number of pixels
Class 0	0.83	0.97	0.90	212794
Class 1	0.62	0.50	0.55	37957
Class 2	0.98	0.84	0.91	85579
Class 3	0.88	0.54	0.67	41870
OA	84.84%			

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Supervised Approaches for Hyperspectral Imaging Classification
CNN-3D Results Discussion

- Errors in the ground-truth annotation due to the manual procedure;
- Target water coverage: given the material's physical properties, there is the possibility that the targets are partially submerged, especially in the case of the orange target;
- The rope target also absorbs water, making it difficult to distinguish between rope and water classes;
- This will create mixed pixels that could produce error in some class pixel classifications;
- Overall, CNN-3D showed potential to detect and classify differents types of marine litter, with overall accuracies of 91.67% and 84.84%.

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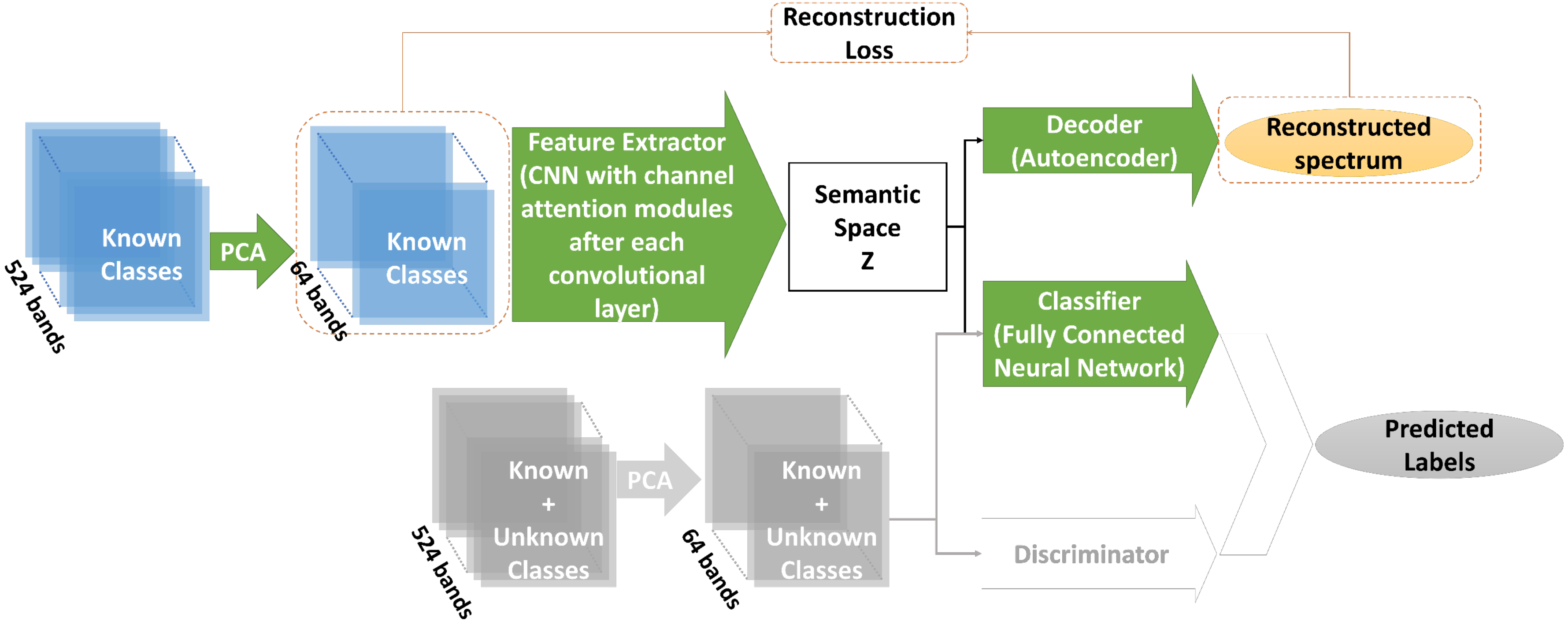
Zero-Shot Learning for Marine Litter Detection and Classification

- Marine litter is always changing (sun and water erosion)
- Appearance of new types of marine litter – more data needed to train the model…



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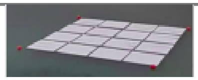
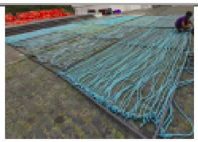
Zero-Shot Learning for Marine Litter Detection and Classification

- Class imbalance
- Feature normalisation
- Low resolution due to flight altitude
- Class 1 can accumulate more water
- Class 3 has gaps in the middle of the target, and it is composed by two different rope targets with variable floatability
- The water contains points with high exposure
- Concrete pier: also contains rocks
- Class 6: boats have different hulls, artefacts inside and different materials
- Camera exposure time

ID	Description	Example	Number of Pixels
Class 0 (**Blue**) Known class	Water		1279132
Class 1 (**Red**) Unknown class	Orange target (low density polyethylene)		8118
Class 2 (**Green**) Known class	White target (White plastic film)		7913
Class 3 (**Magenta**) Unknown class	Rope target		8375
Class 4 (**White**) Known class	Concrete pier		16999
Class 5 (Grey) Known class	Trees		972160
Class 6 (Yellow) Known class	Boats		5023

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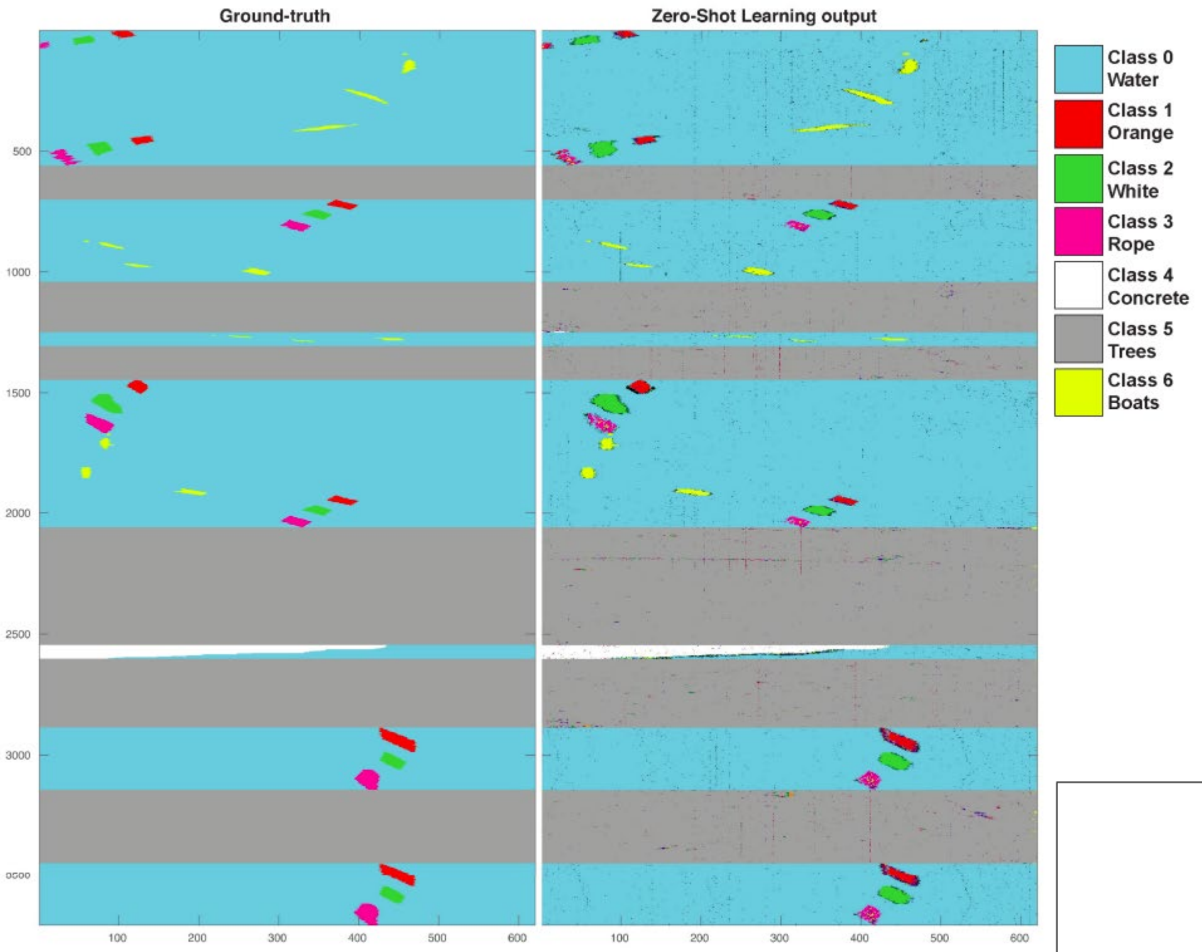
Zero-Shot Learning for Marine Litter Detection and Classification



- Unknown class 1 and 3: recall values over 57% - (true positive pixels were higher than this) (class 1 – more than 66%, while class 3 – more than 56%);
- Class 6 (boats): precision over 58%, recall over 99% - denotes a high number of true positives, but with some false positives (present in the water) – low resolution makes it impossible to understand what is inside the boats, leading to ground-truth errors;

	Class 0 Water Known Class	**Class 1 Orange Target** Unknown class	**Class 2 White Target** Known Class	**Class 3 Rope Target** Unknown Class	**Class 4 Concrete Pier** Known class	**Class 5 Trees** Known Class	**Class 6 Boats** Known Class
Precision	0.9853	0.6659	0.7508	0.5632	0.9784	0.9927	0.5874
Recall	0.9872	0.6946	0.9960	0.5766	0.9885	0.9927	0.9962
F1-Score	0.9862	0.6800	0.8562	0.5698	0.9834	0.9927	0.7390
OA	98.71%						

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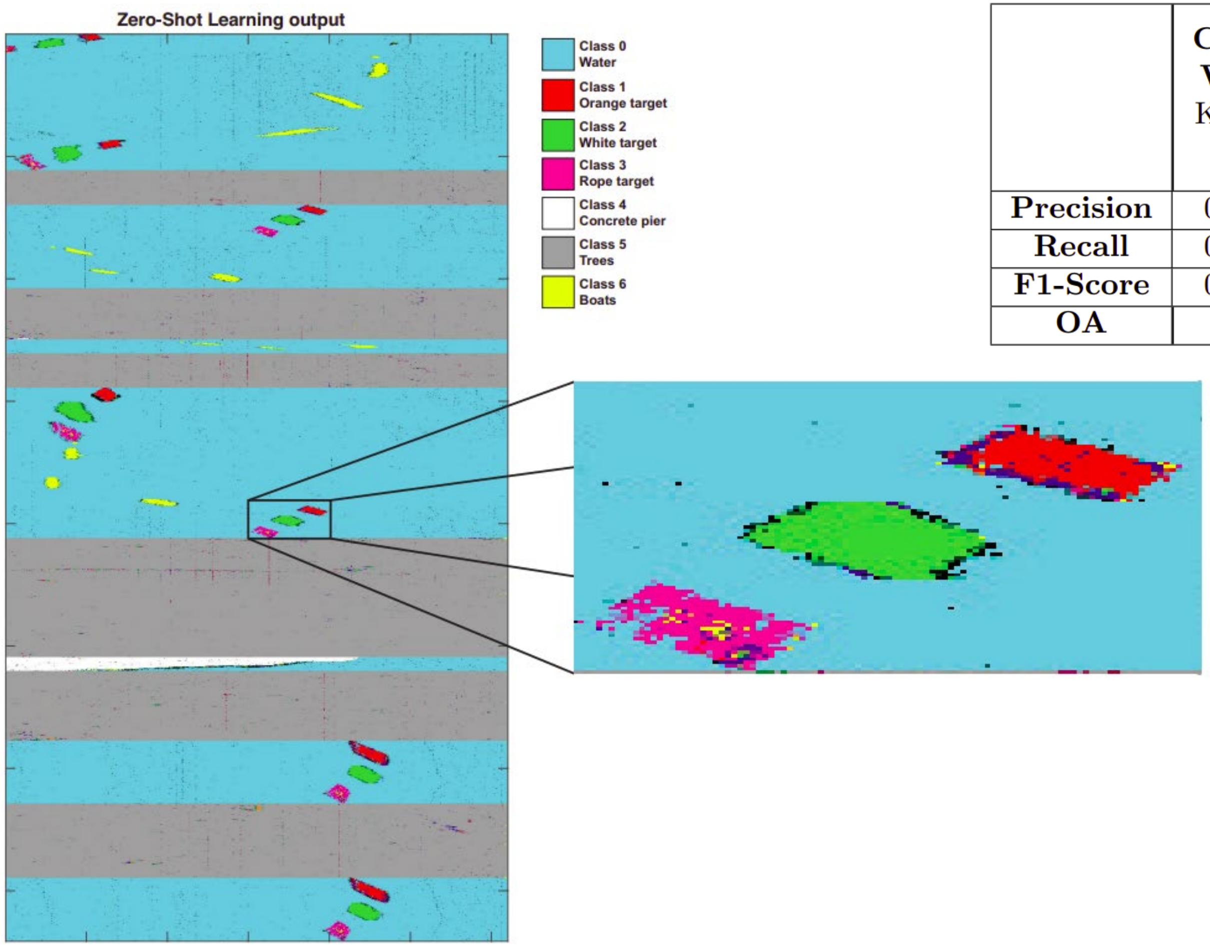
Zero-Shot Learning for Marine Litter Detection and Classification



	Class 0 Water Known Class	Class 1 Orange Target Unknown class	Class 2 White Target Known Class	Class 3 Rope Target Unknown Class	Class 4 Concrete Pier Known class	Class 5 Trees Known Class	Class 6 Boats Known Class
Precision	0.9853	0.6659	0.7508	0.5632	0.9784	0.9927	0.5874
Recall	0.9872	0.6946	0.9960	0.5766	0.9885	0.9927	0.9962
F1-Score	0.9862	0.6800	0.8562	0.5698	0.9834	0.9927	0.7390
OA	98.71%						

- Class 3 (rope target) exhibits some points marked as class 6 (boats) – some boats have ropes inside?
- Camera gain set configured to acquire the artificial target (sun reflections can result in overexposure pixels – waves);
- Ground-truth errors.

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Comparison Between SVM, RF, CNN-3D and ZSL Approaches

- SVM, RF, CNN-3D: four classes;
- SVM, RF and ZSL: F-BUMA dataset;
- CNN-3D: Drone dataset.

F-Buma flight - Flyby over the artificial targets								
Flyby 5								
	Random Forest (RF)				Support Vector Machine (SVM)			
Class	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy
0 Water and Land	0.99	1	0.99	98.09 %	0.99	0.99	0.99	97.06 %
1 Orange target	0.71	0.25	0.37		0.77	0.46	0.58	
2 White target	0.74	0.62	0.67		0.57	0.59	0.58	
3 Rope target	0.38	0.56	0.45		0.21	0.47	0.29	

F-BUMA Flight - ZSL								
Class	0 Water Known class	1 Orange target Unknown class	2 White target Known class	3 Rope target Unknown class	4 Concrete pier Known class	5 Boats Known class	6 Boats Known class	Accuracy
Precision	0.9853	0.6659	0.7508	0.5632	0.9784	0.9927	0.5874	98.71 %
Recall	0.9872	0.6946	0.9960	0.5766	0.9885	0.9927	0.9962	
F1-Score	0.9862	0.6800	0.8562	0.5698	0.9834	0.9927	0.7390	

Drone Flight - CNN3D				
Flyby 4				
Class	Precision	Recall	F1-Score	Accuracy
0 Water	0.98	0.93	0.95	91.67 %
1 Orange target	0.75	0.78	0.77	
2 White target	0.94	0.95	0.94	
3 Rope target	0.69	0.96	0.80	
Flyby 5				
Class	Precision	Recall	F1-Score	Accuracy
0 Water	0.83	0.97	0.90	84.84 %
1 Orange target	0.62	0.50	0.55	
2 White target	0.98	0.84	0.91	
3 Rope target	0.88	0.54	0.67	

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Comparison Between SVM, RF, CNN-3D and ZSL Approaches

Class 1 (orange target):

- Similar precision results, even for the ZSL approach where this class was not given to the algorithm during the training stage;
- SVM and RF recall values are lower than ZSL, when comparing ZSL recall values with CNN-3D are similar;

F-Buma flight - Flyby over the artificial targets								
Flyby 5								
	Random Forest (RF)				Support Vector Machine (SVM)			
Class	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy
1 Orange target	0.71	0.25	0.37		0.77	0.46	0.58	

F-BUMA Flight - ZSL		
Class		1 Orange target Unknown class
Precision		0.6659
Recall		0.6946
F1-Score		0.6800

Drone Flight - CNN3D				
Flyby 4				
Class	Precision	Recall	F1-Score	Accuracy
1 Orange target	0.75	0.78	0.77	
Flyby 5				
Class	Precision	Recall	F1-Score	Accuracy
1 Orange target	0.62	0.50	0.55	

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Comparison Between SVM, RF, CNN-3D and ZSL Approaches

Class 2 (white target):

- ZSL known class;
- Similar results for all four approaches;
- SVM presents the worst results, while CNN-3D the better ones;

F-Buma flight - Flyby over the artificial targets

Flyby 5

Class	Random Forest (RF) Precision	RF Recall	RF F1-Score	RF Accuracy	Support Vector Machine (SVM) Precision	SVM Recall	SVM F1-Score	SVM Accuracy
2 White target	0.74	0.62	0.67		0.57	0.59	0.58	

F-BUMA Flight - ZSL

Class	2 White target Known class
Precision	0.7508
Recall	0.9960
F1-Score	0.8562

Drone Flight - CNN3D

Flyby 4

Class	Precision	Recall	F1-Score	Accuracy
2 White target	0.94	0.95	0.94	

Flyby 5

Class	Precision	Recall	F1-Score	Accuracy
2 White target	0.98	0.84	0.91	

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Comparison Between SVM, RF, CNN-3D and ZSL Approaches

Class 3 (rope target):

- Most challenging for all the methods due to their characteristics (water absorption, gaps in the middle of the target);

- CNN-3D performs slightly better;

- ZSL overcomes both SVM and RF approaches – even considering that this was one of the classes hidden during the training stage of the ZSL model!

F-Buma flight - Flyby over the artificial targets

Flyby 5

	Random Forest (RF)				Support Vector Machine (SVM)			
Class	Precision	Recall	F1-Score	Accuracy	Precision	Recall	F1-Score	Accuracy
3 Rope target	0.38	0.56	0.45		0.21	0.47	0.29	

F-BUMA Flight - ZSL

Class	3 Rope target Unknown class
Precision	0.5632
Recall	0.5766
F1-Score	0.5698

Drone Flight - CNN3D

Class	Precision	Recall	F1-Score	Accuracy
Flyby 4				
3 Rope target	0.69	0.96	0.80	
Flyby 5				
3 Rope target	0.88	0.54	0.67	

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Conclusions

1. **Dataset and Acquisition Setup**

Development of a novel hyperspectral imaging system from 400 to 2500 nm;

2. **Dataset acquisition using two aircrafts (UAV and F-BUMA), using three artificial targets placed in the water and filled with marine litter found in the hotspot.**

3. **Spectral/Spatial Classification Algorithms (Random Forest, Support Vector Machine and CNN-3D)**

Establishment of a baseline for comparation (RF and SVM);

The three algorithms show that are able to detect and classify marine litter;

The presence of submerged target pixels and ground-truth labelling errors decreases the accuracy of the methods.

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Conclusions

4. **Zero-Shot Learning for Hyperspectral Imaging Marine Litter Detection and Classification**

Semi-supervised algorithm able to detect and classify marine litter samples, even from classes that were not used during the training stage of the model;

To the best of our knowledge, this is the first implementation of a ZSL approach for hyperspectral imaging and marine litter classification;

The classification precision for both known and unknown classes shown results higher than 56%.

5. **Test and evaluation the developed algorithms in the dataset collected in a real scenario.**

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Thank you for your attention!

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