Computer Graphics

Marine Image Segmentation

Making sence of the sea, one pixel at a time

Presented by Mohammad Razavi & Niloofar Rohibakhsh

وزارت علوم، تحقیقات و فناوری
موسسه آموزش عالی
زند شیراز
(غیر انتفاعی - غیر دولتی)

Why Do We Need Image Segmentation ?

Introduction

- The ocean covers over 70% of our planet, and understanding it is vital for navigation, safety, and environmental monitoring.
- Marine images are often complex, with waves, ships, and marine life all mixed together.

- Image segmentation helps us separate and analyze these elements.
- This presentation explores how segmentation works in marine images and why it matters.

WHY DO WE NEED IMAGE SEGMENTATION ?

- Raw images are full of visual information, but computers can't understand them like humans do.
- To analyze scenes, we need to separate different objects and regions.

- In marine images, it's crucial to detect ships, waves, oil spills, and sea life.
- Segmentation is the first step to turn images into meaningful data.

WHAT IS MARINE IMAGE SEGMENTATION ?

- Image segmentation is a computer vision technique that divides an image into distinct regions.
- Each region groups pixels with similar features such as color, texture, or intensity.
- The goal is to simplify and/or change the representation of an image into something more meaningful.
- It is often used as a preprocessing step in object detection, recognition, and tracking.

IMAGE SEGMENTATION IN MARINE ENVIRONMENTS

- Marine image segmentation focuses on analyzing visual data from oceans and seas.
- It helps identify key features like ships, waves, marine life, and pollution.
- These images are often challenging due to water reflections, motion blur, low contrast, and occlusion.
- Specialized algorithms and deep learning models are used to handle these unique conditions.

Types of Image Segmentation

There are several types of image segmentation methods, including:

1) Semantic Segmentation:
Classifies each pixel into a category (e.g., water, ship, sky).

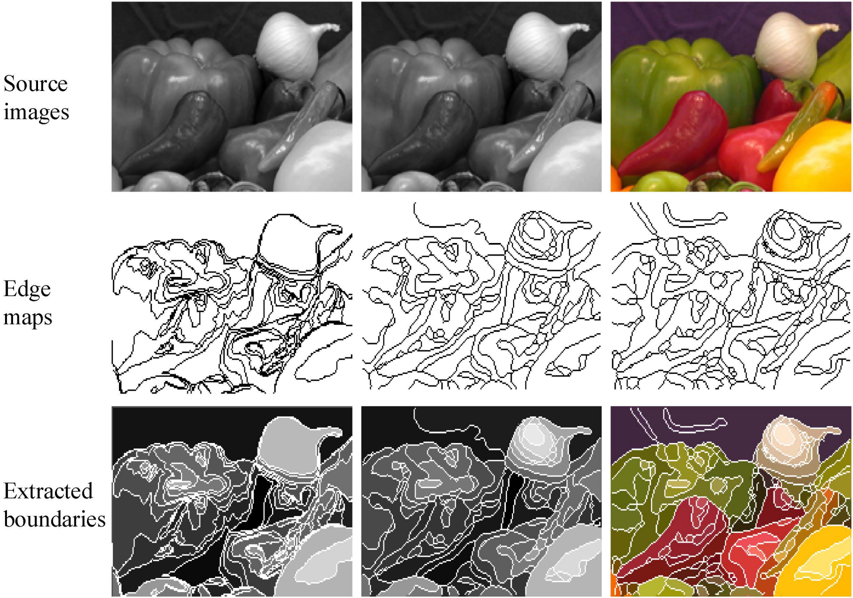
2) Instance Segmentation:
Detects and separates individual objects of the same class.

3) Panoptic Segmentation:
Combines semantic and instance segmentation.

4) Threshold-based Segmentation:
Divides image based on pixel intensity.

5) Edge-based Segmentation:
Uses edges and gradients to find object boundaries.

6) Region-based Segmentation:
Groups pixels into regions with similar characteristics.



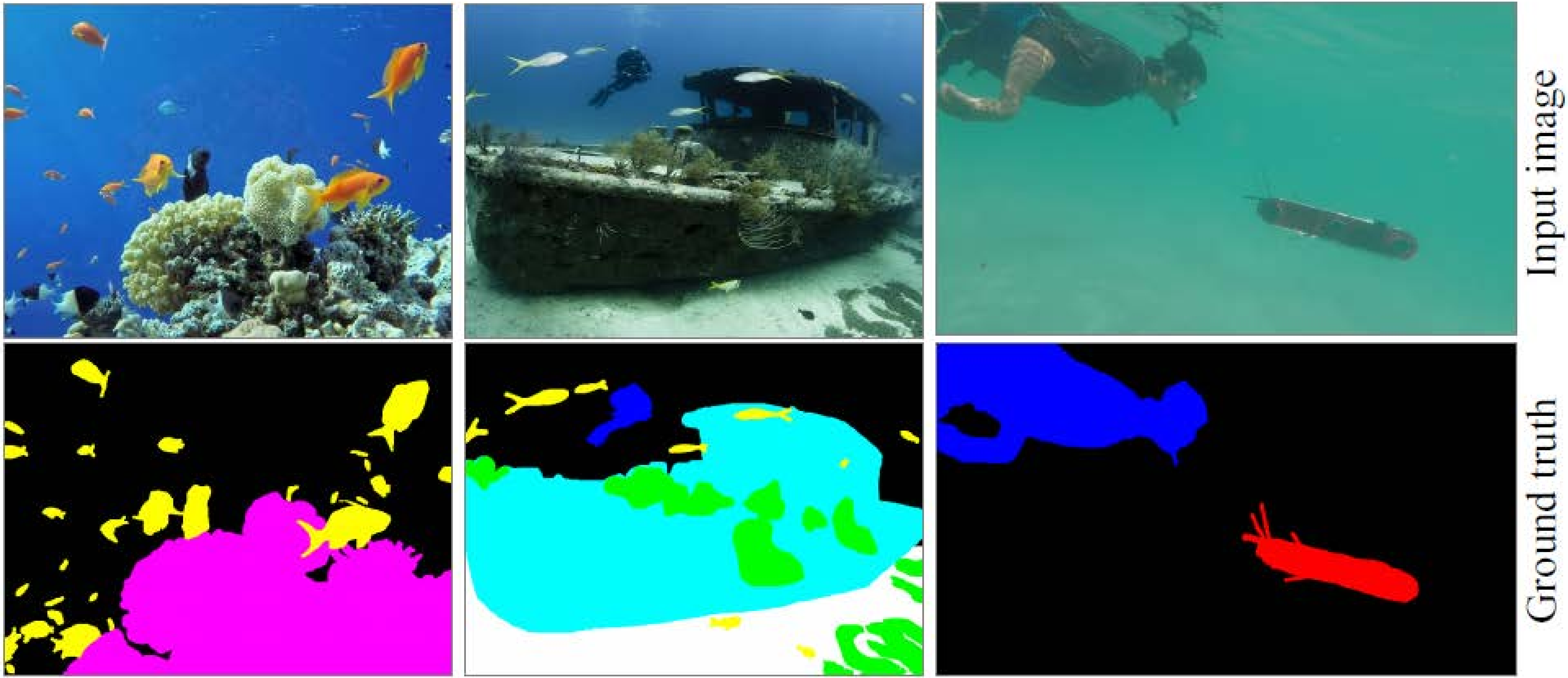
(a) PMVIF with Gray (b) PMLCD with Gray (c) PMLCD with Color

(**a**) Image

(**b**) Semantic segmentation

(**c**) Instance segmentation

(**d**) Panoptic segmentation


Input image
Ground truth

Applications in Marine Image Segmentation

1) **Ship detection and tracking:**
Enhances maritime surveillance and traffic control.

2) **Oil spill detection:**
Helps in early identification and environmental response.

3) **Marine life monitoring:**
Assists in detecting and classifying fish, whales, or coral reefs.

4) **Search and rescue operations:**
Locates boats, people, or debris in emergency situations.

5) **Seabed mapping and exploration:**
Supports underwater archaeology and resource exploration.

Challenges in Marine Image Segmentation

1) **Low contrast:** Underwater and sea surface images often have poor lighting and color balance.

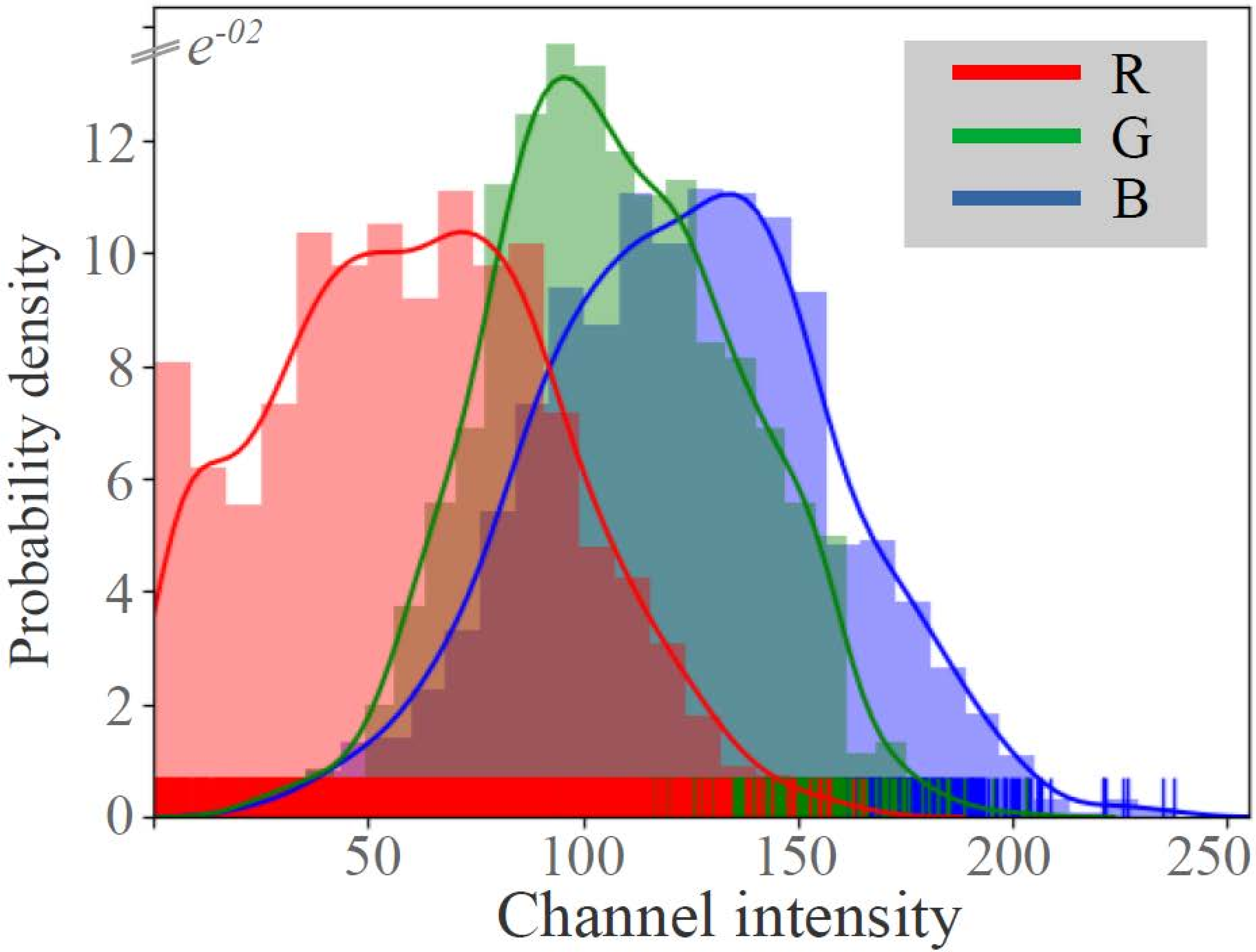
2) **Water reflection and noise:** Sunlight reflections and moving waves distort image quality.

3) **Occlusion:** Objects like fish or boats may overlap or hide each other.

4) **Motion blur:** Caused by camera movement or fast-moving marine objects.

5) **Data scarcity:** Lack of labeled datasets for training accurate models.

6) **Environmental variability:** Conditions like turbidity, weather, and depth affect image clarity.



(c) Distributions of averaged pixel intensity values.

Techniques for Marine Image Segmentation

1) Deep learning approaches:

- CNNs (Convolutional Neural Networks) for feature extraction.
- U-Net and Mask R-CNN for pixel-wise segmentation.

2) Preprocessing techniques:

- Color correction and de-noising to improve clarity.
- Histogram equalization to enhance contrast.

3) Data augmentation:

- Rotation, flipping, and noise injection to increase training data diversity.

4) Transfer learning:

- Using pre-trained models to overcome limited data availability.

5) Use of specialized datasets:

- Datasets like SeaDronesSee and Fish4Knowledge offer marine-specific images.

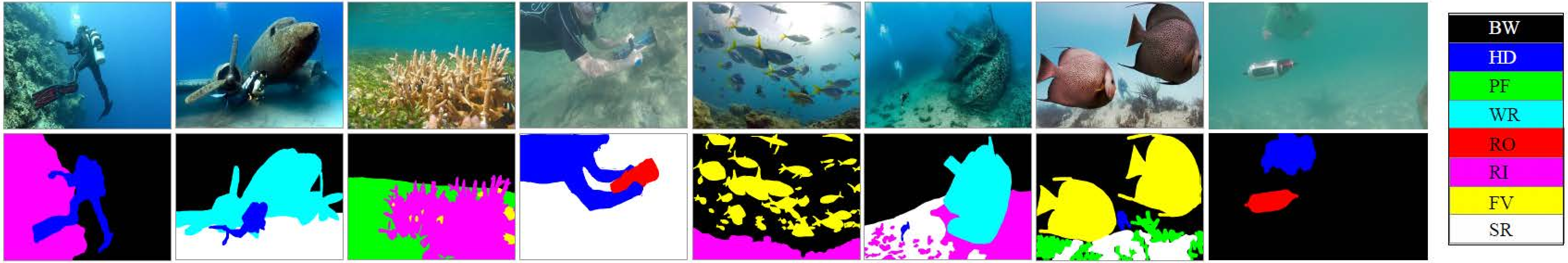
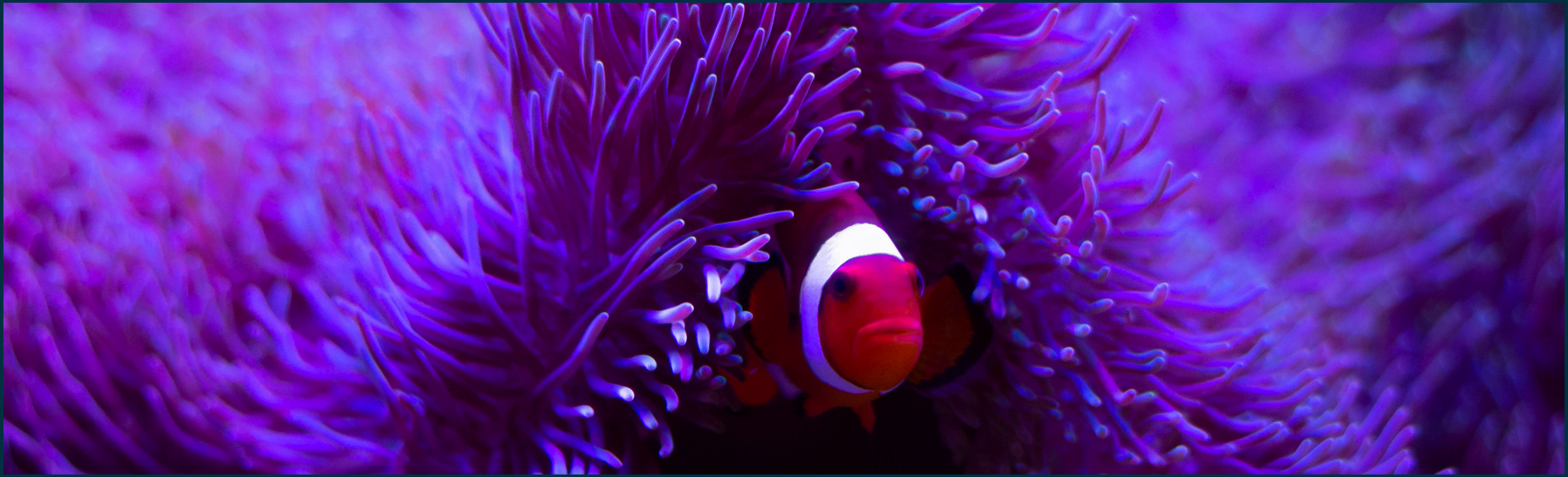


Fig. 3: A few sample images and corresponding pixel-annotations are shown on the top, and bottom row, respectively.

TABLE I: The object categories and corresponding color codes for pixel annotations in the SUIM dataset.

Object category	RGB color	Code
Background (waterbody)	000	BW
Human divers	001	HD
Aquatic plants and sea-grass	010	PF
Wrecks or ruins	011	WR
Robots (AUVs/ROVs/instruments)	100	RO
Reefs and invertebrates	101	RI
Fish and vertebrates	110	FV
Sea-floor and rocks	111	SR

End



Conclusion

Marine image segmentation is a powerful tool for understanding and protecting ocean environments. Despite the challenges posed by water conditions and limited data, advances in deep learning and image processing are making segmentation more accurate and reliable. With continued research, this field has the potential to significantly contribute to marine science, safety, and sustainability.

	Model	HD	WR	RO	RI	FV	**Combined**	Saliency Pred.
$\mathcal{F}$ (↑)	FCN8$_{CNN}$	76.34 ± 2.24	70.24 ± 2.26	39.83 ± 3.87	61.65 ± 2.36	76.24 ± 1.87	64.86 ± 2.52	75.62 ± 1.79
	FCN8$_{VGG}$	89.10 ± 1.50	82.03 ± 1.94	74.01 ± 3.23	79.19 ± 2.27	90.46 ± 1.18	82.96 ± 2.02	89.63 ± 1.24
	SegNet$_{CNN}$	59.60 ± 2.02	41.60 ± 1.65	31.77 ± 3.03	41.88 ± 2.66	60.08 ± 1.91	46.97 ± 2.25	56.96 ± 1.58
	SegNet$_{ResNet}$	80.52 ± 3.26	77.65 ± 3.15	62.45 ± 3.90	82.30 ± 1.96	91.47 ± 1.01	76.88 ± 2.66	86.88 ± 1.83
	UNet$_{GRAY}$	85.47 ± 2.21	79.77 ± 2.01	60.95 ± 3.31	69.95 ± 2.57	84.47 ± 1.39	75.12 ± 2.30	83.96 ± 1.40
	UNet$_{RGB}$	89.60 ± 1.84	86.17 ± 1.73	68.87 ± 3.30	79.24 ± 2.70	91.35 ± 1.14	83.05 ± 2.14	89.99 ± 1.29
	PSPNet$_{MobileNet}$	80.21 ± 1.19	70.94 ± 1.61	72.04 ± 2.21	72.65 ± 1.62	79.19 ± 1.74	76.01 ± 1.67	78.42 ± 1.59
	DeepLab$_{V3}$	89.68 ± 2.09	77.73 ± 2.18	72.72 ± 3.35	78.28 ± 2.70	87.95 ± 1.59	81.27 ± 2.30	85.94 ± 1.72
	SUIM-Net$_{RSB}$	89.04 ± 1.31	65.37 ± 2.22	74.18 ± 2.11	71.92 ± 1.80	84.36 ± 1.37	78.86 ± 1.79	81.36 ± 1.72
	SUIM-Net$_{VGG}$	93.56 ± 0.98	86.02 ± 1.03	78.06 ± 1.50	83.49 ± 1.39	93.73 ± 0.87	86.97 ± 1.15	91.91 ± 0.85
$mIOU$ (↑)	FCN8$_{CNN}$	67.27 ± 2.50	81.64 ± 2.16	36.44 ± 3.67	78.72 ± 2.50	70.25 ± 2.28	66.86 ± 2.62	75.63 ± 1.89
	FCN8$_{VGG}$	79.86 ± 1.50	85.77 ± 2.09	65.05 ± 3.00	85.23 ± 2.07	81.18 ± 1.46	79.42 ± 2.02	85.22 ± 1.24
	SegNet$_{CNN}$	62.76 ± 2.35	66.75 ± 2.57	36.63 ± 3.12	63.46 ± 3.18	62.48 ± 2.32	58.42 ± 2.71	65.90 ± 2.12
	SegNet$_{ResNet}$	74.00 ± 2.88	82.68 ± 2.94	58.63 ± 3.61	89.61 ± 1.15	82.96 ± 1.38	77.58 ± 2.39	83.09 ± 1.96
	UNet$_{GRAY}$	78.33 ± 2.34	85.14 ± 2.14	57.25 ± 3.00	79.96 ± 2.55	78.00 ± 1.90	75.74 ± 2.38	82.77 ± 1.59
	UNet$_{RGB}$	81.17 ± 2.02	87.54 ± 2.00	62.07 ± 3.12	83.69 ± 2.58	83.83 ± 1.47	79.66 ± 2.24	85.85 ± 1.54
	PSPNet$_{MobileNet}$	75.76 ± 1.47	86.82 ± 1.26	72.66 ± 1.47	85.16 ± 1.65	74.67 ± 1.90	77.41 ± 1.56	80.87 ± 1.56
	DeepLab$_{V3}$	80.78 ± 2.07	85.17 ± 2.08	66.03 ± 3.16	83.96 ± 2.52	79.62 ± 1.85	79.10 ± 2.34	83.55 ± 1.65
	SUIM-Net$_{RSB}$	81.12 ± 1.76	80.68 ± 1.74	65.79 ± 2.10	84.90 ± 1.77	76.81 ± 1.82	77.77 ± 1.64	80.86 ± 1.64
	SUIM-Net$_{VGG}$	85.09 ± 1.45	89.90 ± 1.29	72.49 ± 1.61	89.51 ± 1.25	83.78 ± 1.55	84.14 ± 1.43	87.67 ± 1.24

Thank You

For Your Attention