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Visiting Research Scientist at University of Girona

Incoming PhD Student in Underwater Robotics
Heriot Watt University
The National Robotarium
University of Girona

Supervisors:
Prof. Yvan R. Petillot, Dr. Ignacio Carlucho, Prof.Pere Ridao Rodriguez

INVESTIGATION OF THE CHALLENGES OF UNDERWATER-VISUAL-MONOCULAR-SLAM

Best Paper Award at ISPRS GSW 2023

Michele Grimaldi[2,3], David Nakath[1,2], Mengkun She[1,2], Kevin Köser[1,2]

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(2) GEOMAR

(3) Universitat de Girona

Motivation

Pilot structure in Viana do Castelo, Portugal (ATLANTIS H2020)

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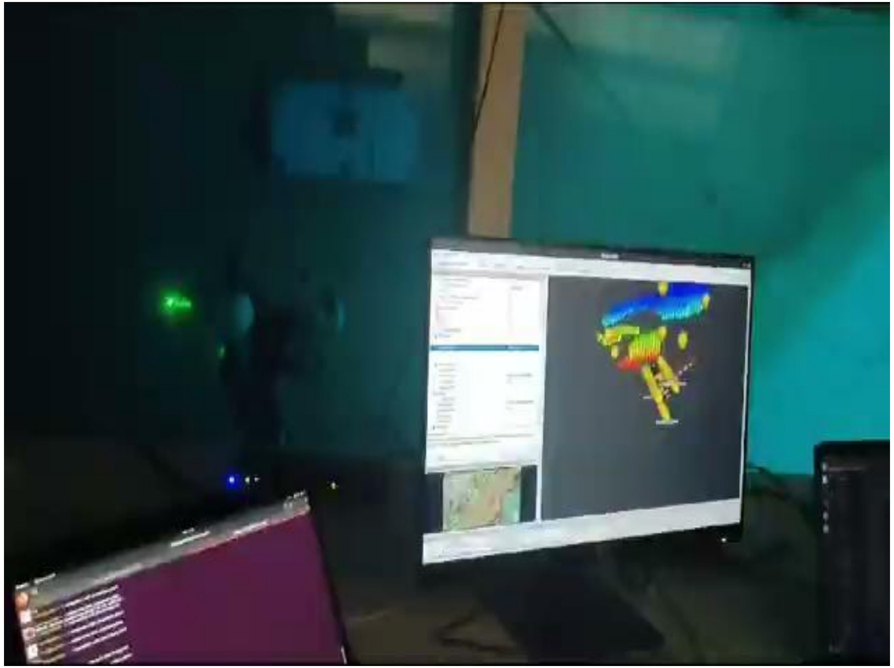
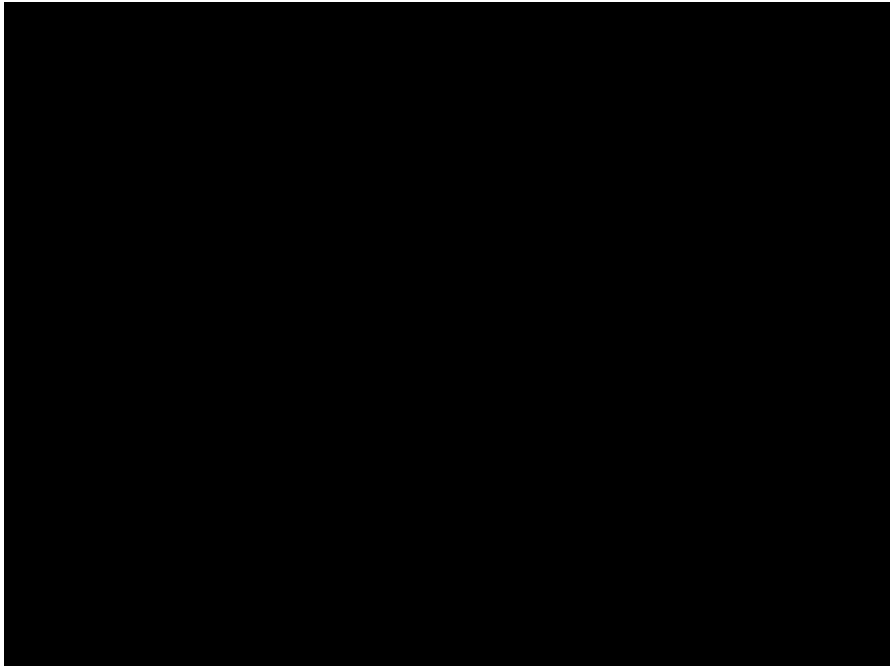
Motivation



VICOROB pool, ATLANTIS and OPTHIROV projects

Motivation

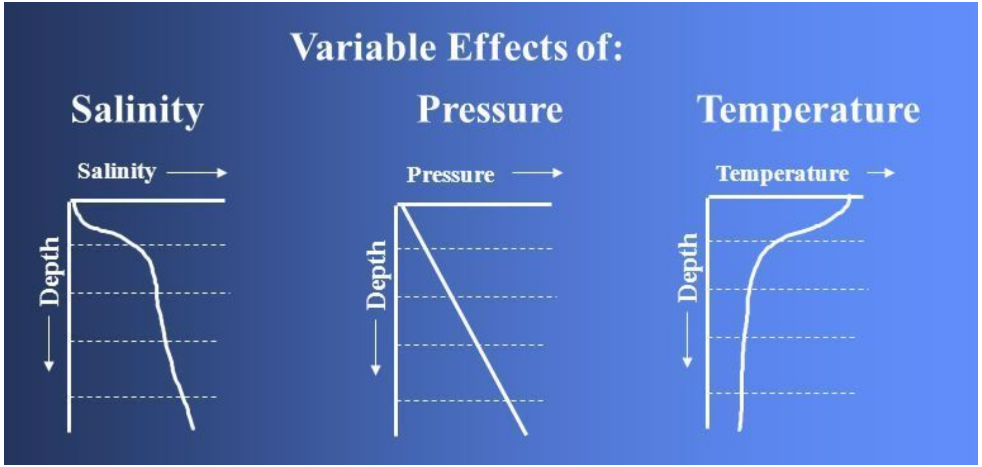


VICOROB pool, ATLANTIS and OPTHIROV projects

Motivation

In real conditions, performances depend on:

Sound propagation: Salinity, Pressure, Temperature



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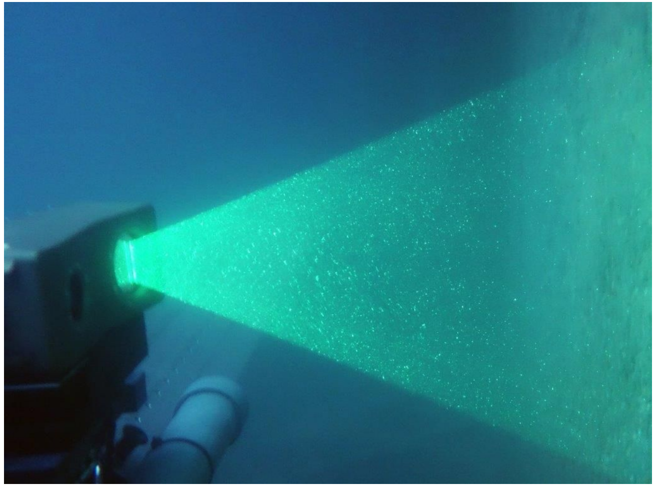
Motivation

In real conditions, performances depend on:

Sound propagation: Salinity, Pressure, Temperature

Laser: Turbidity, Color, Light conditions, Water Type



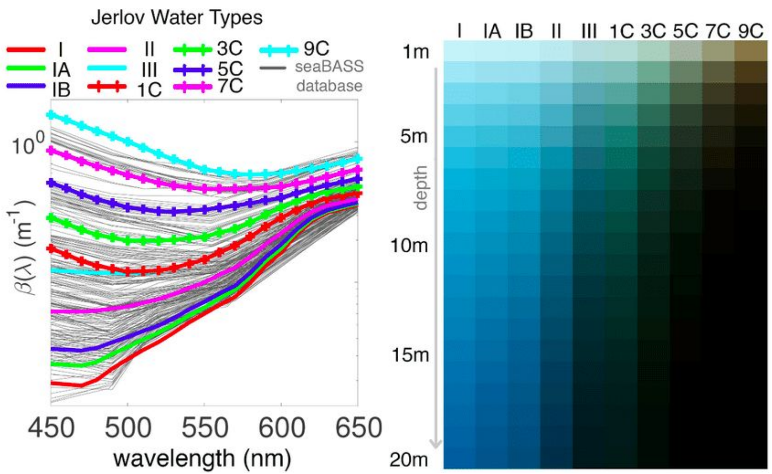
Motivation

In real conditions, performances depend on:

Sound propagation: Salinity, Pressure, Temperature

Laser: Turbidity, Color, Light conditions, Water Type

Camera: Turbidity, Light conditions, Water Type, Environment’s textures / reflectivity



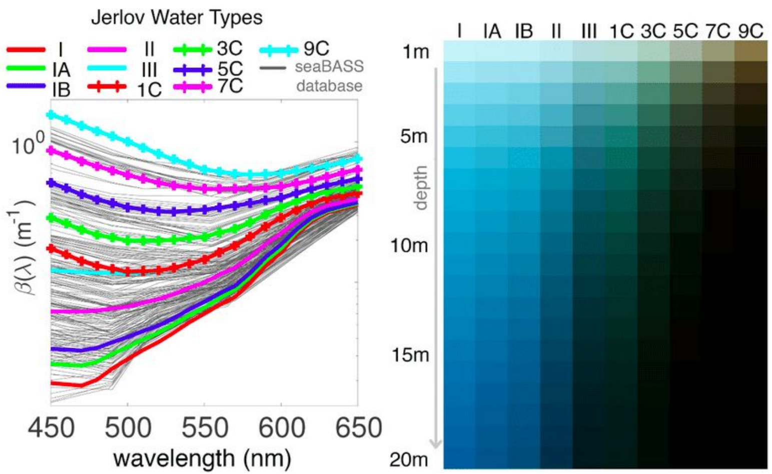
Motivation

In real conditions, performances depend on:

Sound propagation: Salinity, Pressure , Temperature

Laser: Turbidity , Color , Light conditions, Water Type

Camera: ~~Turbidity~~ , Light conditions, Water Type, Environment’s textures



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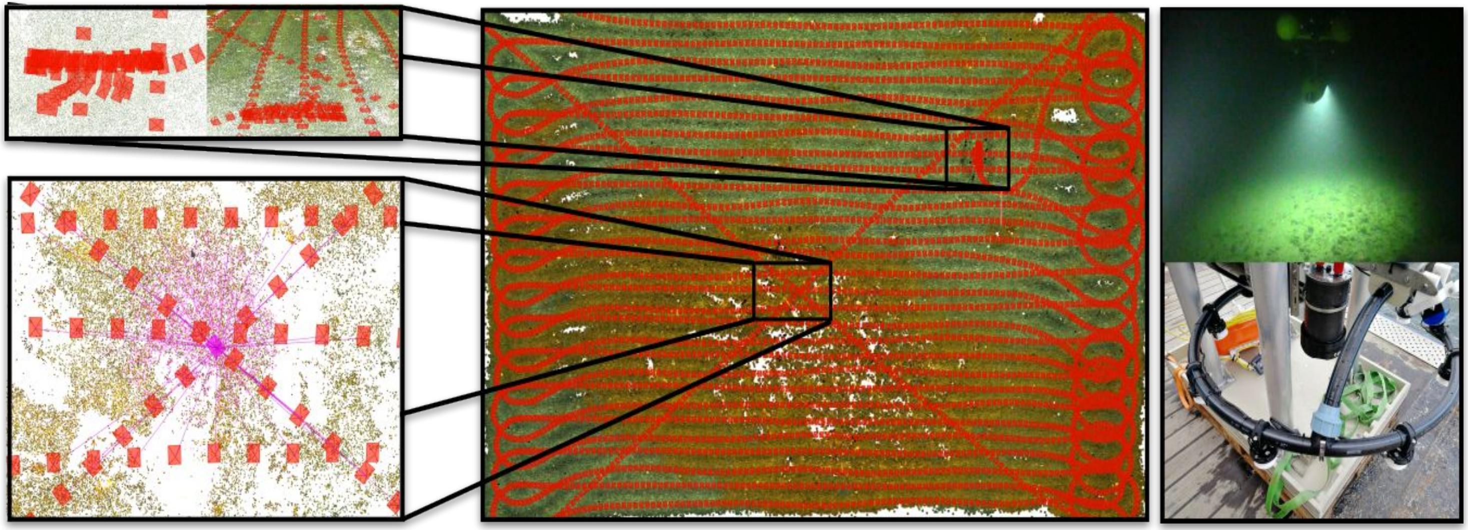
Real mission datasets



3 Datasets, 3 different conditions with GIRONA 500 ANTON and LUISE (GEOMAR)

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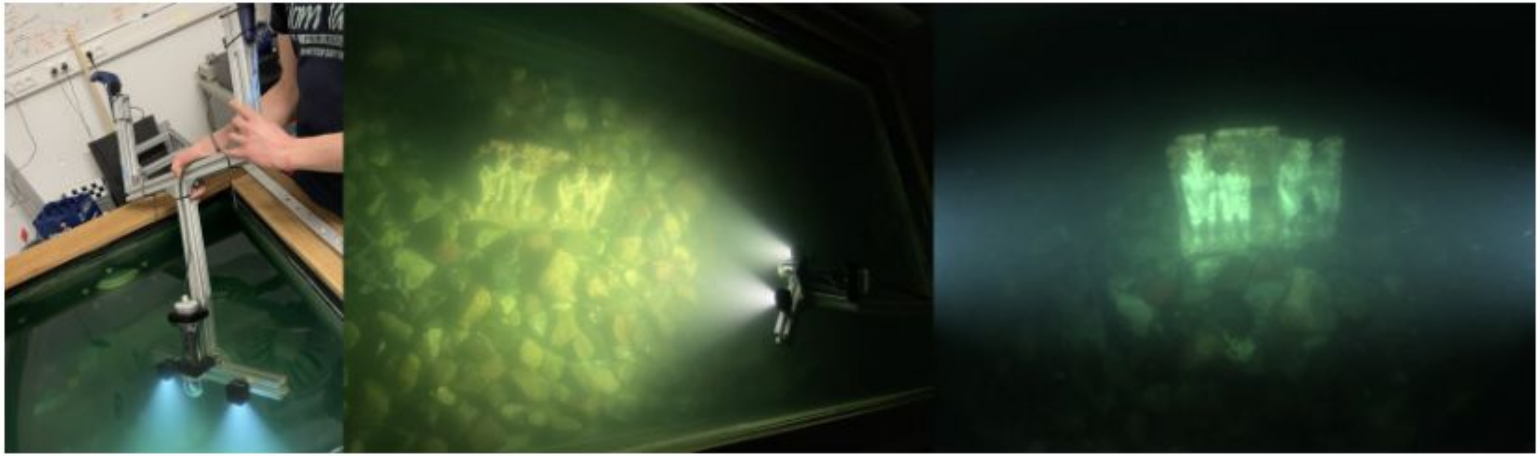
Real mission datasets

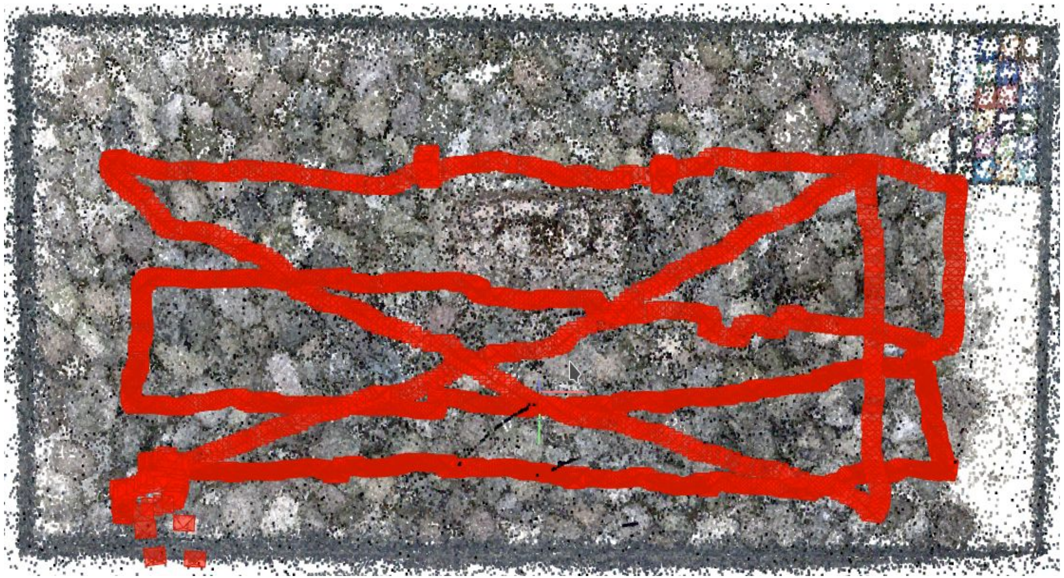
3 Datasets, 3 different conditions with GIRONA 500 ANTON and LUISE (GEOMAR)

Tank datasets



In-air and underwater, 2 trajectory types, 3 different Illumination conditions

Tank datasets



2 Medium, 2 Trajectory types, 3 different Illumination conditions

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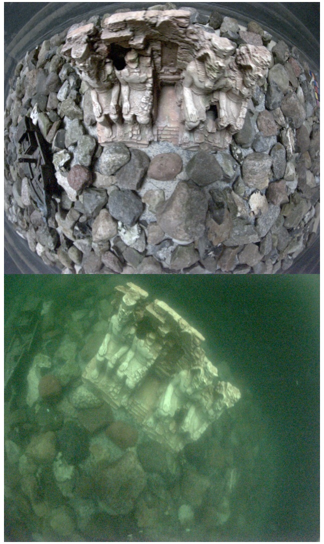
Light Impact on the Medium

a) sunlight illuminated scene



a)

Light Impact on the Medium

a) sunlight illuminated scene

b) mixed light illuminated scene

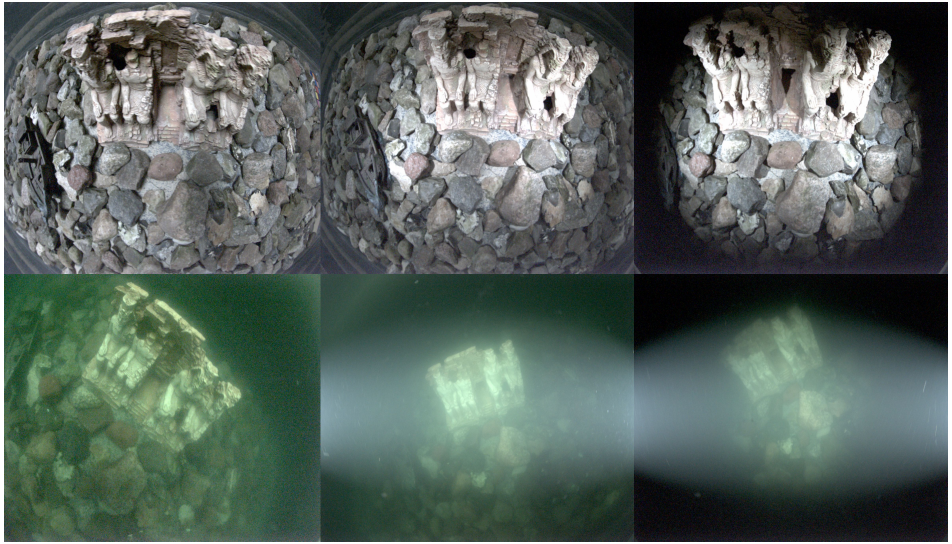
a) b)

Light Impact on the Medium

a) sunlight illuminated scene

b) mixed light illuminated scene

c) artificial light illuminated scene



a) b) c)

Image enhancement methods

Statistics:

1) CLAHE

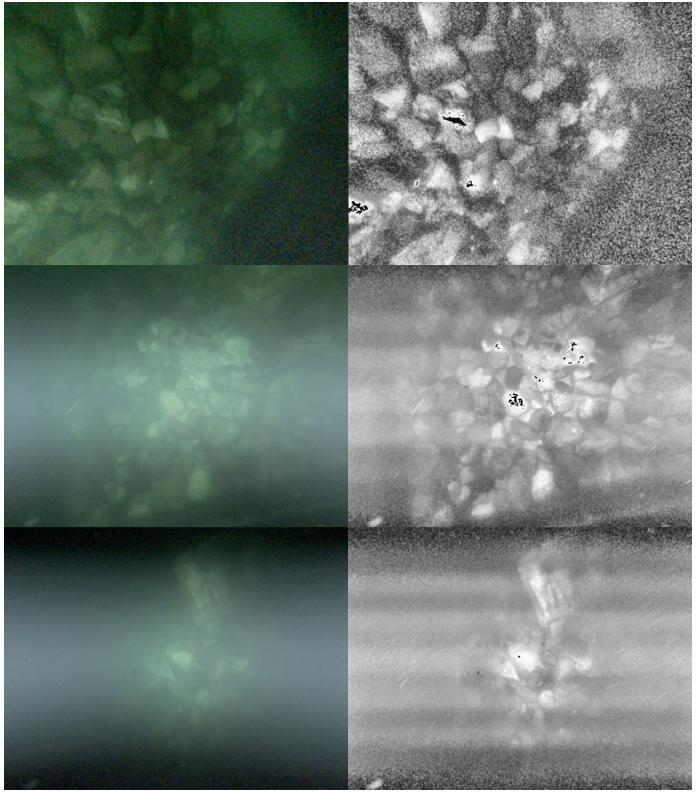


Image enhancement methods

Statistics:

1) CLAHE
2) UDCP

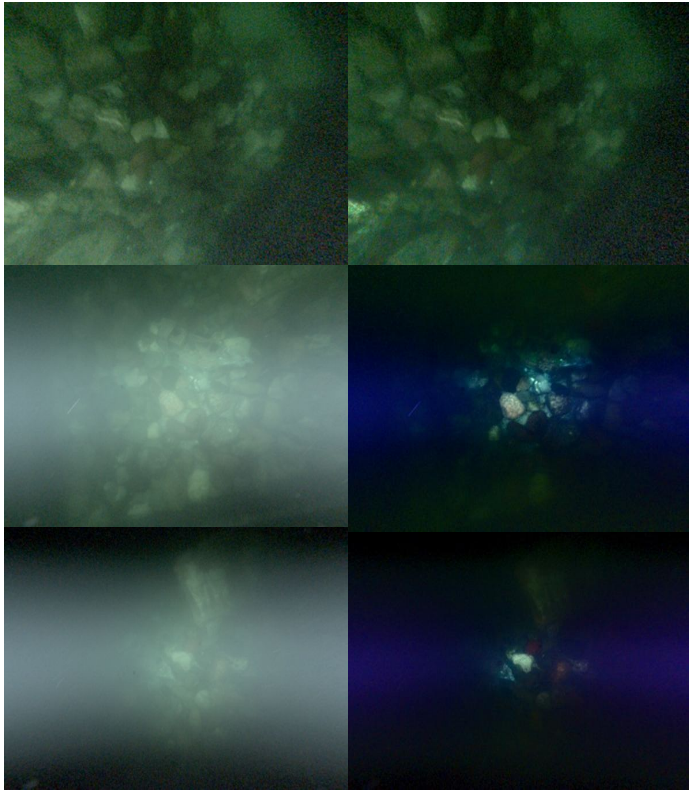


Image enhancement methods

Statistics:

1) CLAHE
2) UDCP

Heuristics:

3) Median-heuristic (Köser, 2020)

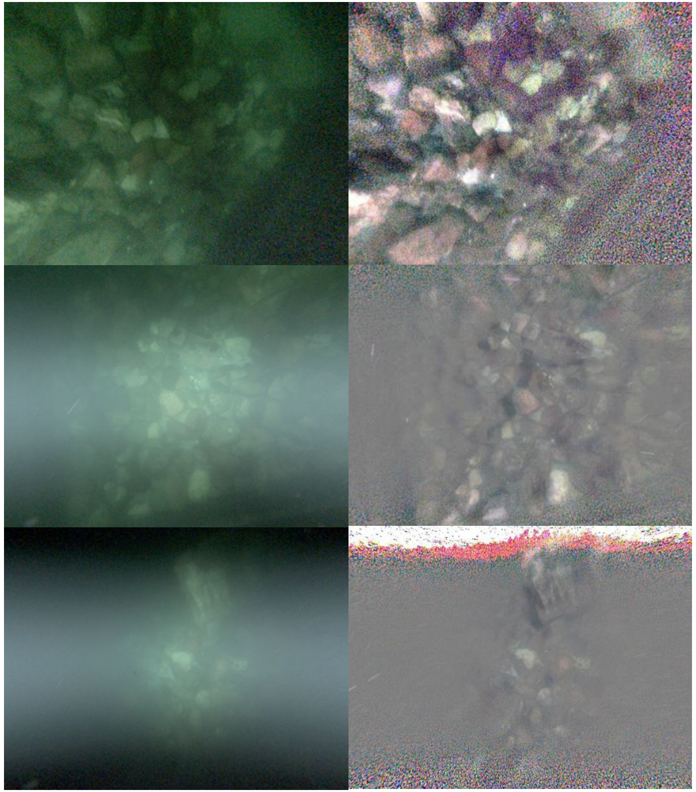


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Image enhancement methods

Statistics:

1) CLAHE
2) UDCP

Heuristics:

3) Median-heuristic (Köser, 2020)

Machine Learning:

4) UWGAN -> Water type 1

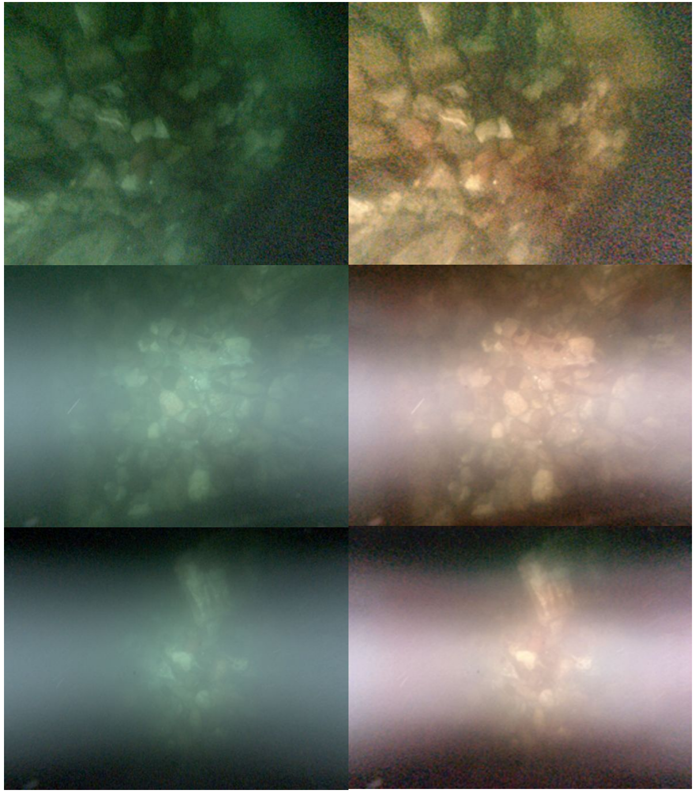

Image enhancement methods

Statistics:

1) CLAHE
2) UDCP

Heuristics:

3) Median-heuristic (Köser, 2020)

Machine Learning:

4) UWGAN -> Water type 1
5) UWGAN -> Water type 2

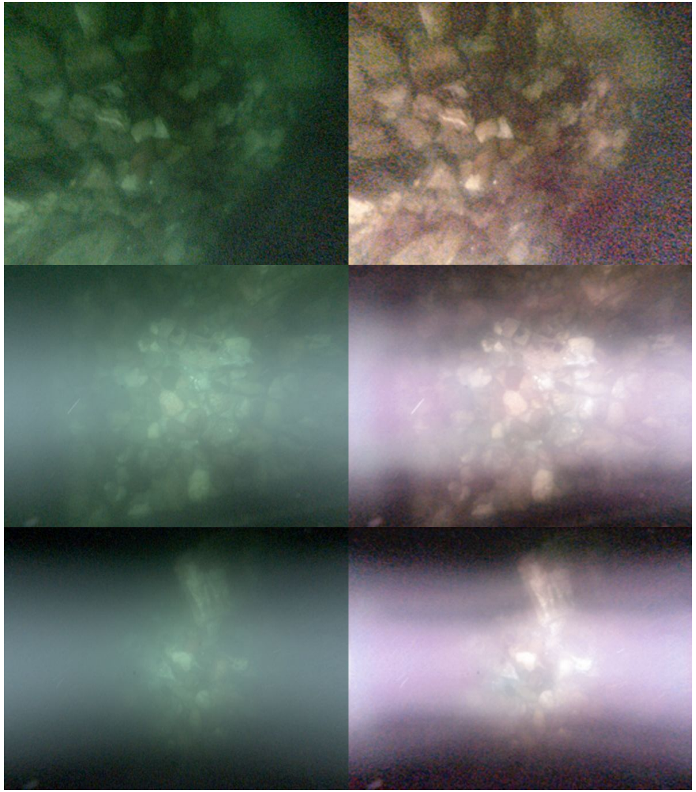

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Image enhancement methods

Statistics:

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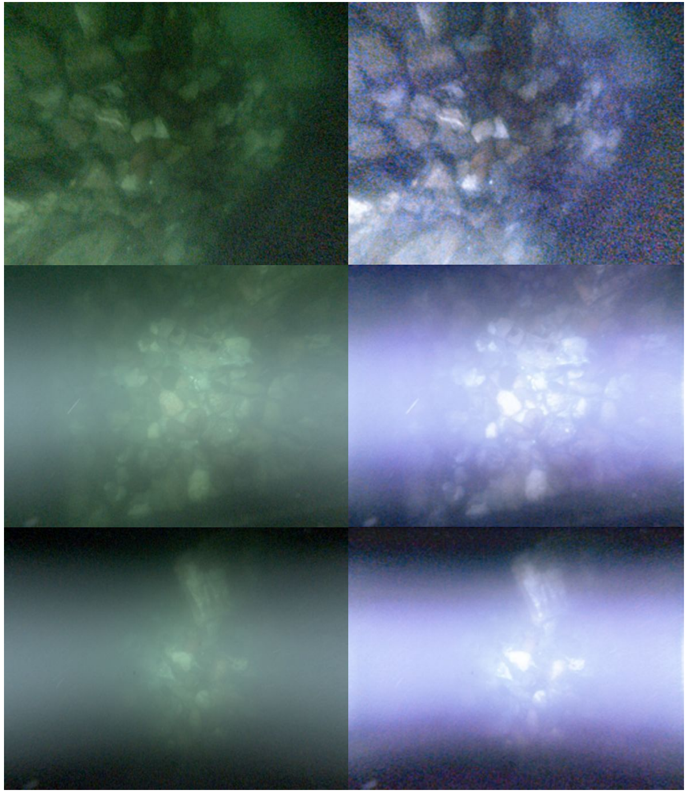
4) UWGAN -> Water type 1
5) UWGAN -> Water type 2
6) UWGAN -> Water type 3



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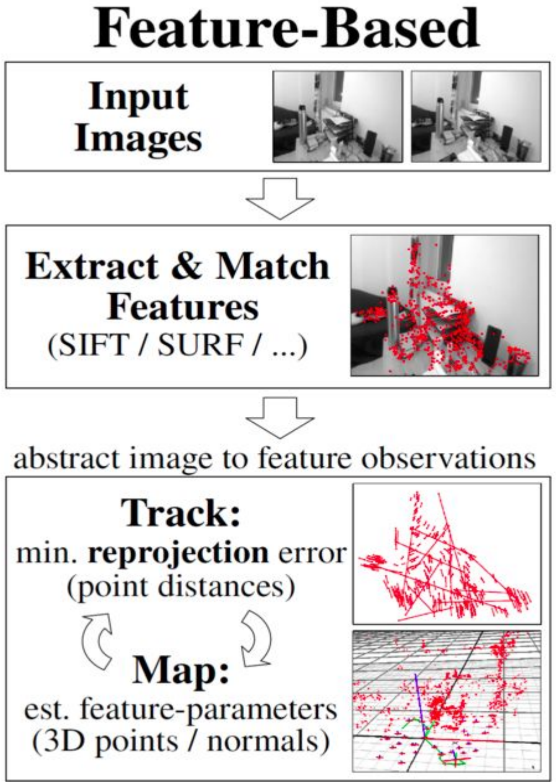
SLAM Methods

1) ORB SLAM 2
2) ORB SLAM 3



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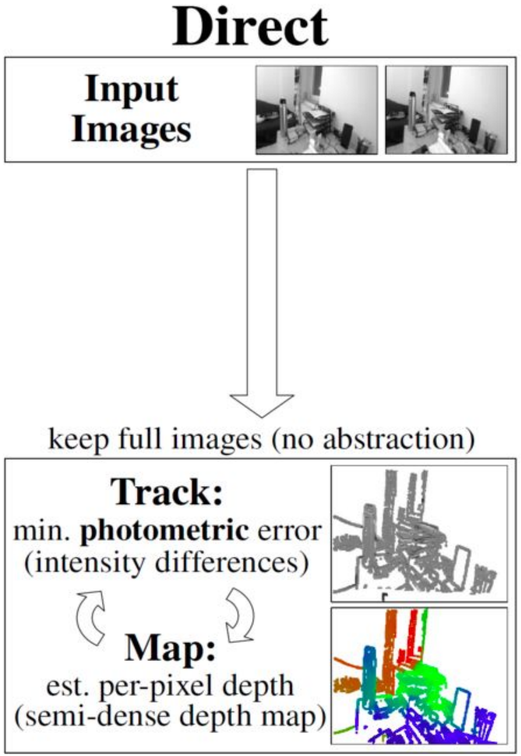
SLAM Methods

1) ORB SLAM 2
2) ORB SLAM 3
3) LSD SLAM



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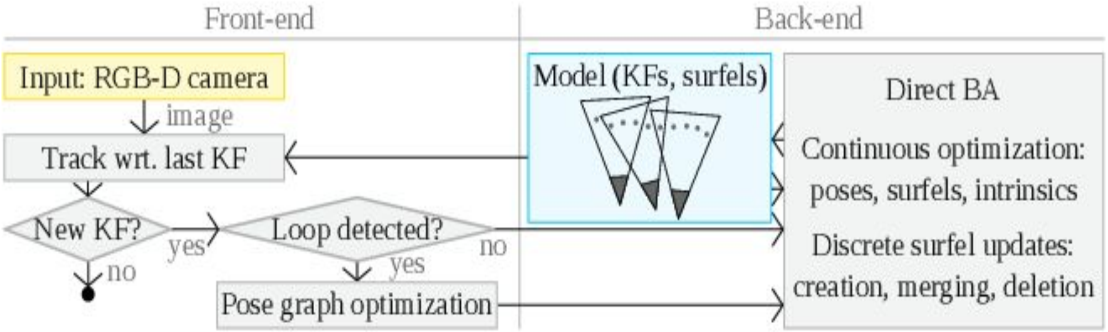
SLAM Methods

1) ORB SLAM 2
2) ORB SLAM 3
3) LSD SLAM
4) BADSLAM



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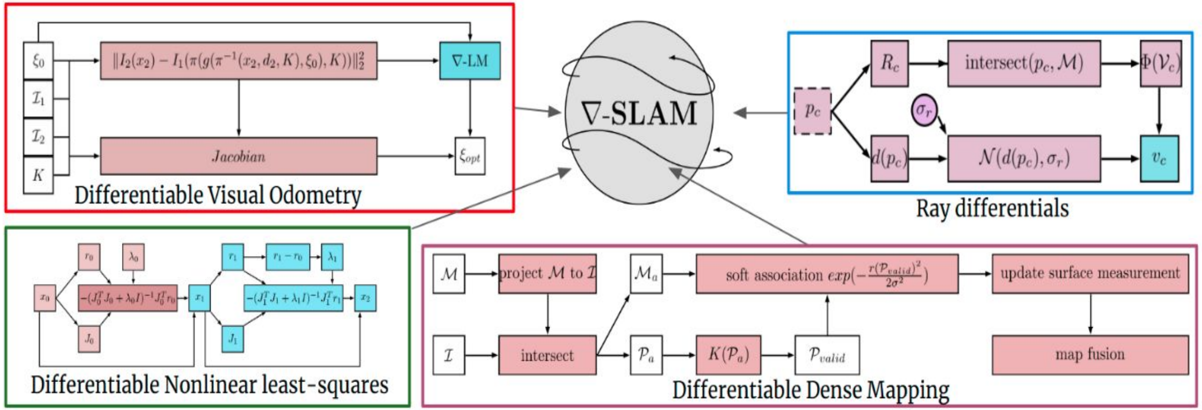
SLAM Methods

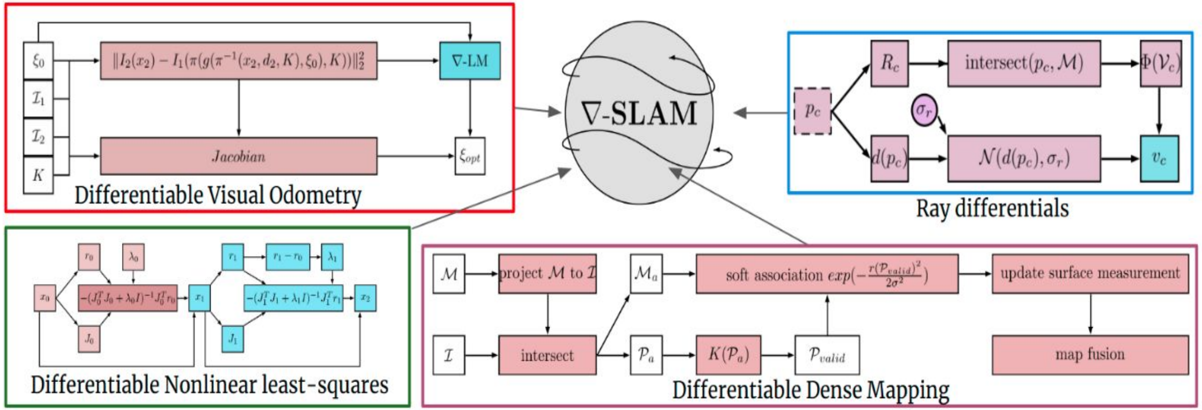
1) ORB SLAM 2
2) ORB SLAM 3
3) LSD SLAM
4) BADSLAM
5) GRADSLAM



SLAM Methods

1) ORB SLAM 2
2) ORB SLAM 3
3) LSD SLAM
4) BADSLAM
5) GRADSLAM

Depth



Depth Map Estimation

In-Air :

1) MonoDepth2 (Godard, ICCV 2019)
2) Colmap

Depth Map Estimation

In-Air :
1) MonoDepth2 (Godard, ICCV 2019)
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Underwater :
1) UW-Net (Gupta , ICIP 2019)
2) UDepth (Yu, ICRA 2023)
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Depth Map Estimation

In-Air :
1) MonoDepth2 (Godard, ICCV 2019)
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2) UDepth (Yu, ICRA 2023)
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Forward looking depth estimators!

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Results: Tank in-air

T1-7, Tank in-air							
	T1	T2	T3	T4	T5	T6	T7
ORB-SLAM2	$1.68^\circ \mid 0.09$	$1.31^\circ \mid 0.08$	$2.12^\circ \mid 0.12$	$1.68^\circ \mid 0.10$	$2.47^\circ \mid 0.15$	$2.23^\circ \mid 0.21$	$2.54^\circ \mid 0.16$
ORB-SLAM3	$1.60^\circ \mid 0.09$	$1.23^\circ \mid \mathbf{0.07}$	$2.94^\circ \mid 0.17$	$1.92^\circ \mid 0.12$	$2.27^\circ \mid 0.14$	$2.22^\circ \mid 0.30$	$2.23^\circ \mid 0.29$
LSD-SLAM	$1.89^\circ \mid 0.10$	$1.68^\circ \mid 0.09$	$1.98^\circ \mid 0.20$	$2.20^\circ \mid 0.24$	$1.87^\circ \mid 0.20$	FAILED	FAILED
BADSLAM (Monodepth2)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (Colmap)	$\mathbf{1.38}^\circ \mid 0.08$	$1.47^\circ \mid 0.11$	$1.87^\circ \mid 0.12$	$1.94^\circ \mid 0.20$	$2.09^\circ \mid 0.25$	$2.07^\circ \mid 0.19$	$2.17^\circ \mid 0.23$
GRADSLAM (Monodepth2)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM (Colmap)	$1.45^\circ \mid 0.12$	$1.42^\circ \mid 0.13$	$2.10^\circ \mid 0.15$	$2.22^\circ \mid 0.17$	$2.3^\circ \mid 0.27$	$2.28^\circ \mid 0.24$	$2.41^\circ \mid 0.28$

In air the SLAM approaches work !

- **except w/ forward looking neural depth estimators**
- **Colmap-depth shows that approaches can work w/ correct depth**

Results: Tank with Homogeneous Illumination

T8, Water Tank, homogenous illumination, lawn mower

	Base	CLAHE	UDCP	UW-GAN Water 1	UW-GAN Water 2	UW-GAN Water 3	Median
ORB-SLAM2	3.5°|1.42	**2.2°**|1.28	3.12°|1.41	4.0°|1.52	4.1°|1.53	3.9°|1.61	NOT INIT
ORB-SLAM3	4.5°|1.61	3°|**1.19**	2.6°|1.51	3.3°|1.54	3.8°|1.50	3.3°|1.59	NOT INIT
BADSLAM (UDepth)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (UW-Net)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
LSD-SLAM	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UDepth)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UW-Net)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED

T9, Water Tank, homogenous illumination, scanning trajectory

	Base	CLAHE	UDCP	UW-GAN Water 1	UW-GAN Water 2	UW-GAN Water 3	Median
ORB-SLAM2	2.7°|1.34	2.2°|1.26	2.2°|1.52	2.7°|1.47	2.8°|1.46	2.9°|1.61	NOT INIT
ORB-SLAM3	2.9°|1.53	**1.8°|1.24**	2.6°|1.51	2.62°|1.49	3.32°|1.59	2.9°|1.47	NOT INIT
BADSLAM (UDepth)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (UW-Net)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
LSD-SLAM	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UDepth)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UW-Net)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED

Only ORB-SLAMs pipeline were effectives :

- **Depth estimators not adapted**
- **Photometric methods like LSD-SLAM cannot work in low light conditions**

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Results: Tank with Artificial and Mixed Illumination

No pipeline was effective on mixed and artificial illuminated datasets

Features found near the light cones boundaries

No movement detected for the features

T13, Water Tank, artificial illumination, scanning trajectory							
	Base	CLAHE	UDCP	UW-GAN Water 1	UW-GAN Water 2	UW-GAN Water 3	Median
ORB-SLAM2	NOT INIT	TR-Lost	NOT INIT	NOT INIT	NOT INIT	NOT INIT	NOT INIT
ORB-SLAM3	NOT INIT	TR-Lost	NOT INIT	NOT INIT	NOT INIT	NOT INIT	NOT INIT
BADSLAM (UDepth)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (UW-Net)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
LSD-SLAM	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UDepth)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UW-Net)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED

T11, Water Tank, mixed illumination, scanning trajectory							
	Base	CLAHE	UDCP	UW-GAN Water 1	UW-GAN Water 2	UW-GAN Water 3	Median
ORB-SLAM2	NOT INIT	TR-Lost	NOT INIT	NOT INIT	NOT INIT	NOT INIT	NOT INIT
ORB-SLAM3	NOT INIT	TR-Lost	NOT INIT	NOT INIT	NOT INIT	NOT INIT	NOT INIT
BADSLAM (UDepth)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	NOT INIT
BADSLAM (UW-Net)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
LSD-SLAM	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UDepth)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UW-Net)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED

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Results: Real Missions

A1, Real mission w/ Girona 500 AUV							
	Base	CLAHE	UDCP	UW-GAN Water 1	UW-GAN Water 2	UW-GAN Water 3	Median
ORB-SLAM2	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost
ORB-SLAM3	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost
BADSLAM (UDepth)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (UW-Net)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (Colmap)	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost
LSD-SLAM	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UDepth)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UW-Net)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(Colmap)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED

A2, Real mission w/ Girona 500 AUV							
	Base	CLAHE	UDCP	UW-GAN Water 1	UW-GAN Water 2	UW-GAN Water 3	Median
ORB-SLAM2	NOT INIT	TR-Lost	TR-Lost	NOT INIT	NOT INIT	NOT INIT	TR-Lost
ORB-SLAM3	NOT INIT	TR-Lost	NOT INIT	NOT INIT	NOT INIT	NOT INIT	TR-Lost
BADSLAM (UDepth)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (UW-Net)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (Colmap)	NOT INIT	TR-Lost	TR-Lost	NOT INIT	NOT INIT	NOT INIT	TR-Lost
LSD-SLAM	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UDepth)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UW-Net)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(Colmap)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED

A3, Real mission w/ Girona 500 AUV							
	Base	CLAHE	UDCP	UW-GAN Water 1	UW-GAN Water 2	UW-GAN Water 3	Median
ORB-SLAM2	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost
ORB-SLAM3	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost
BADSLAM (UDepth)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (UW-Net)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (Colmap)	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost
LSD-SLAM	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UDepth)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UW-Net)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(Colmap)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED

No pipeline was effective :

- **light conditions**
- **low texture environments**

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Results: Real Missions

A1, Real mission w/ Girona 500 AUV							
	Base	CLAHE	UDCP	UW-GAN Water 1	UW-GAN Water 2	UW-GAN Water 3	Median
ORB-SLAM2	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost
ORB-SLAM3	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost
BADSLAM (UDepth)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (UW-Net)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (Colmap)	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost
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GRADSLAM(Colmap)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED

A2, Real mission w/ Girona 500 AUV							
	Base	CLAHE	UDCP	UW-GAN Water 1	UW-GAN Water 2	UW-GAN Water 3	Median
ORB-SLAM2	NOT INIT	TR-Lost	TR-Lost	NOT INIT	NOT INIT	NOT INIT	TR-Lost
ORB-SLAM3	NOT INIT	TR-Lost	NOT INIT	NOT INIT	NOT INIT	NOT INIT	TR-Lost
BADSLAM (UDepth)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (UW-Net)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (Colmap)	NOT INIT	TR-Lost	TR-Lost	NOT INIT	NOT INIT	NOT INIT	TR-Lost
LSD-SLAM	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UDepth)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UW-Net)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(Colmap)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED

A3, Real mission w/ Girona 500 AUV							
	Base	CLAHE	UDCP	UW-GAN Water 1	UW-GAN Water 2	UW-GAN Water 3	Median
ORB-SLAM2	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost
ORB-SLAM3	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost
BADSLAM (UDepth)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (UW-Net)	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
BADSLAM (Colmap)	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost	TR-Lost
LSD-SLAM	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UDepth)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(UW-Net)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED
GRADSLAM(Colmap)	FAILED	NA	FAILED	FAILED	FAILED	FAILED	FAILED

No pipeline was effective :

- **light conditions**
- **low texture environments**

SLAM is solved in air!

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Conclusion

- Real mission conditions are still challenging:

  - water quality

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  - good overlap and visibility => more time to finish the path

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- Tradeoff between altitude, consistency of the data and energy
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- Lack of tow-down depth estimators

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Future work

- Employ physical based methods to undo water and lights
  - ex Sea-Thru (Akkaynak, CVPR 2018)
  - Inverse Rendering (Nakath et al. CVPRws 2021)

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IMU

(a) Camera top view (b) Camera side view

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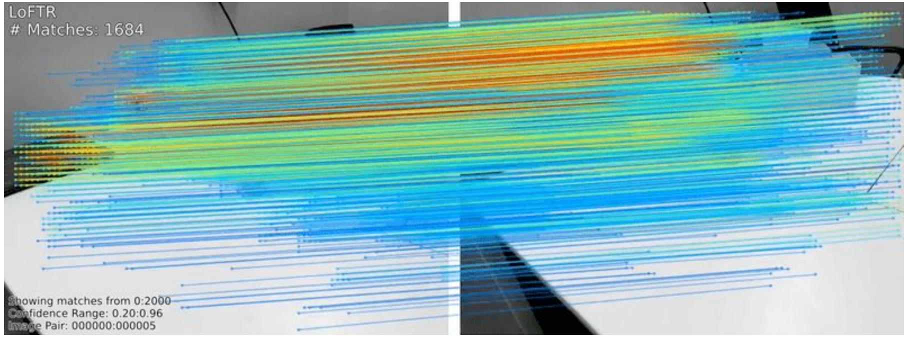
- Add inertial measurements
- Use deep learning feature detector/descriptor/matching
    - ex loFTR (effective on low texture environments)



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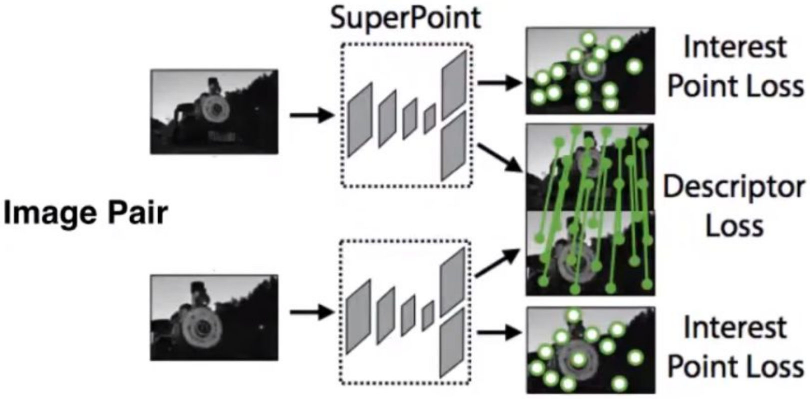
- Employ physical based methods to undo water and lights
- Add inertial measurements
- Use deep learning feature detector/descriptor/matching
    - ex loFTR
- Use other types of SLAM methods
    - SuperPoint SLAM
    - GCvN2 SLAM



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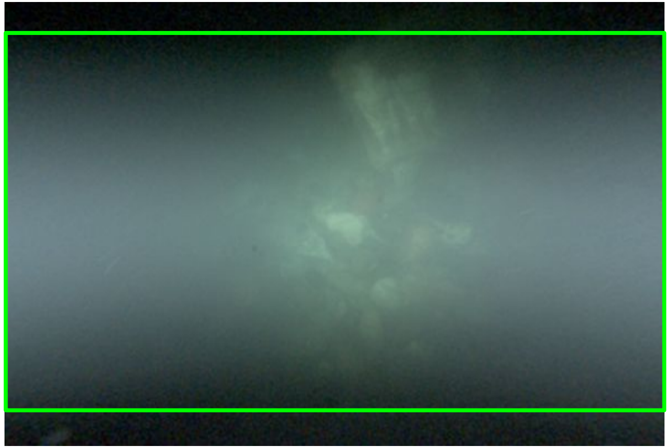
Enhance the part of the image in the range of the light cones



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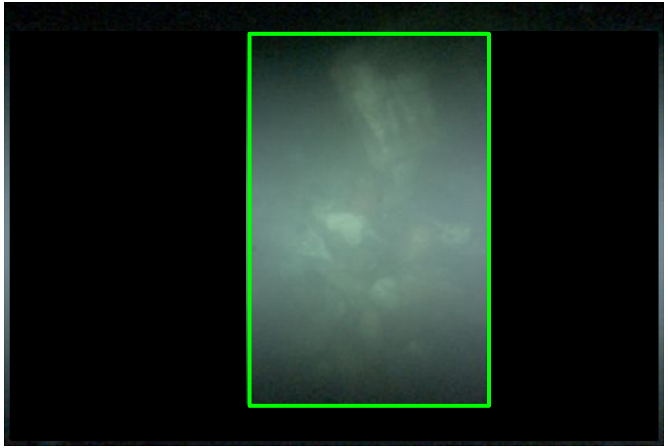
Work with a portion of the image in the cones intersection



Thank you!

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