



An appraisal of backscatter removal and refraction calibration models for improving the performance of vision-based mapping and navigation in shallow underwater environments

Fickrie Muhammad

Prof. Dr-Ing. Harald Sternberg

• Introduction

VbM – Problem arise – why VbM?

• Methodology

Refraction – Image quality - Integration

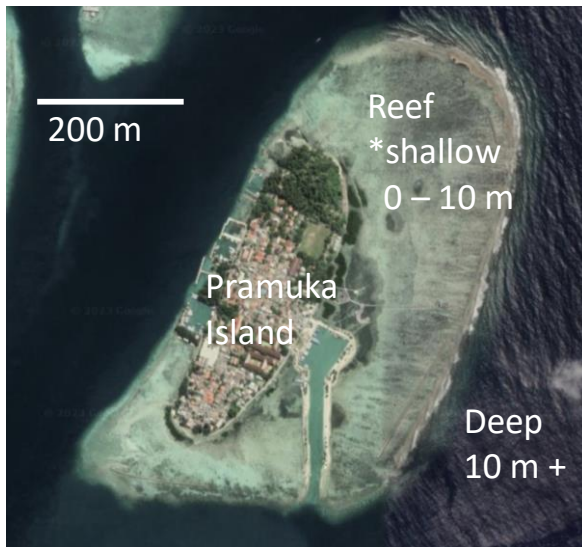
• Discussion

Results -conclusion

1. Introduction

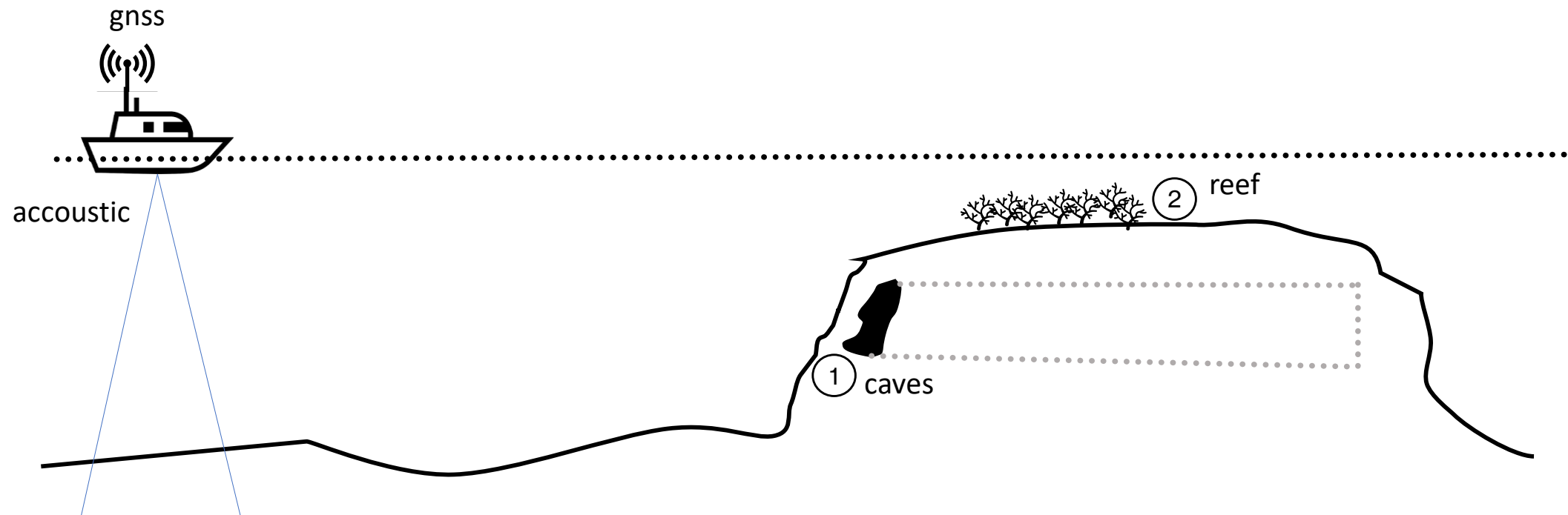
VbM – Vision based Mapping (and Navigation)

Introduction

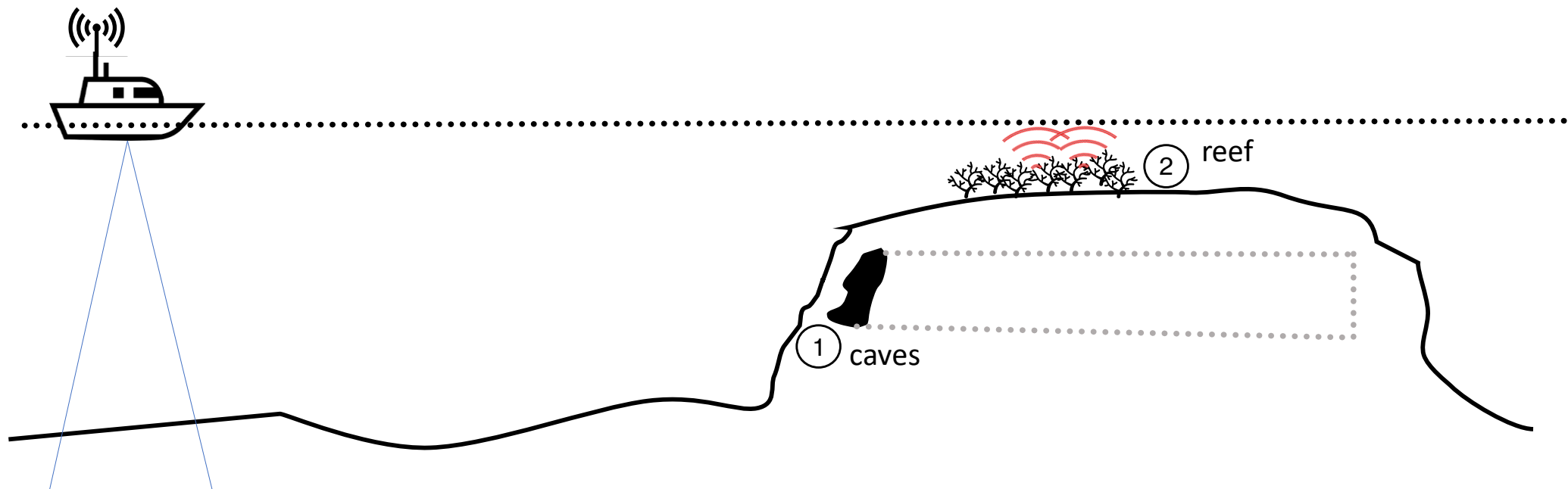


- Example study area in Pramuka Island, Indonesia
- How do we obtain bathymetry information from this area?

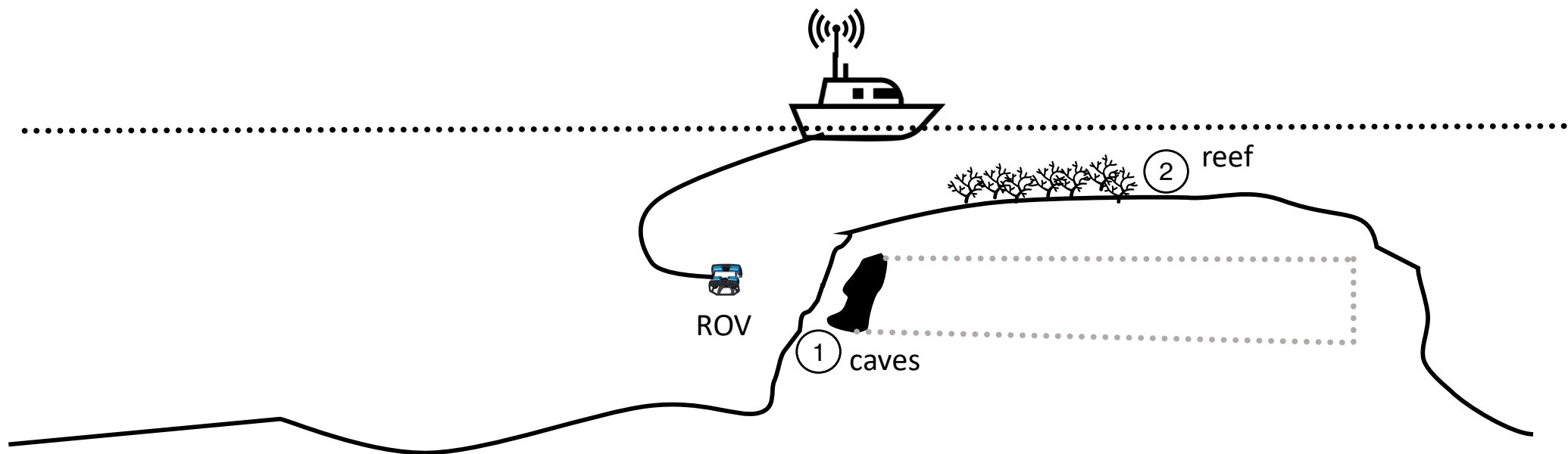
Introduction



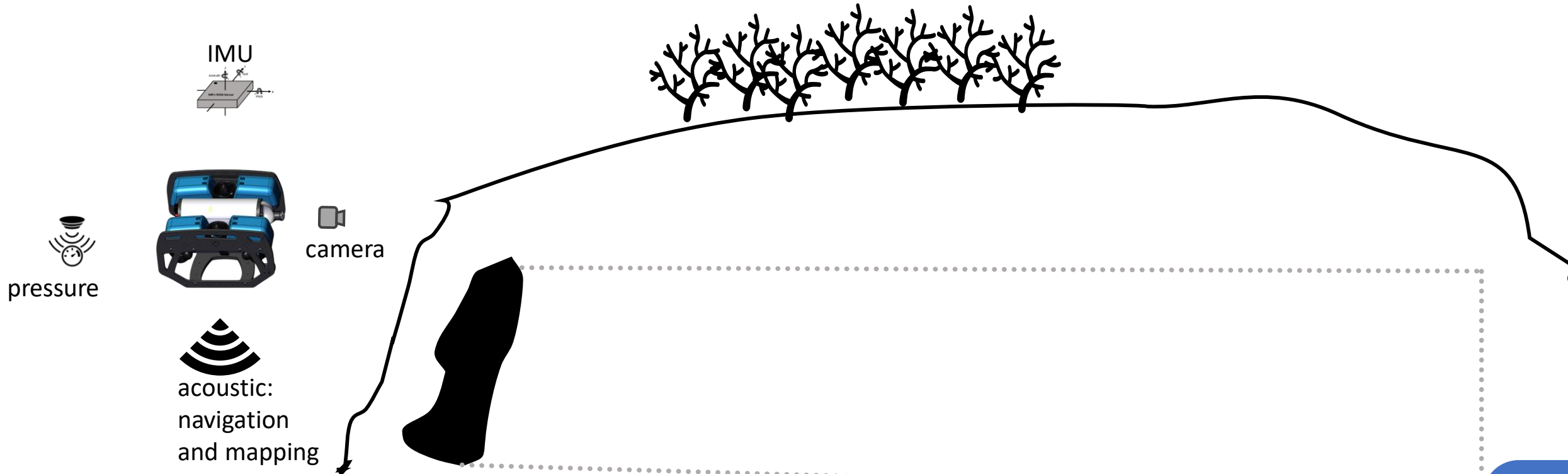
Introduction



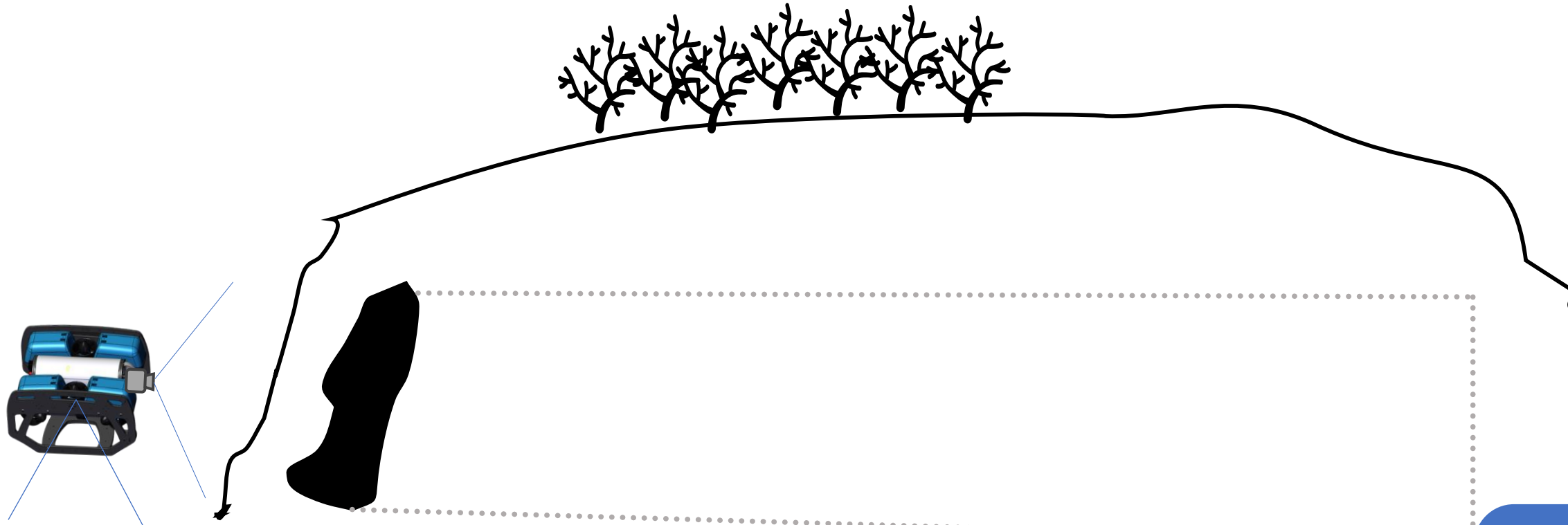
Introduction



Introduction



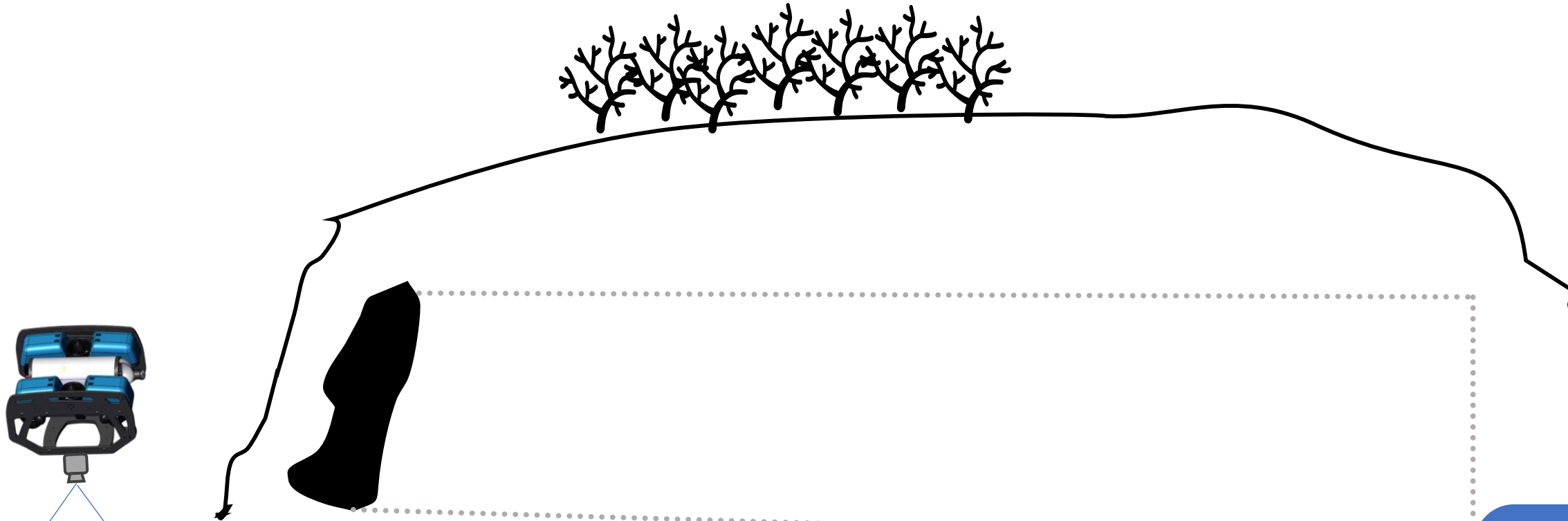
Introduction



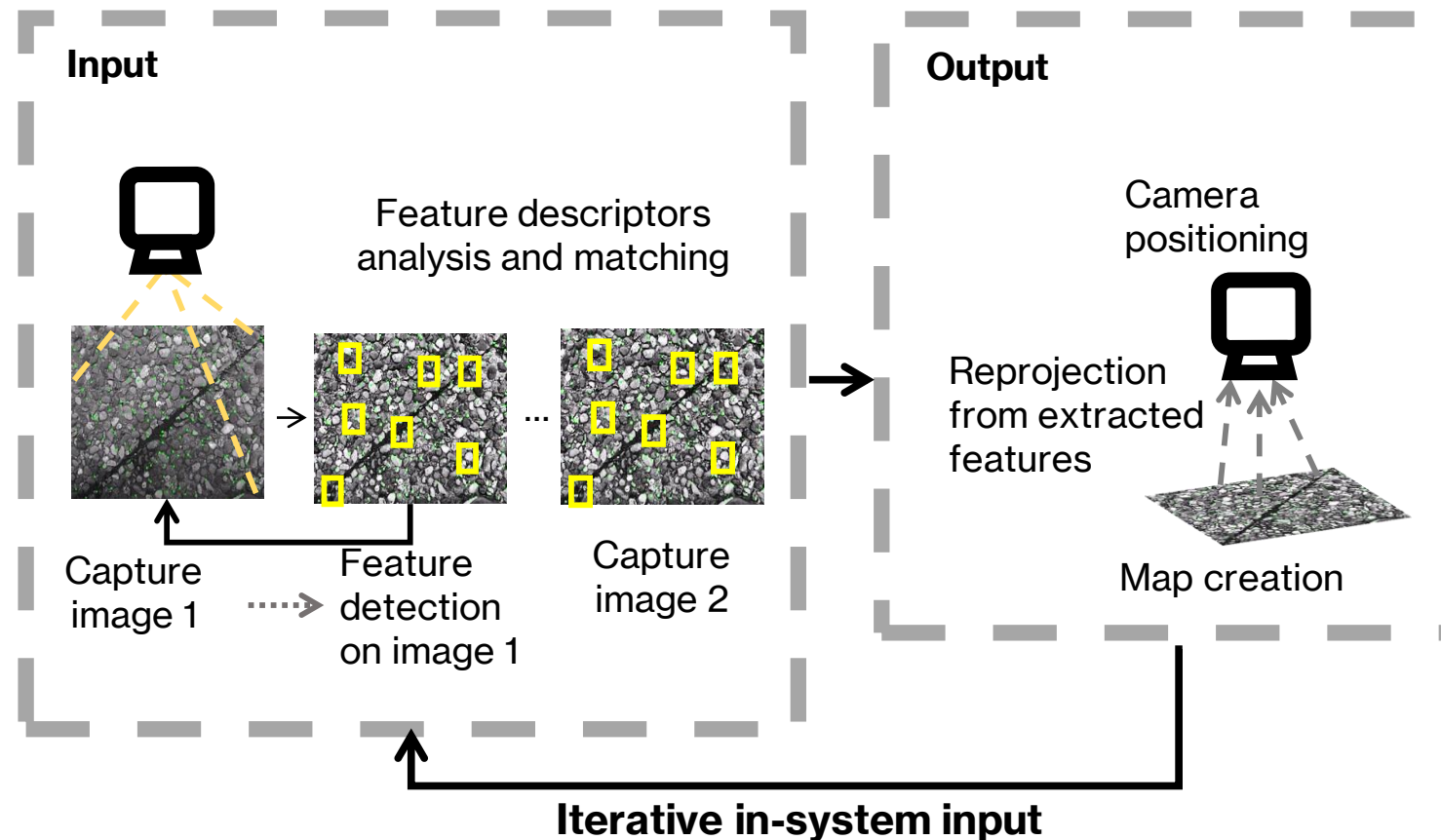
Introduction



Introduction

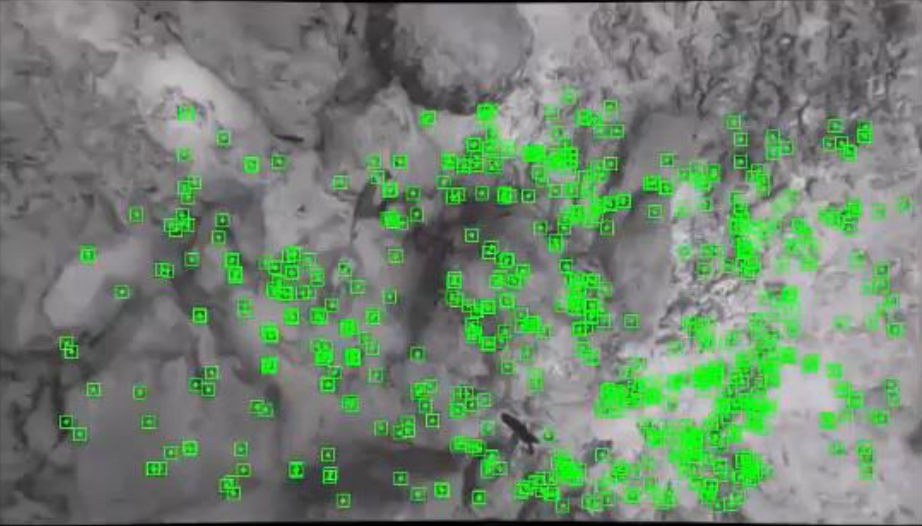


VbM: Simultaneous Localization and Mapping (SLAM)



SLAM

ORB-SLAM3: Current Frame




SLAM MODE | Maps: 1, KFs: 11, MPs: 4590, Matches: 764
pz: -0.007482
fps: 30
color order: RGB (ignored if grayscale)

ORB Extractor Parameters:
- Number of Features: 1250
- Scale Levels: 6
- Scale Factor: 1.2
- Initial Fast Threshold: 20
- Minimum Fast Threshold: 7
There are 1 cameras in the atlas
Camera 0 is pinhole
gtk-Message: 13:54:57.028: Failed to load module "canberra-gtk-module"
Starting the Viewer
First KF:0; Map Init KF:0
New Map created with 517 points
Tracking: Waiting to the next step

ORB-SLAM3: Map Viewer

- Follow Camera
- Camera View
- Top View
- Show Points
- Show KeyFrames
- Show Graph
- Show Inertial Graph
- Localization Mode
- Reset
- Stop
- Step By Step
- Step
- Show LBA opt.



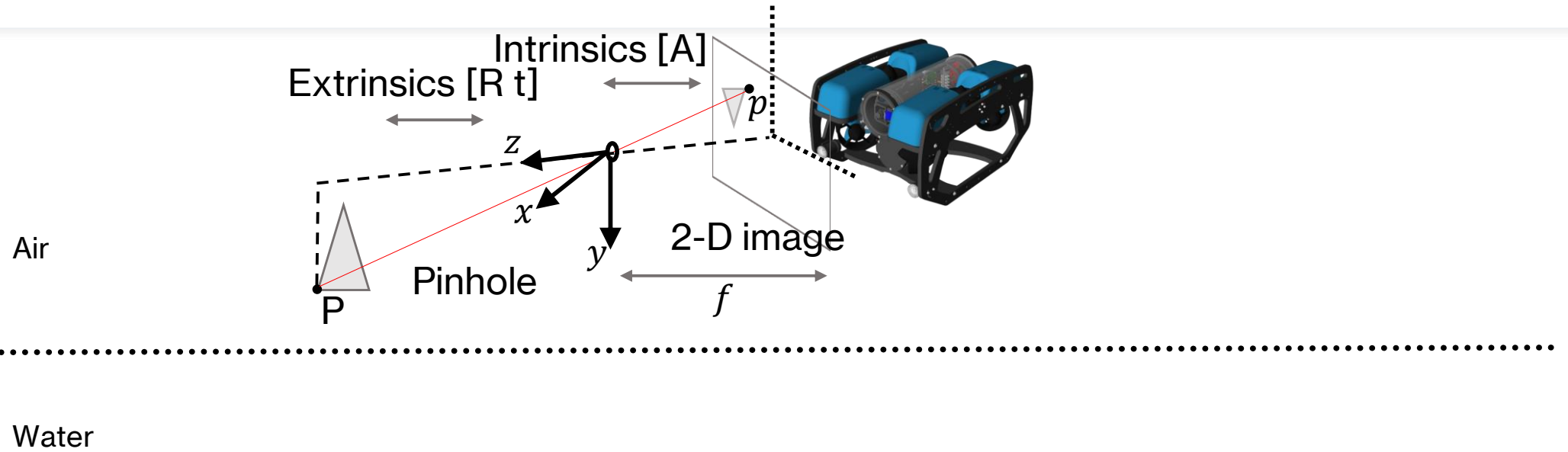
A 3D point cloud visualization of the SLAM map, showing a dense collection of points in red, blue, and green, representing the environment's geometry.



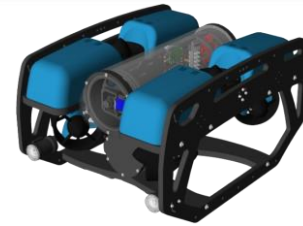
Problem

Challenge of using VbM underwater

Problem: refraction



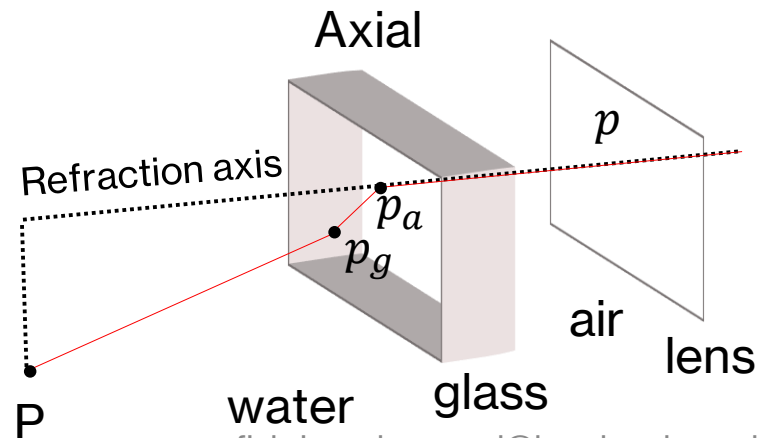
Problem: Refraction



Air

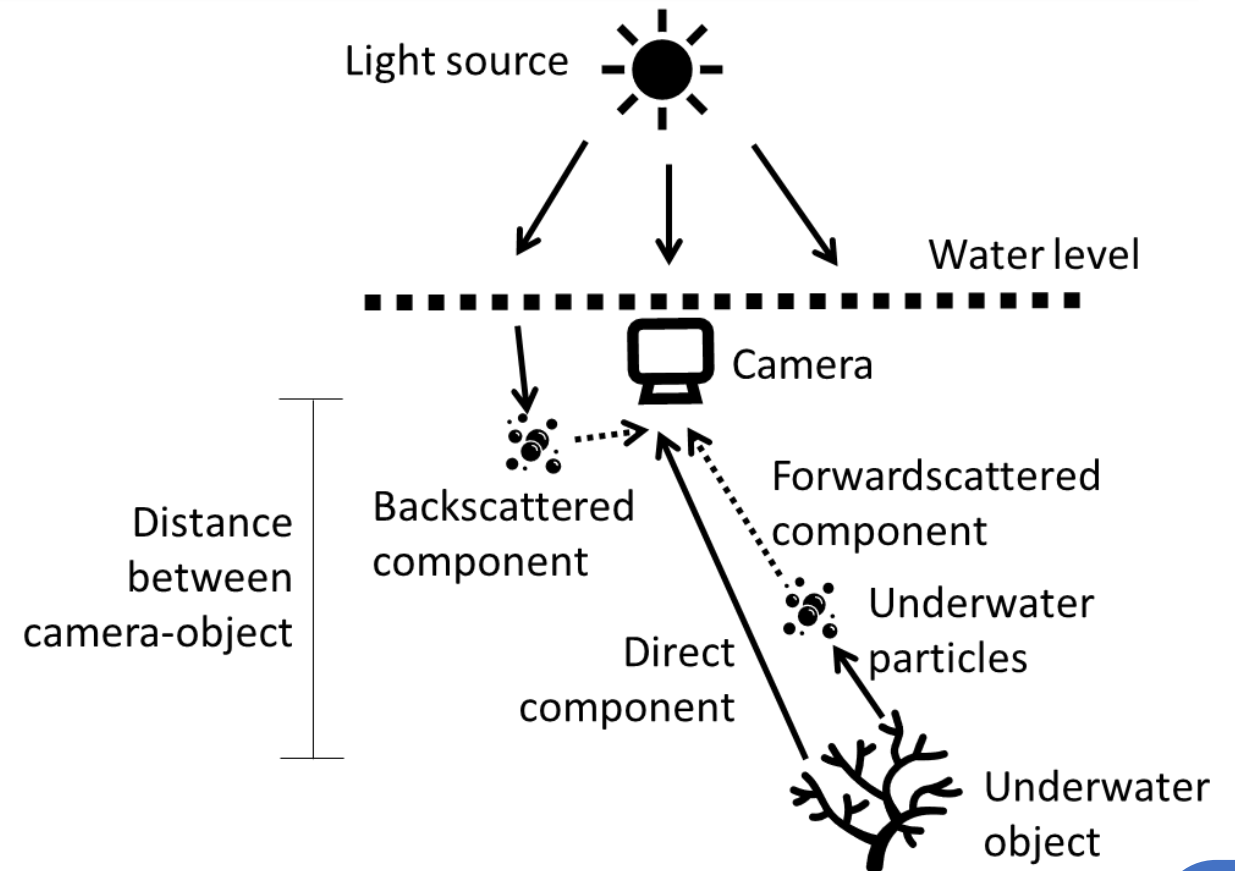


Water



Problem: Bias

- **Underwater Bias** is often presented due to the existence of suspended material such as microbial life forms or microparticle sediments.
- The most common bias from the light transmission is **color bias** due to light absorption and scattering phenomenon in water medium.



Problem: Bias

- **Underwater Bias** is often presented due to the existence of suspended material such as microbial life forms or microparticle sediments.
- The most common bias from the light transmission is **color bias** due to light absorption and scattering phenomenon in water medium.

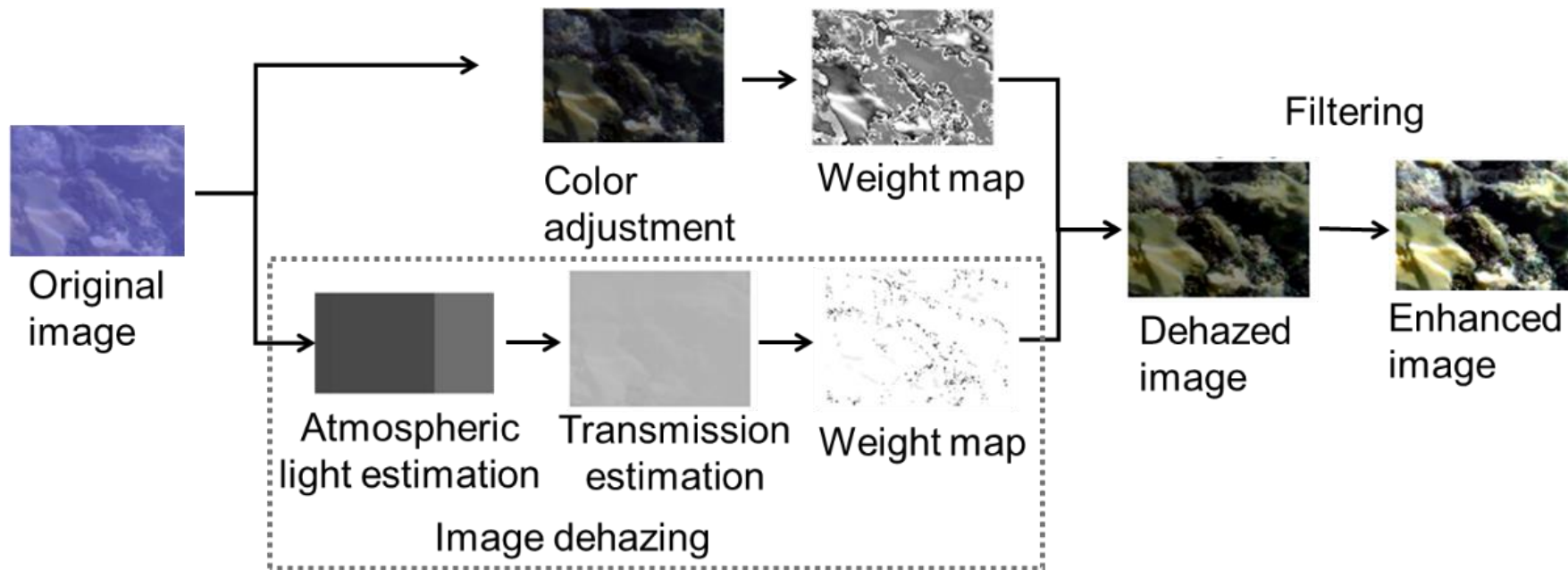


2. Methodology

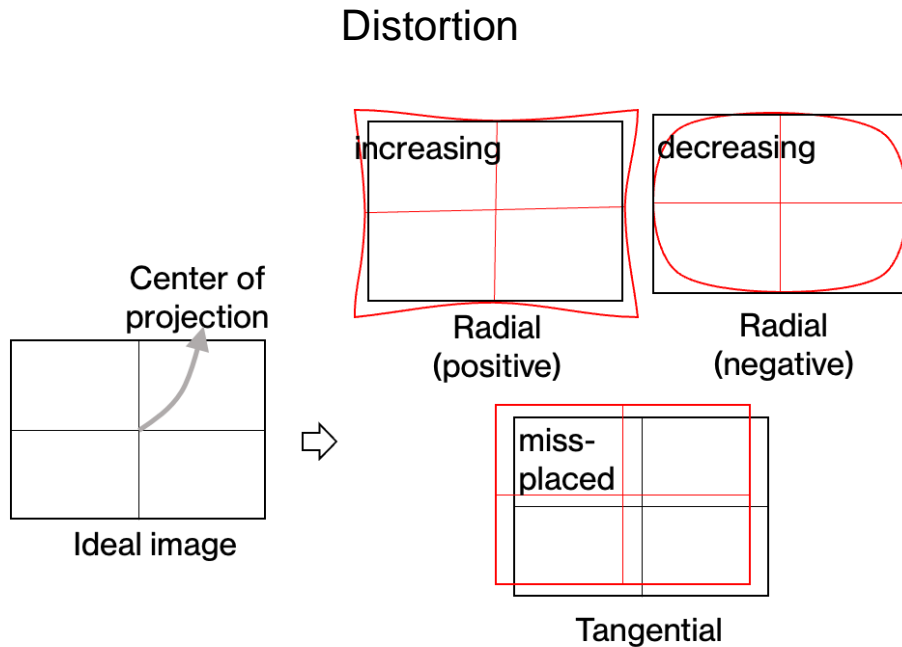
Dealing with challenges

Underwater Bias

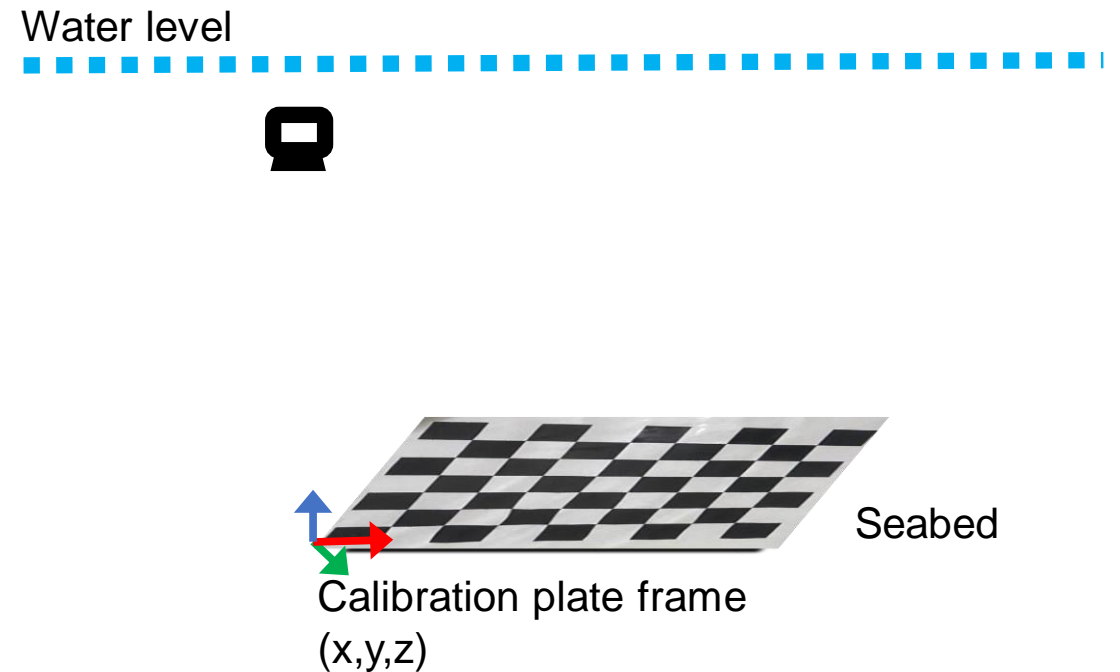
Backscatter removal (BR)



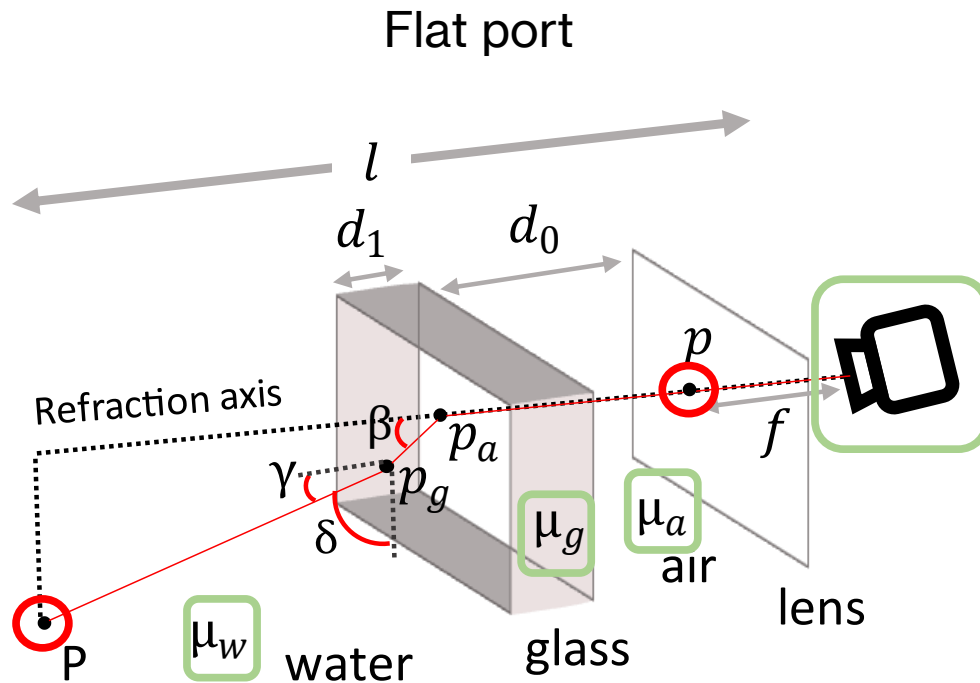
Distortion



Multiview calibration



Refraction



The incident angle in each medium is then correlated with Snell's law:

$$\mu_i \sin \theta_i = \mu_{i+1} \sin \theta_{i+1}$$

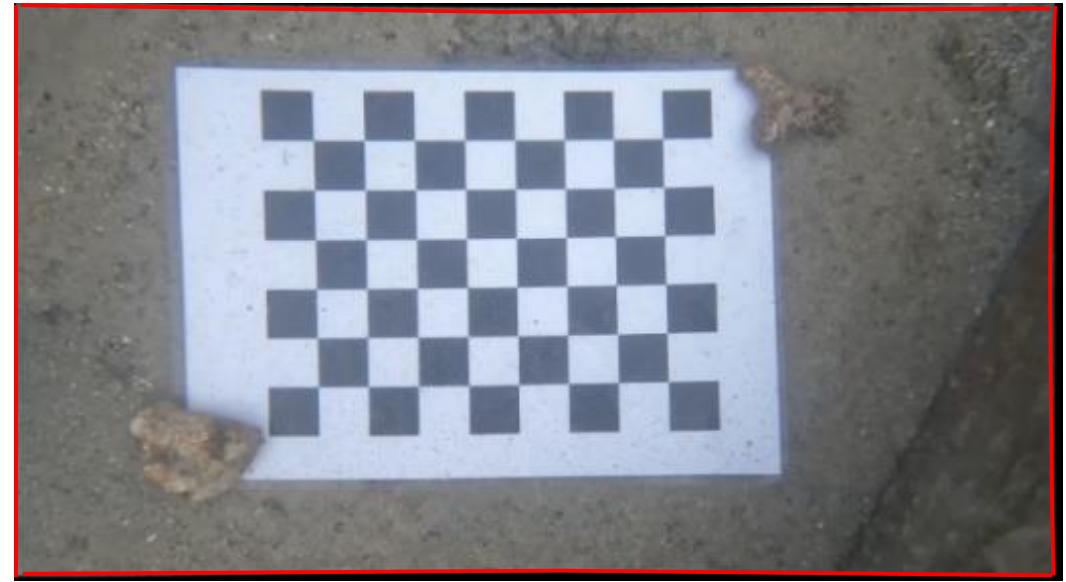
where :

- μ is the refraction indices of the medium layer
- θ is the incident angle between the refraction axis
- optical axis n (normal vector).
- Ray transmission is correlated with the focal length f
- Distance between each medium d
- Total medium distance l

Refraction

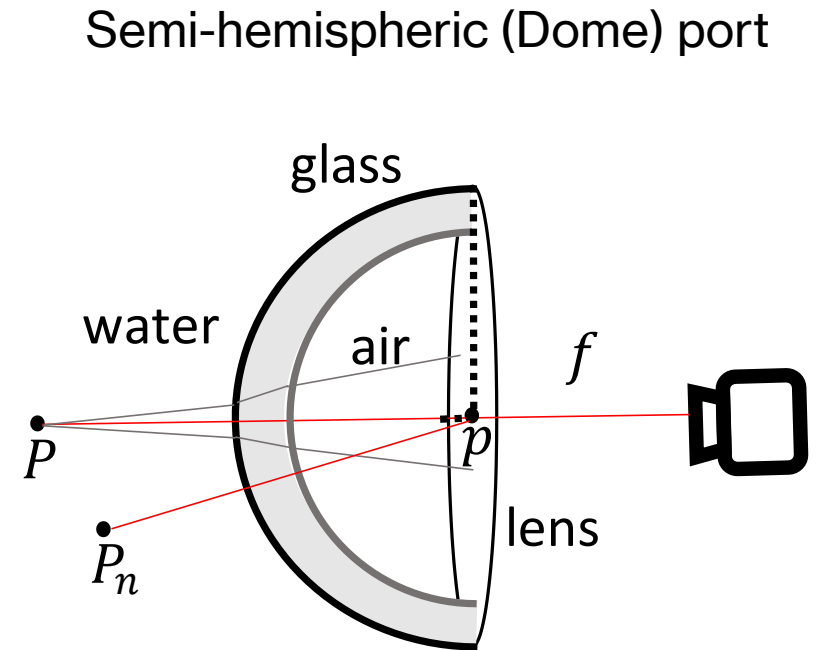
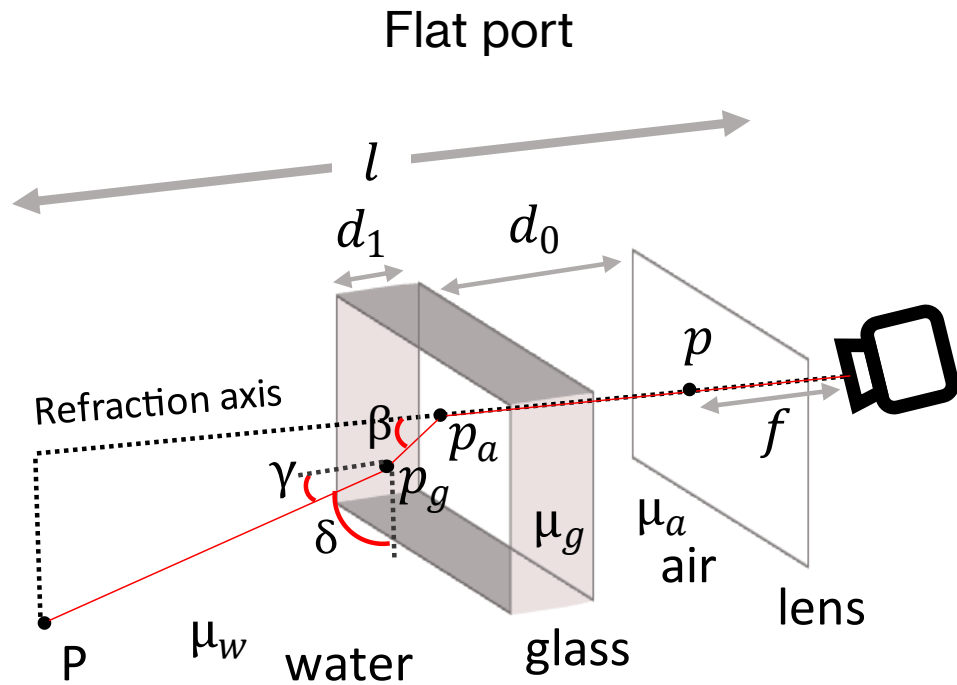


Original



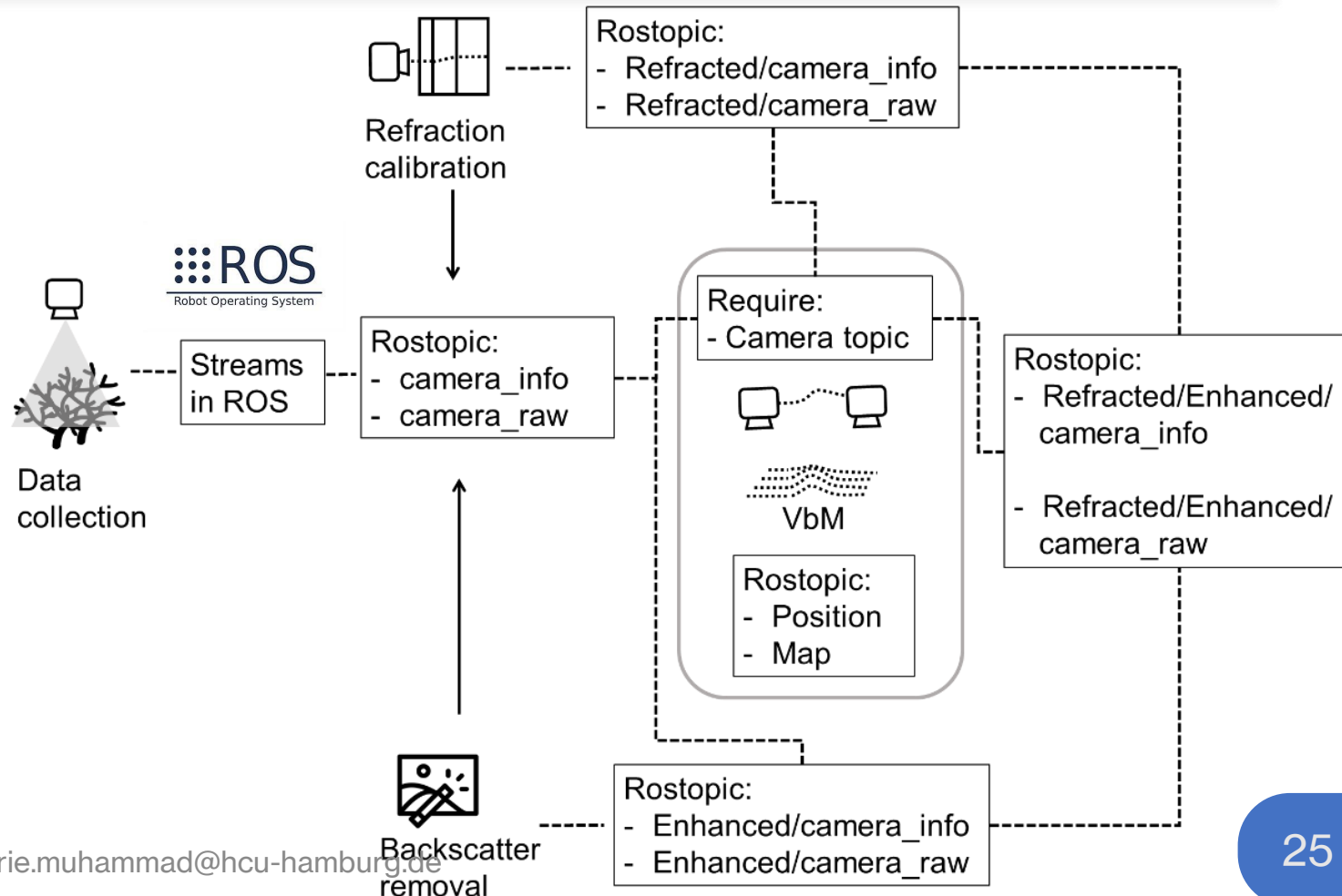
Undistort

Refraction



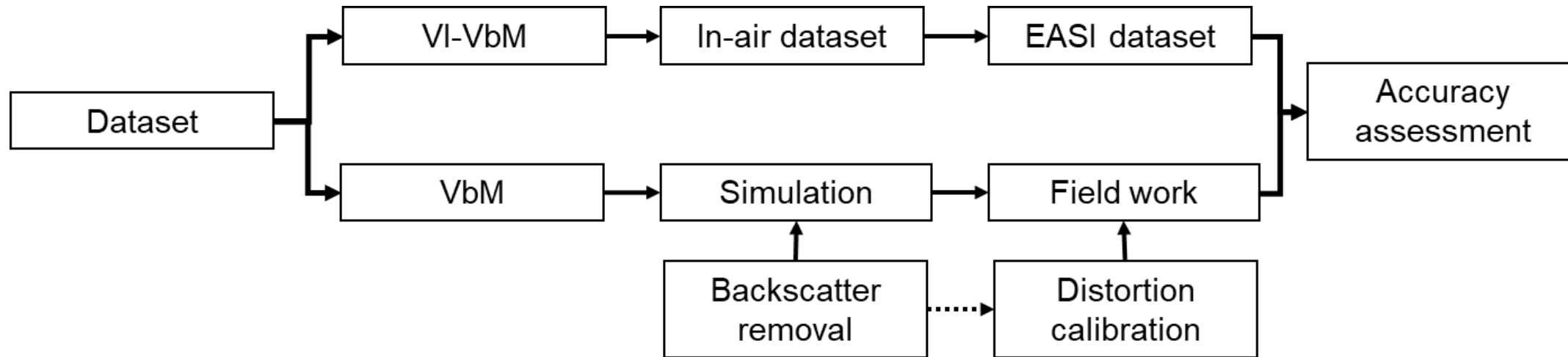
Methodology: Synthesis of Algorithm

- Initially, the VbM can utilize the original image stream (**camera_raw**) topic.
- The refraction adjustment and image enhancement shall also be computed and published in separate tasks due to underwater limitations.
- Refraction calibration is prioritized, as it is crucial due to the inherent refraction distortion underwater in VbM generating second image node (remapped as **Refracted/camera_raw**).
- The undistorted image serves as the input for image enhancement, producing a second output image topic (**Enhanced/camera_raw**)



Methodology: VbM

- The research is structured into three phases to evaluate the underwater VbM: simulation, fieldwork, and accuracy assessment

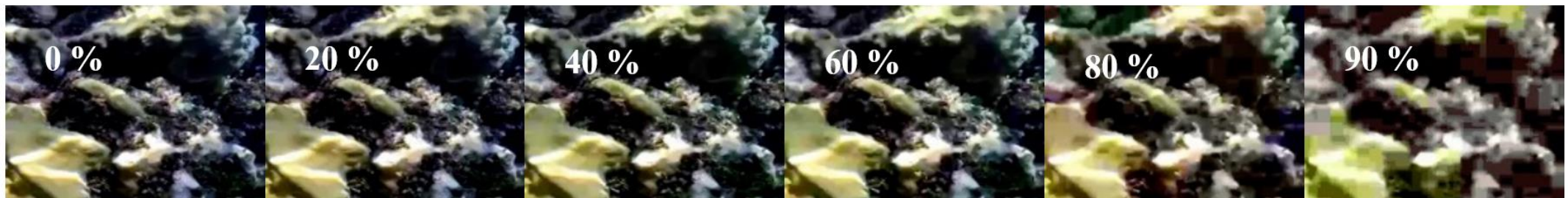


Research sequence

Methodology: Simulation

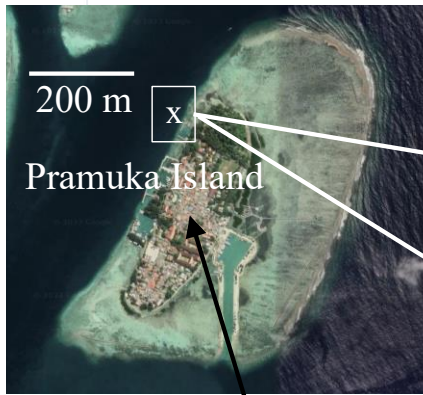


Simulation

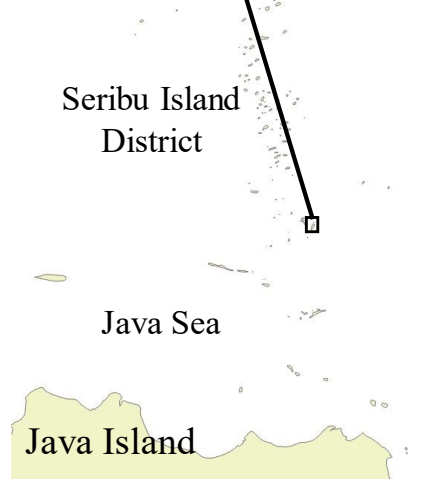


After backscatter removal

Methodology: Fieldwork



(1) The harbor pond dataset and
(2) The coral reef dataset



Data Article

Underwater imaging dataset in a very shallow water environment of Pramuka Island, Seribu Island District, Indonesia

Fickrie Muhammad^{a,*}, Poerbandono^a, Harald Sternberg^b,
Eka Djunarsjah^a, Hasanuddin Z. Abidin^c

^aHydrography Research Group, Faculty of Earth Sciences and Technology, Bandung Institute of Technology, Indonesia

^bDepartment of Hydrography and Geodesy, HafenCity University Hamburg, Germany

^cGeodesy Research Group, Faculty of Earth Sciences and Technology, Bandung Institute of Technology, Indonesia



ARTICLE INFO

Article history:
Received 5 June 2023
Revised 12 July 2023
Accepted 21 July 2023
Available online 26 July 2023

Dataset link: [Underwater Imaging Dataset in Near Shore Coral Reef Environments at Pramuka Island, Seribu Island District, Indonesia \(Original data\)](#)

Dataset link: [Underwater Imaging Dataset in Small Harbor Pond Bay at Pramuka Island, Seribu Island District, Indonesia \(Original data\)](#)

Keywords:
Computer vision
Ar-Track marker tracking
Underwater imagery
Natural seabed
Coral reef environment

ABSTRACT

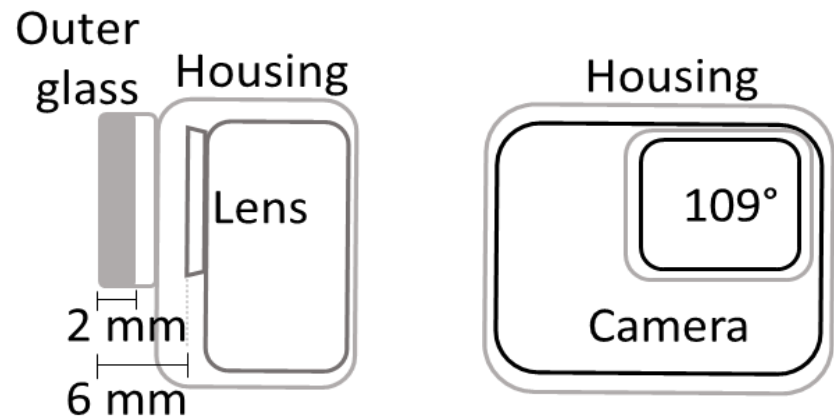
In this article, we present a dataset of underwater videos captured through manual dives in a complex and unstructured seabed area dominated by harbor structures and coral reefs. The area is shallow (0.5 – 7.0 m depth) with an enclosed embayment for the harbor area, offering protection from ocean currents and waves. The coral reef area is located in a more open ocean sloping gently toward the deeper seafloor, leading to a more pronounced rolling shutter effect and camera motion.

The dataset was collected using a GoPro Hero 10 camera, employing a standard wide lens with a horizontal field of view (FoV) of 109° and 768 × 432 image resolution. The camera is also equipped with an Inertial Measurement Unit (IMU) sensor, comprising a 200 Hz frequency accelerometer and gyroscope. During underwater deployment, the camera is protected with a 5 mm thick flat glass panel. This camera setting hence creates three medium layers of water-glass-air leading to additional refraction distortion.

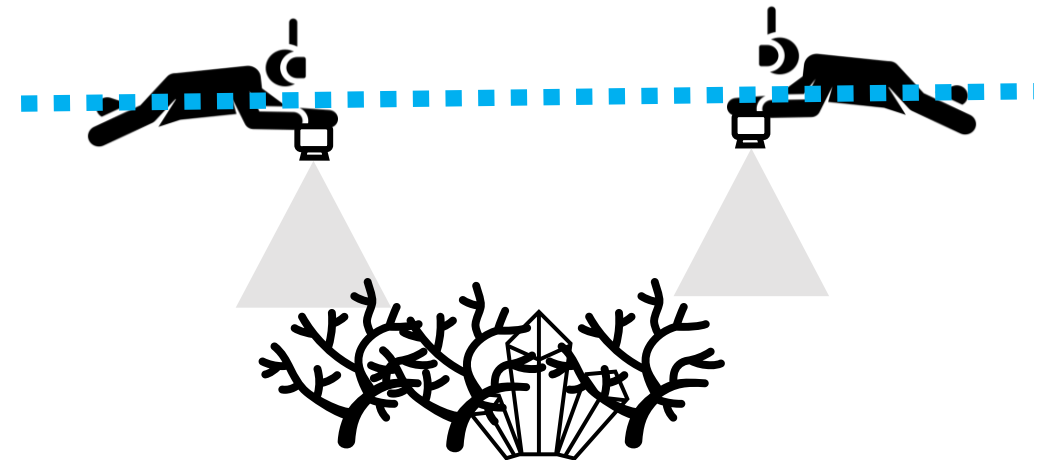
To address the refraction distortion, the dataset has been subject to pre-calibration utilizing flat refractive geometry found in the Pinax camera model. The Pinax camera model

Methodology: Fieldwork

Hardware



Survey

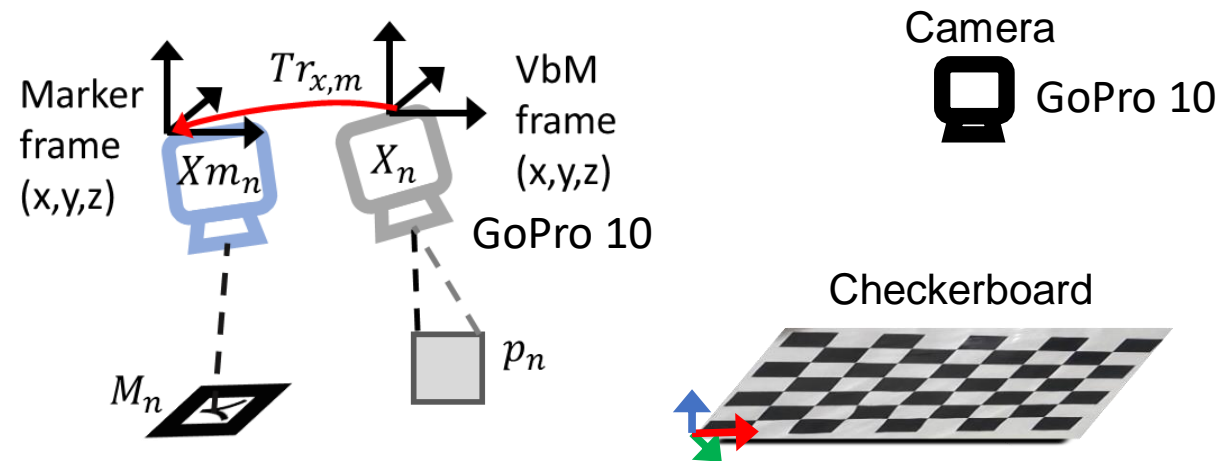


Fieldwork dataset



Methodology: Accuracy Assessment

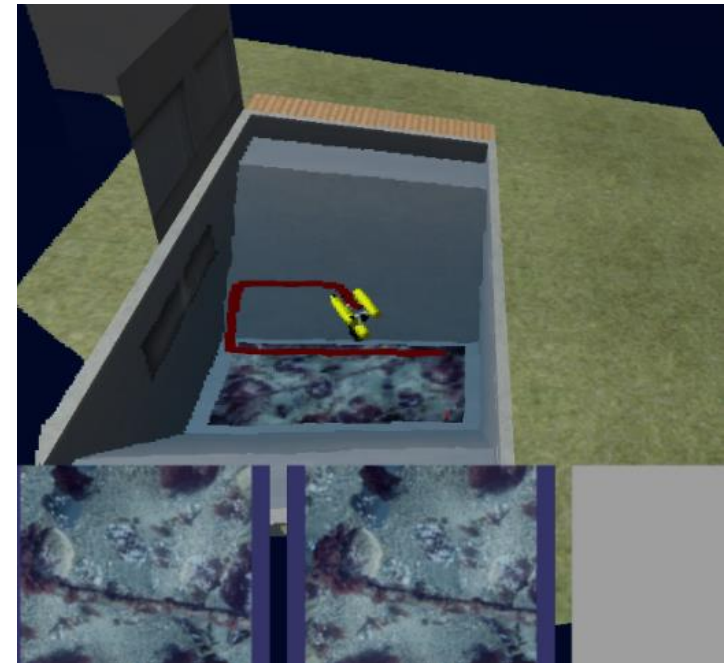
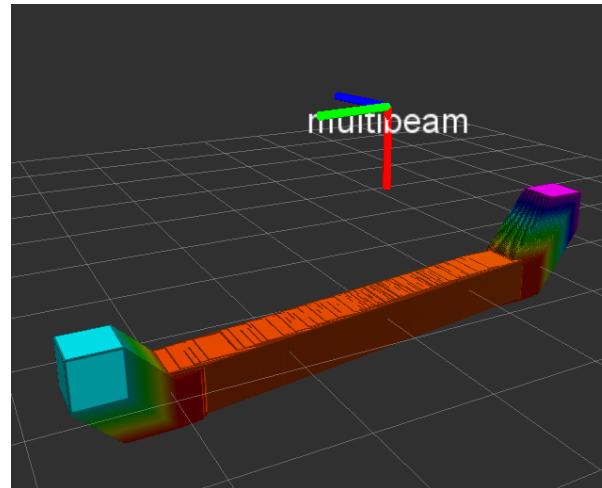
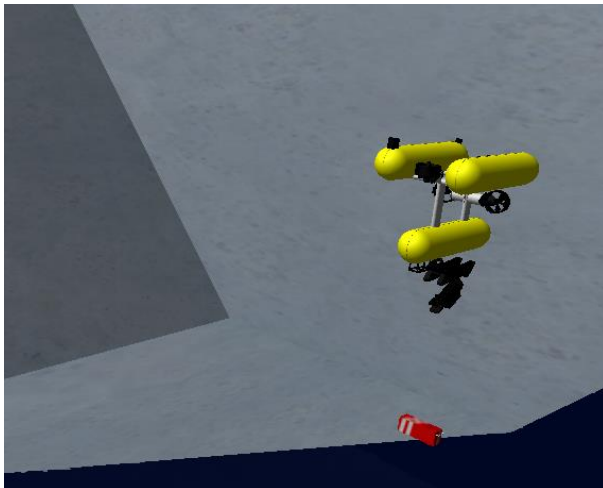
Field work dataset



- Marker tracking
- Checkerboard measurement

Methodology: Accuracy Assessment

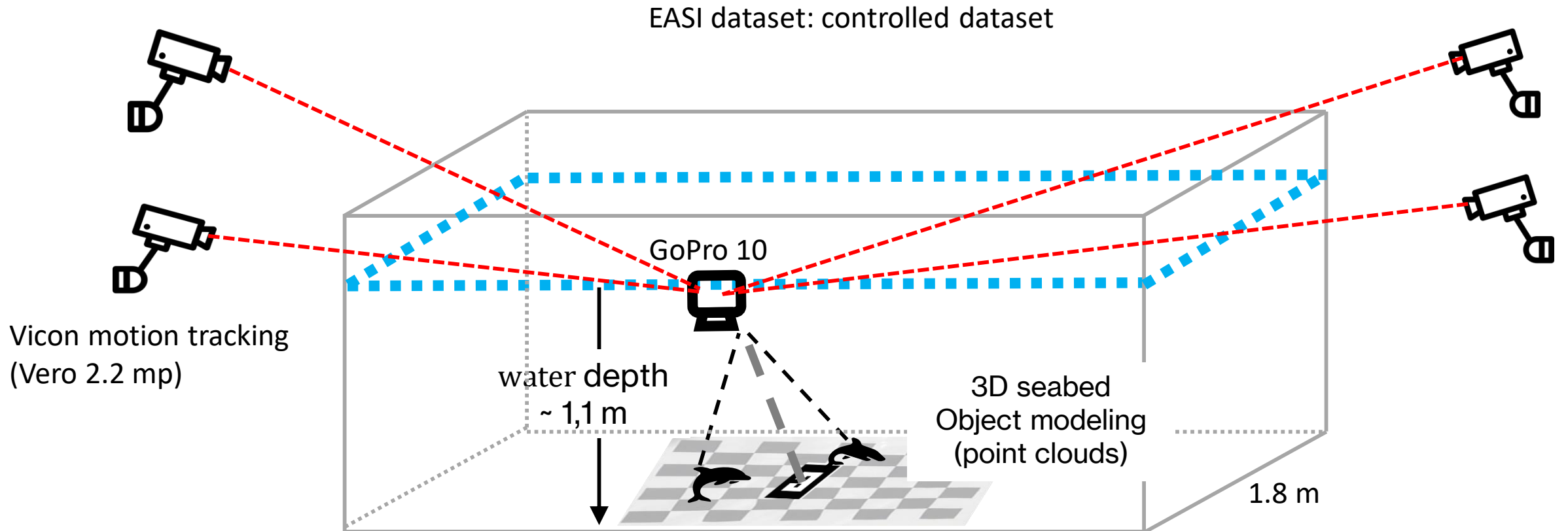
Simulation dataset



The Girona 500 AUV :

- GNSS
- IMU
- Camera
- MBES

Methodology: Accuracy Assessment



3. Discussion

Interpretation of results, conclusion, and remarks

Image Enhancement

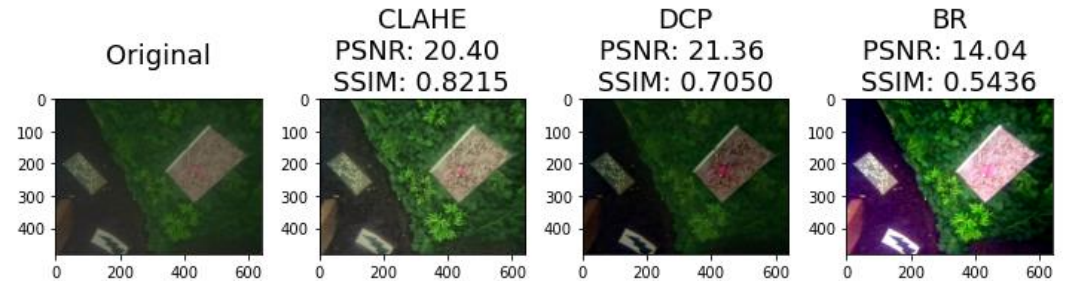
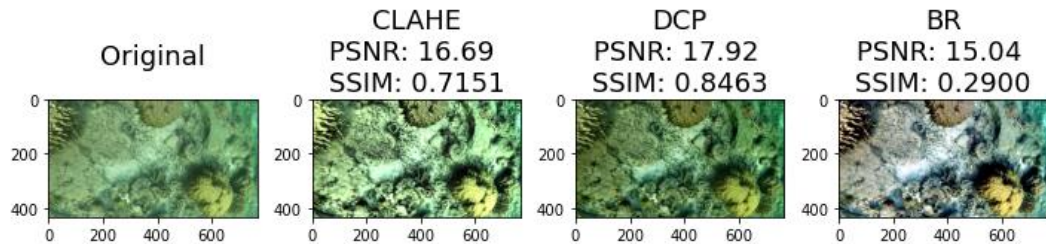
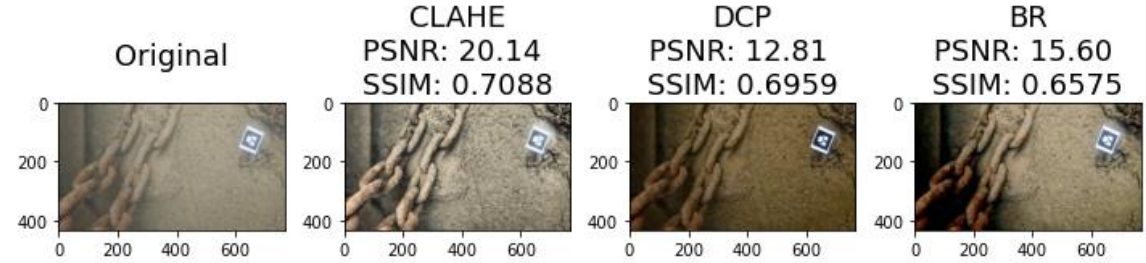
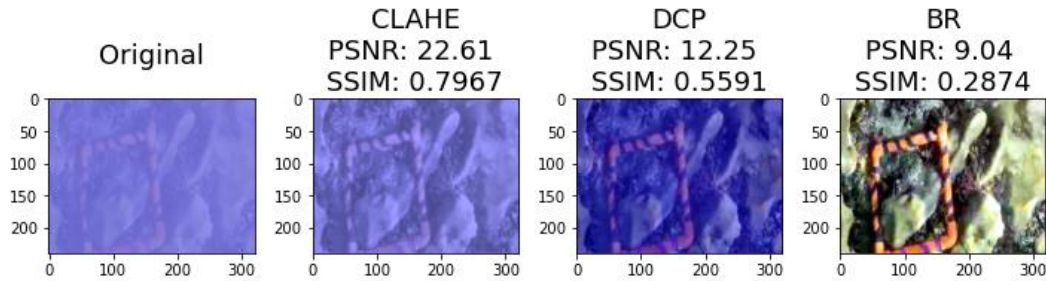
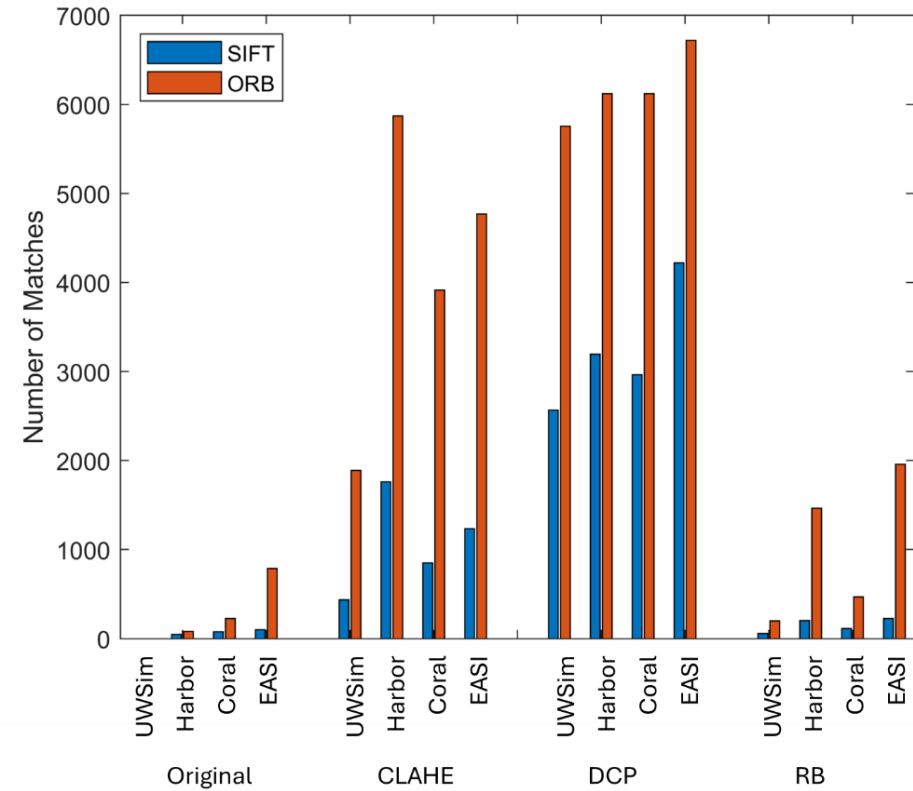
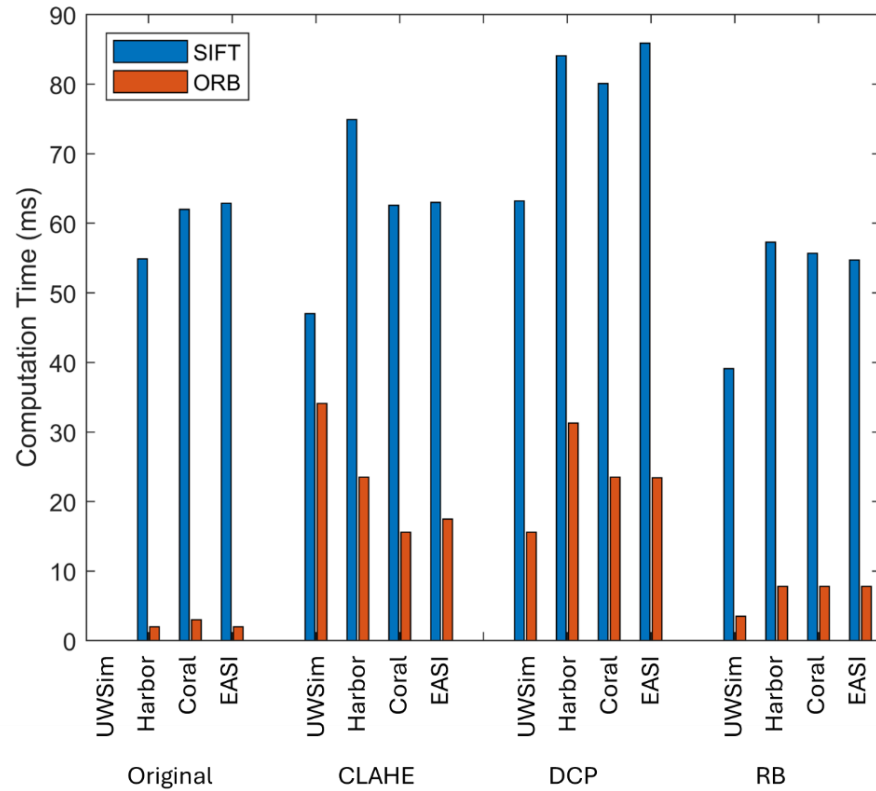
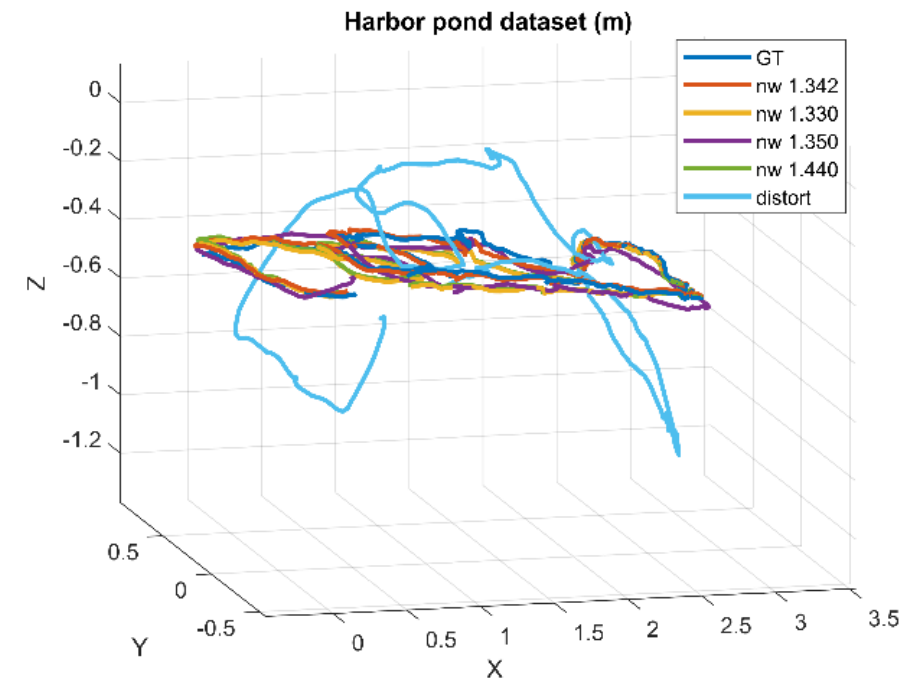
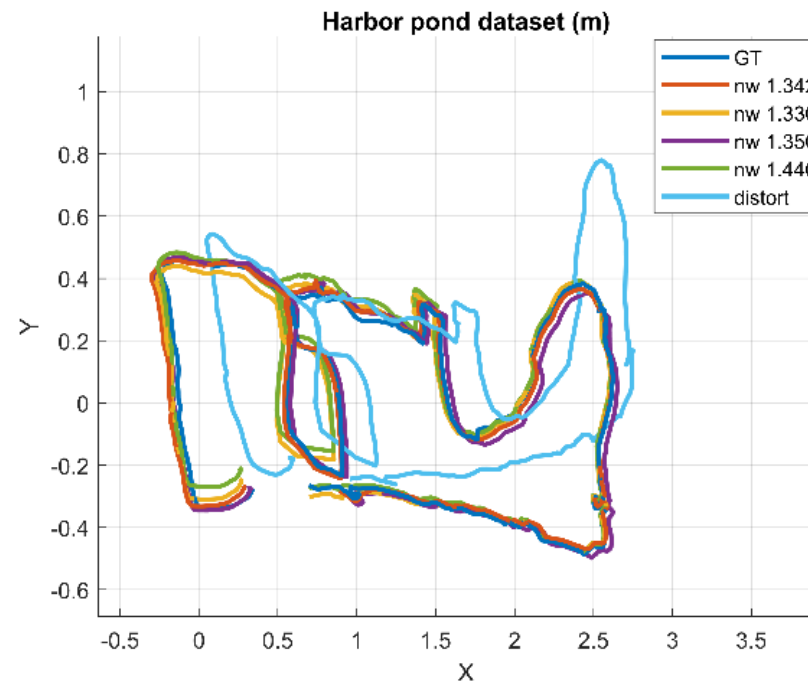


Image Enhancement



Calibration: Refraction Index Sensitivity

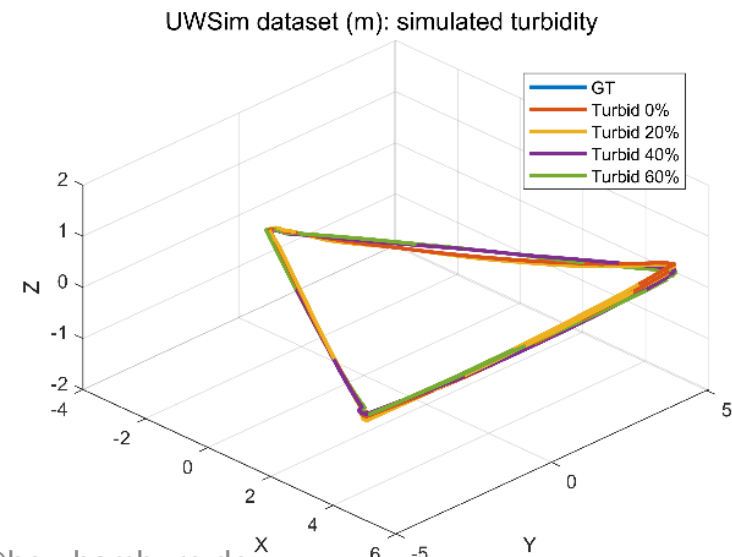
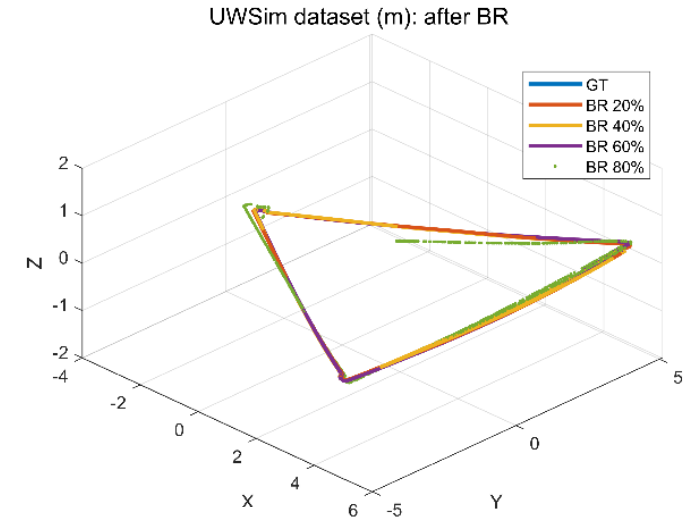
- Additional tests are run using varying salinity inputs from 1.330 to 1.350, with seawater salinity ranging from 3.5 to 27 percent.
- Results show that the Absolute Trajectory Error (ATE) is less than 5 cm.
- This suggests that even in regions with fluctuating salinity levels, VbM can still produce comparable results.



Experiment: UWSim Dataset

UWSim Dataset

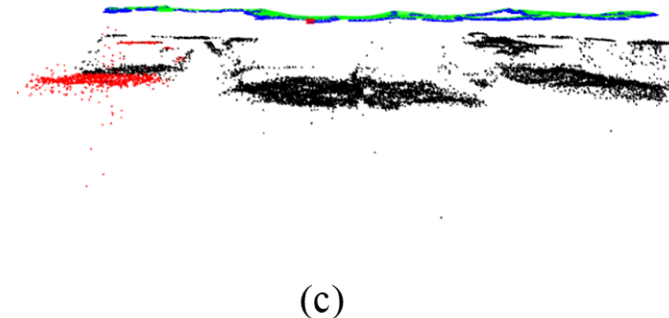
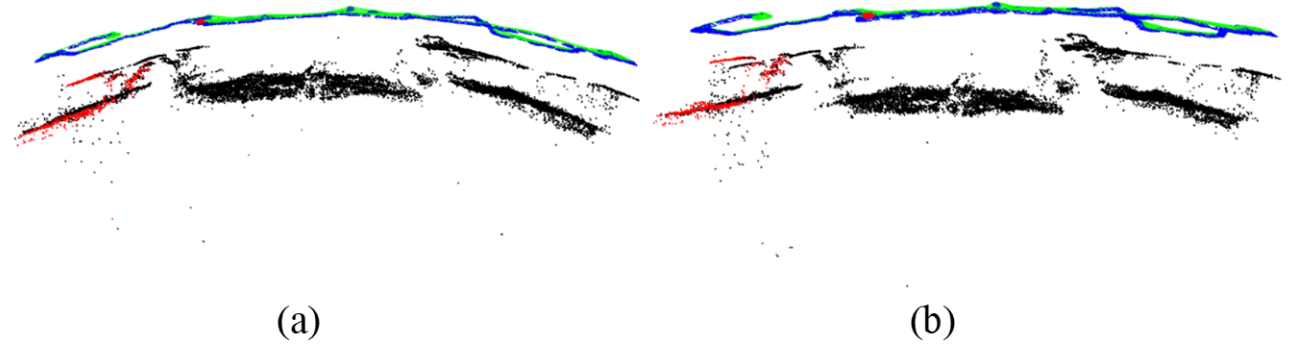
- BR image enhancement significantly increases feature matches from approximately 100 to between 500 and 700.
- At 80% turbidity, the VbM system loses tracking after 126 seconds out of a 284-second image stream, covering 44.4% of the trajectory, hindering loop closure and drift minimization.
- The VbM system maintains radial errors below 0.2 meters in up to 60% turbidity over a 56.27-meter track.
- At 80% turbidity, image enhancement aids in regaining feature detection, but accumulated drift increases radial error to 0.5 meters, resulting in a 0.7% overall track error rate.



Experiment: Harbor Pond Dataset

Experiment: Harbor Pond Dataset

- The in-air and underwater calibration is not suitable for larger areas where **the distortion bowing-effect (frown-shaped)** is detected
- The bowing effect is pronounced in the direct calibration input primarily because the wide image format retains more distortion along the image edges and the refraction effect
- However, the longer the track is, the more error will be accumulated with this setup

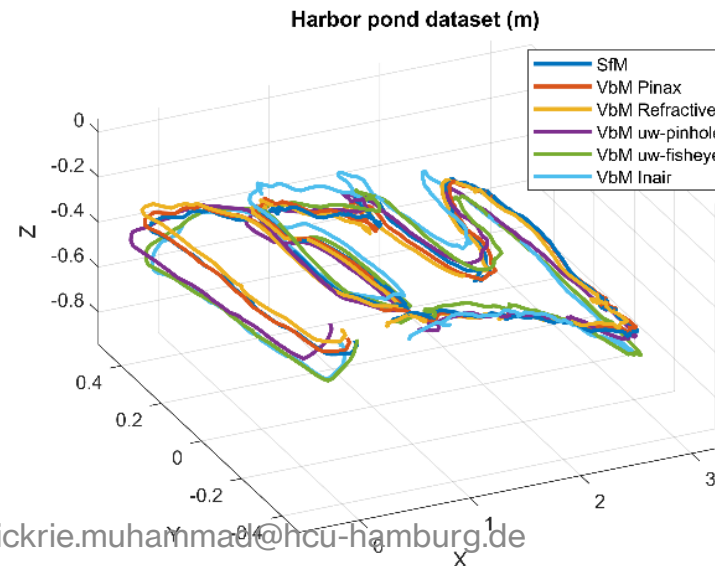


(a) In air calibration (b) Underwater calibration
(c) Pinax calibration

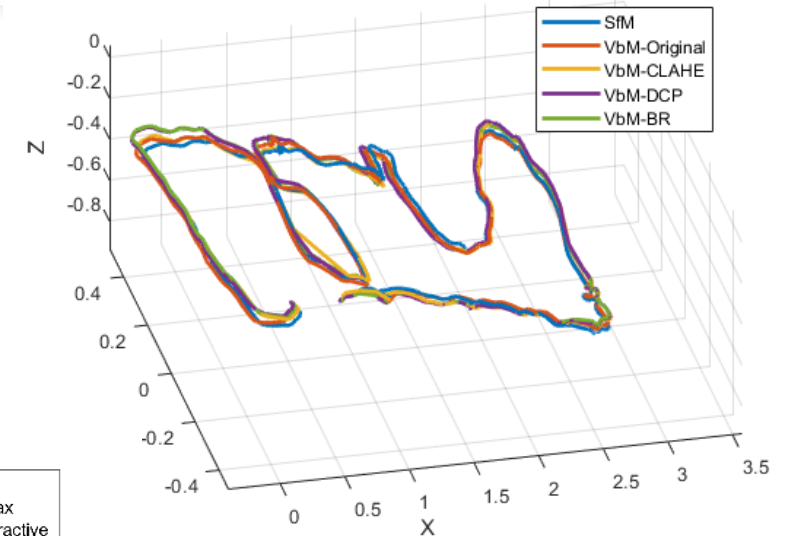
Experiment: Harbor Pond Dataset

- The bowing effect negatively impacts trajectory optimization during global bundle adjustments, causing significant scaling errors.
- Using the VbM system with Pinax calibration, the harbor pond dataset shows radial errors within 5 centimeters.
- Underwater calibration techniques result in higher radial errors, ranging between 10 and 15 centimeters.

Calibration



Harbor pond dataset (m)

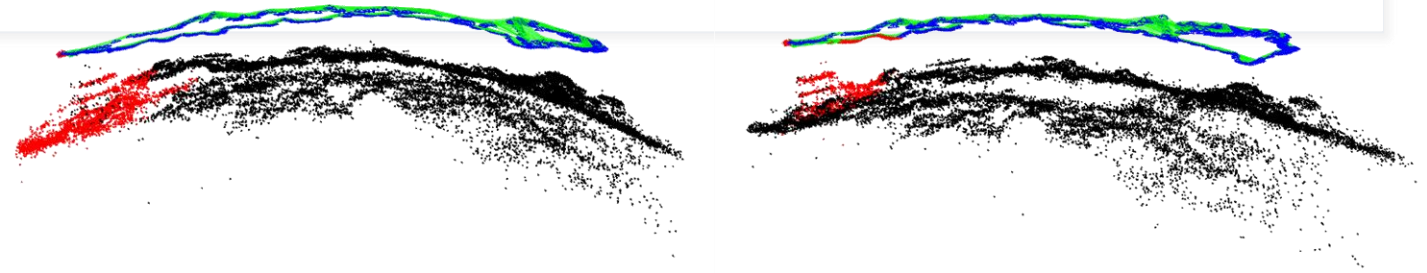


Pinax + Image enhancement

Experiment: Coral Reef Dataset

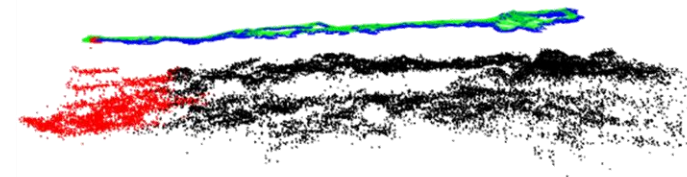
Experiment: Coral Reef Dataset

- The VbM in this experiment is able to run at 80 FPS and generate total 444 Keyframes during the VbM running.
- The area coverage is approximately 4 x 6 mm wide making the algorithm detect more seabed objects during the VbM run
- It is noticed that the accumulated error as bowing effect (**frown-shaped**) is increasing greatly in parallel with the track length



(a)

(b)

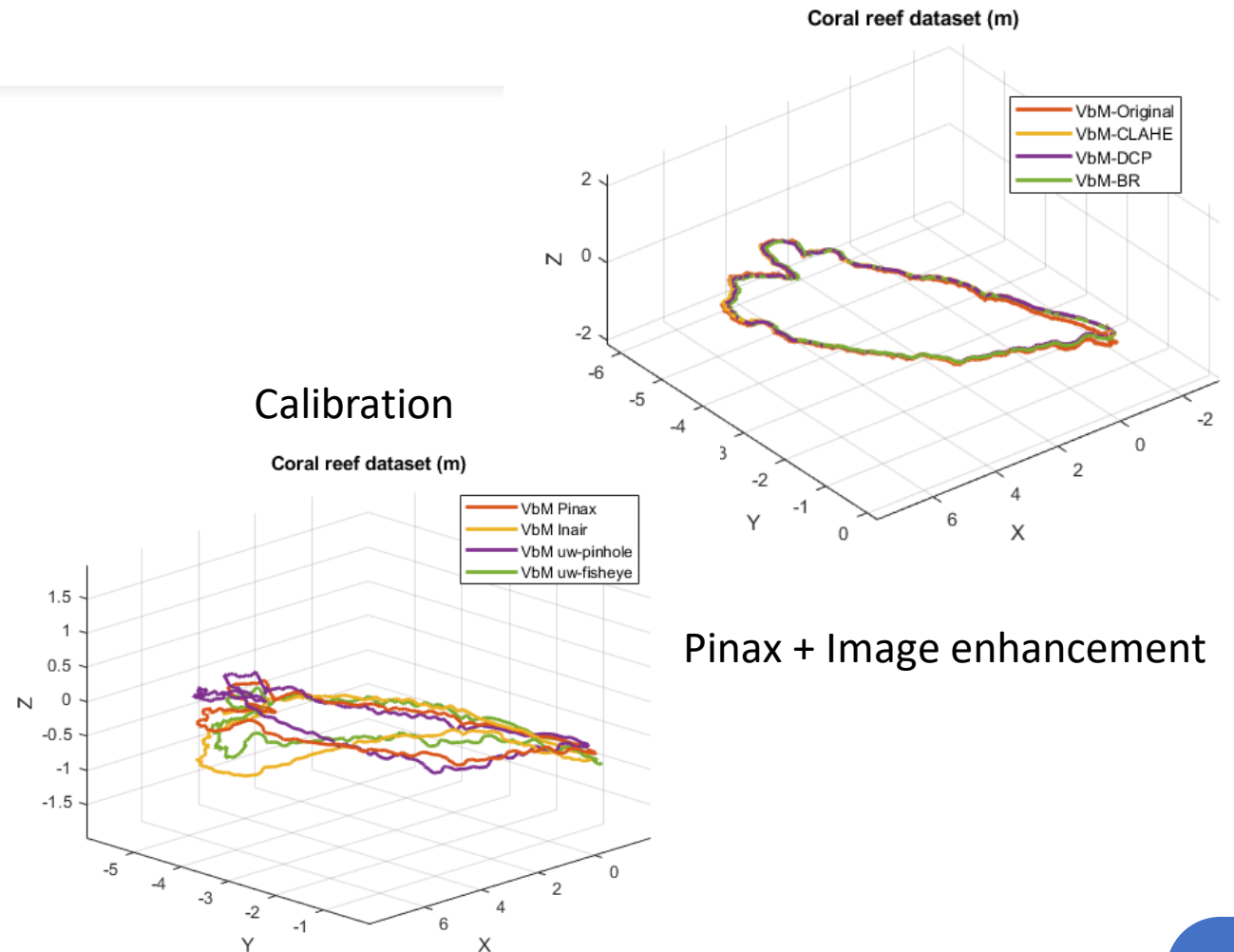


(c)

(a) In air calibration (b) Underwater calibration (c) Pinax calibration

Experiment: Coral Reef Dataset

- Image enhancement is applied to the coral reef dataset and used with distortion calibration to obtain the final VbM trajectory.
- The VbM with refractive Pinax calibration model is preferred for alignment due to less distortion.
- Direct calibration in the coral reef dataset reveals radial errors up to 0.6 meters compared to the Pinax-calibrated trajectory.
- Initial errors persist in the dataset due to reliance on SfM for scaling the VbM trajectory.
- The absence of a loop-closing function in SfM contributes to these inaccuracies, highlighting the need for this feature to improve precision.

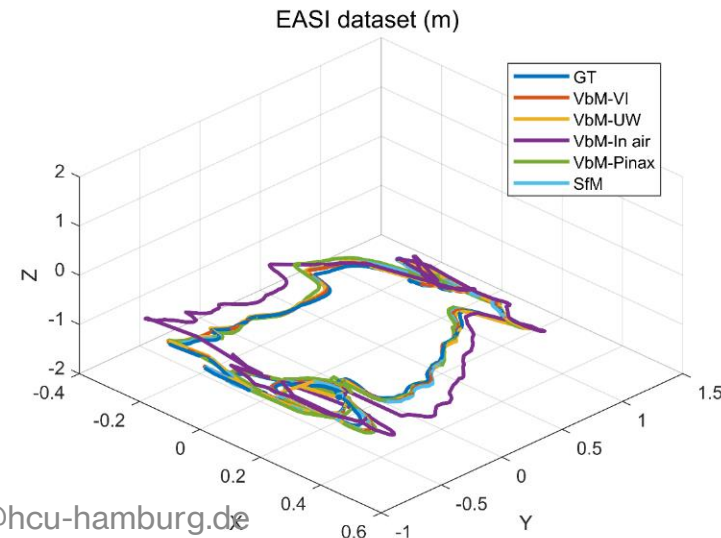
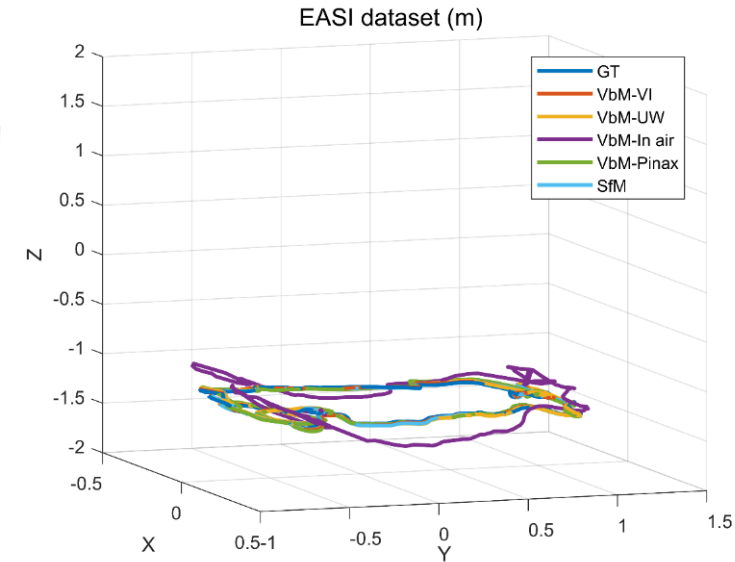


Pinax + Image enhancement

Experiment: Visual-Inertial Dataset

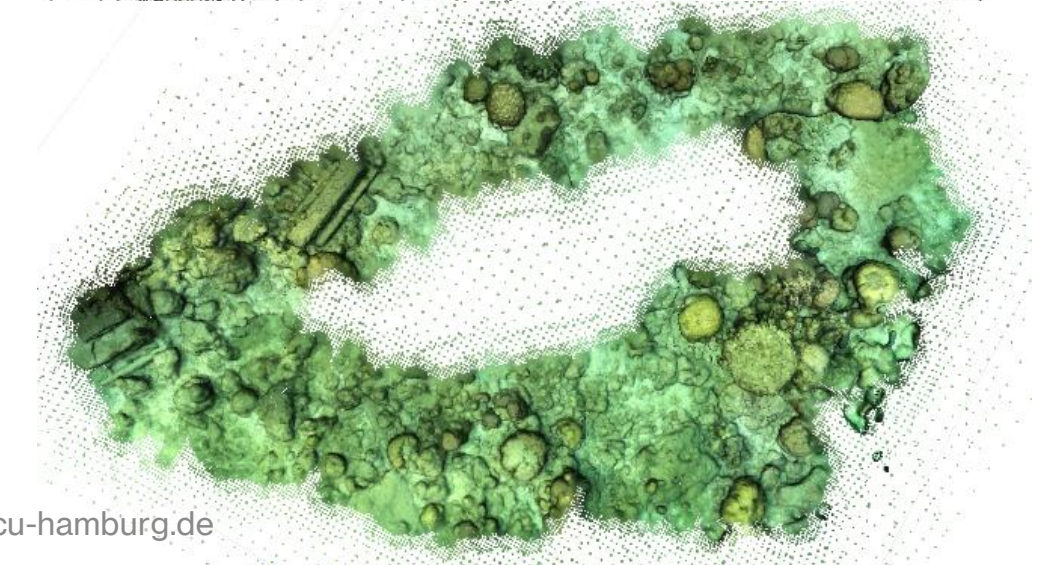
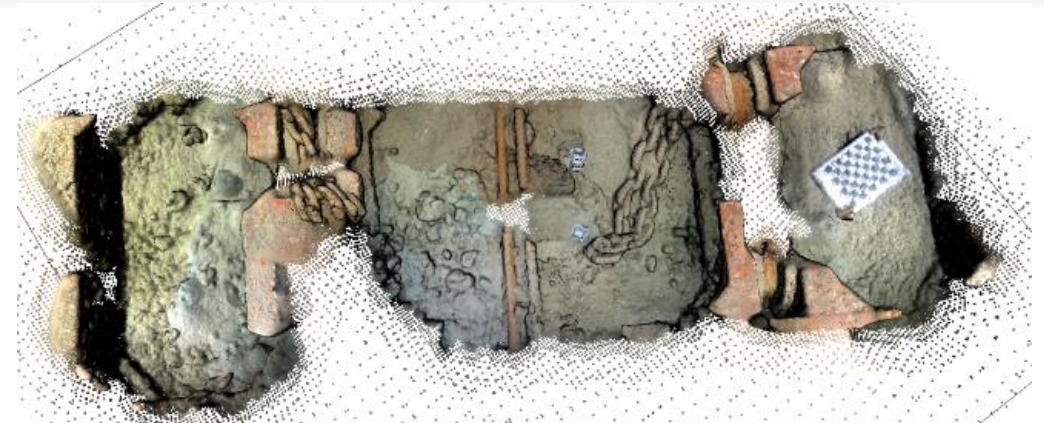
EASI Dataset: visual-inertial

- In-air calibration fails to correct the bowing effect caused by refraction.
- Direct underwater and refractive Pinax calibration yield comparable trajectories.
- In-air calibration produces the largest error, up to 25 cm or 3% of the total trajectory length.
- Underwater and Pinax calibration inputs achieve similar accuracy with errors less than 10 cm or 1%.



Dense Reconstruction

Dense Reconstruction



Dense Reconstruction



Clustering Views for Multi-View Stereo (CMVS)

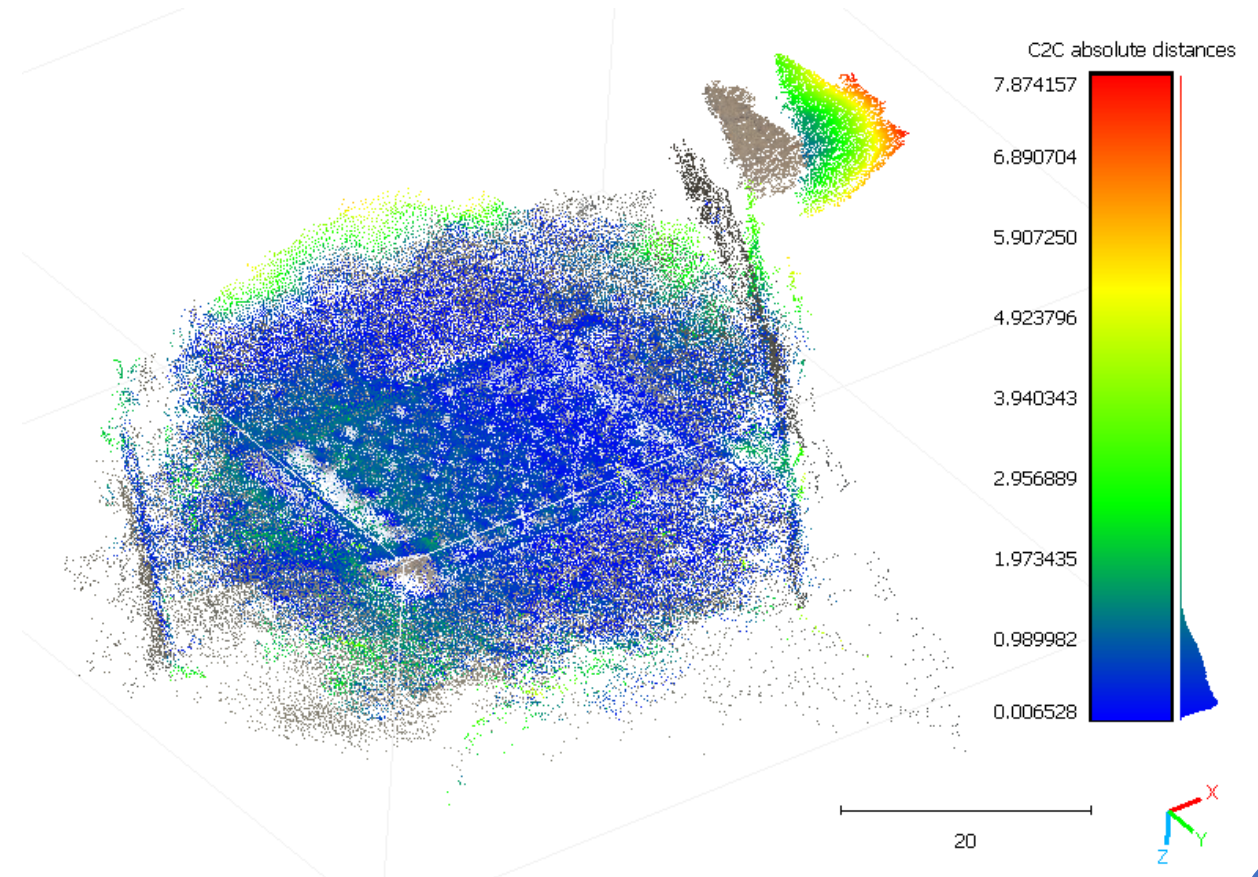
Poisson filter



Point Cloud Assessment

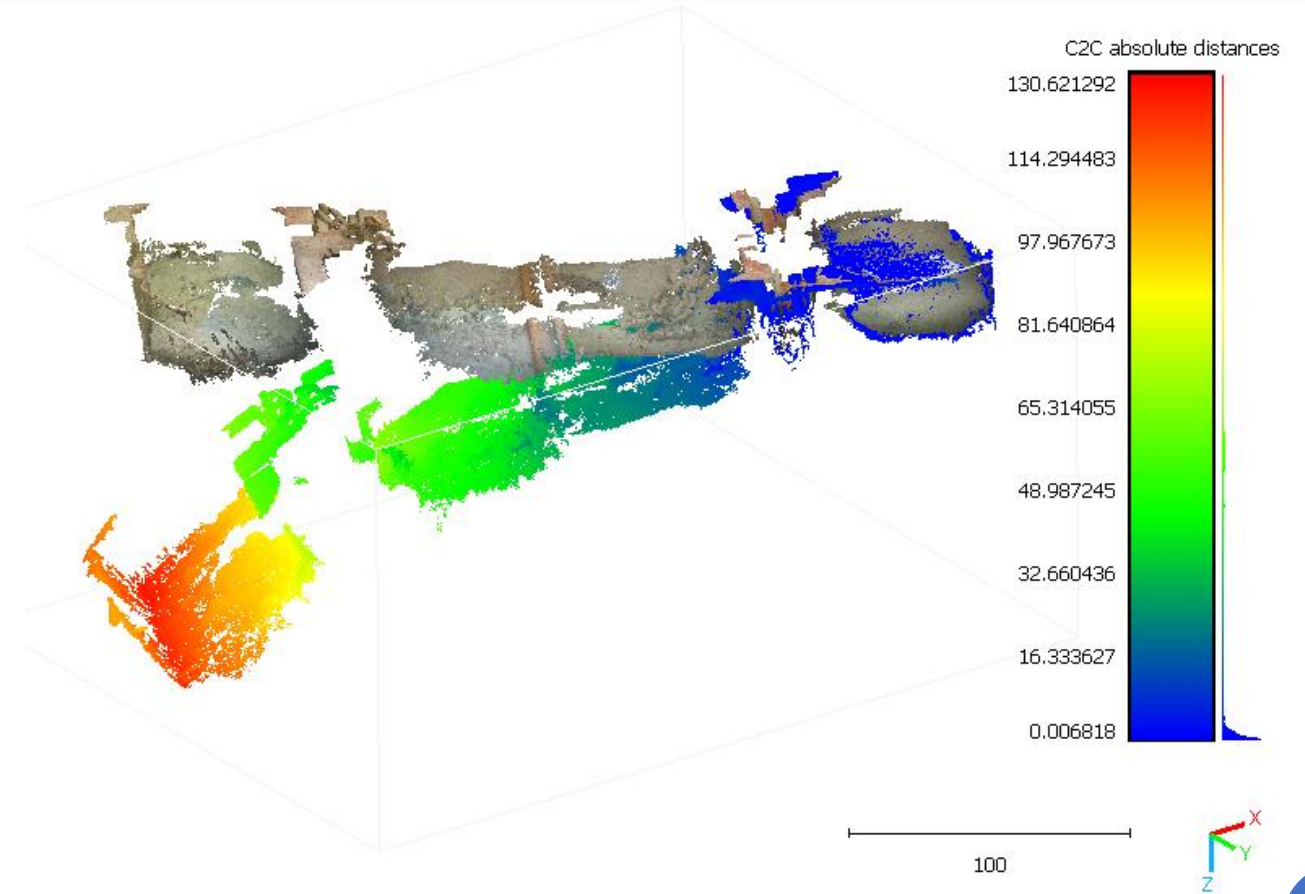
Harbor Pond Dataset

- Small-scale reconstructions show similar models without bowing effects
- Centimeter-level differences is spotted, with a maximum of 8 cm with continuous scanning



Harbor Pond Dataset

When the same features aren't consistently detected across images, pronounced bowing effects lead to up to 1.3 m discrepancies.





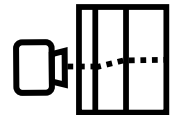
Conclusion

Conclusion

- Underwater environments present significant challenges for Vision-based Mapping (VbM) due to scattering and light attenuation.
- **Backscatter Removal (BR)** Algorithm: Outperforms CLAHE and DCP in feature detection, effectively adjusting contrast, removing haze, and correcting color, effective up to 90% turbidity but struggles with suspended particles.
- **Limitations:** High computational load, causing lag in real-time applications.
- The **automatic calibration** with **Pinax** method outperforms the conventional approach, particularly in the presence of radial, tangential, bowing distortion due to medium differences.
- Visual-inertial integration provides metric positioning with centimeter level error (less than 10 cm)
- In contrast, VbM using **SLAM** is capable of continuing its positioning along the track until it reaches the original position, allowing for the correction of all positions along the track through **the loop-closing** function
- Real-time processing achieved by integrating with the **Robot Operating System (ROS)**, dividing tasks for efficient load management.



Backscatter
removal

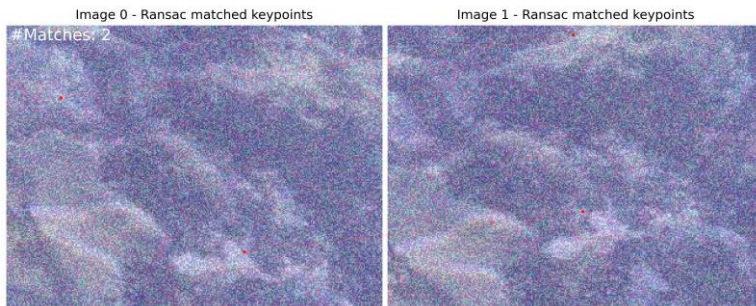


Refraction
calibration

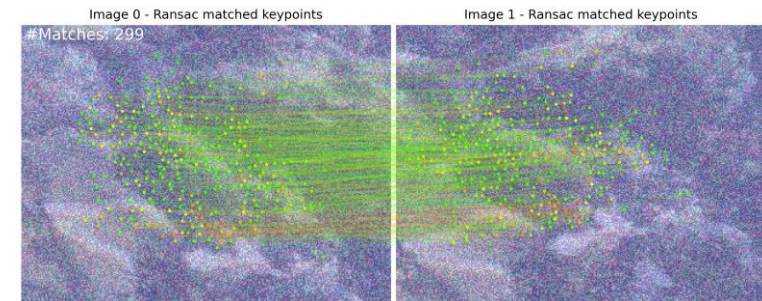
 **ROS**
Robot Operating System

Remarks: Deep learning for feature detection and matching

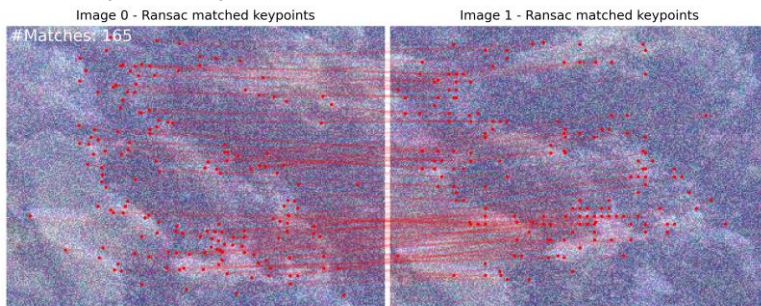
Conventional (Sift)



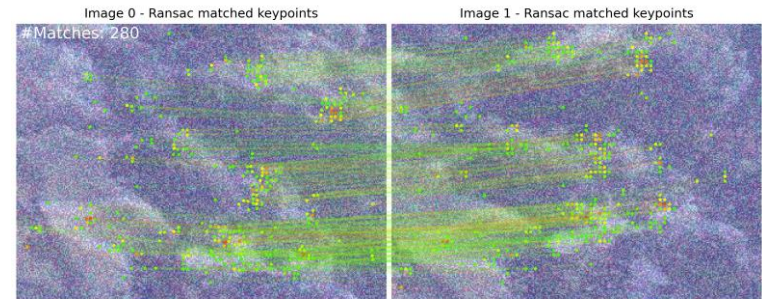
DL (Disk+lightglue)



DL (Xfeat)

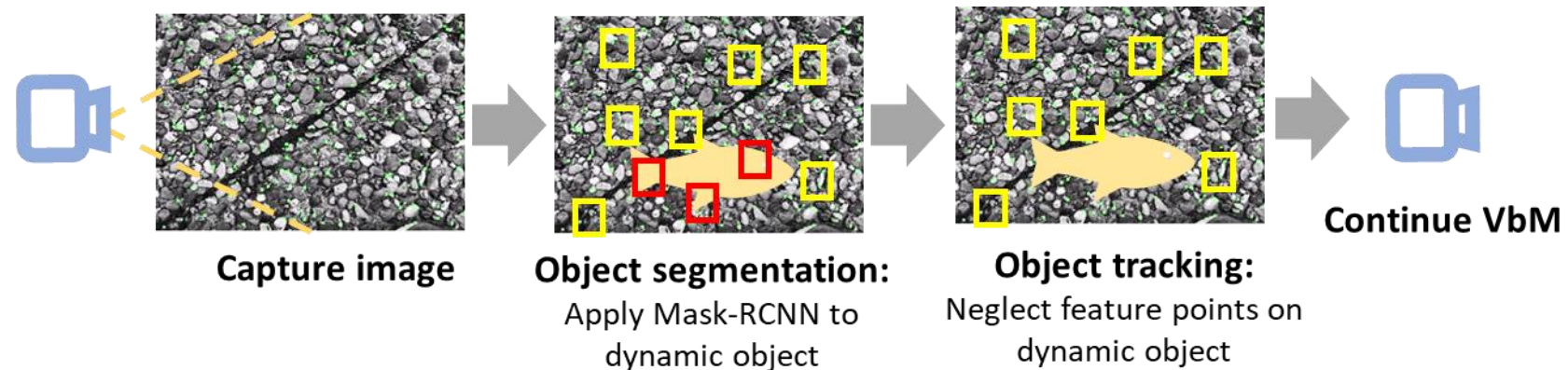


DL (LoFTR)



Remarks: Semantic segmentation of dynamic objects

Architecture of semantic VbM with dynamic and static object classification. The feature points that lie on dynamic objects drawn in red will be neglected when estimating the camera position.



Thank You



hcu HafenCity
Universität
Hamburg

DAAD
Deutscher Akademischer Austausch Dienst
German Academic Exchange Service