Water Surface Level Estimation Based on the Fast Segment Anything Model for Coastal Monitoring Systems

Presented by

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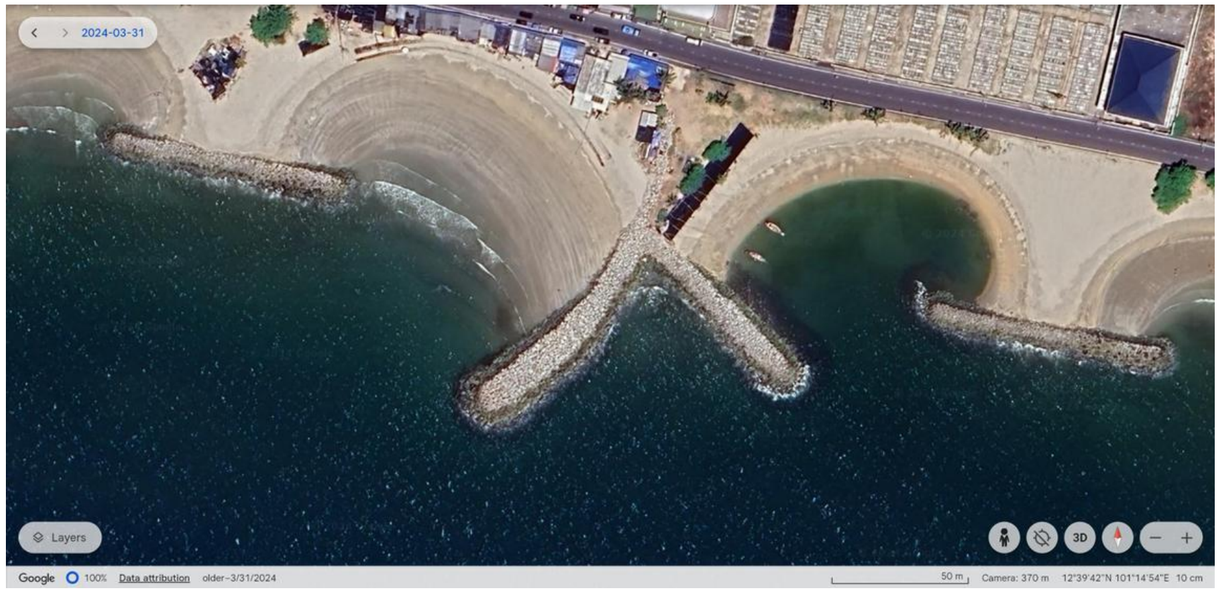
Outline

1. Background
2. Proposed Method
3. Experiment, Result, and Evaluation
4. Discussion and Conclusion

Background

Coastal Erosion



Source: Google Earth Satellite Image

Thailand

- 66 M population, 77 Provinces
- ~21 M population living in the coastal area (23 coastal provinces)
- ~3150 km shore-line
- Critical Area: 16 Province with >5m erosion per year especially around the Gulf of Thailand

Background

Preventive Protection Measure

Artificial Mangrove Root

Break Water Barrier

G-Aoss

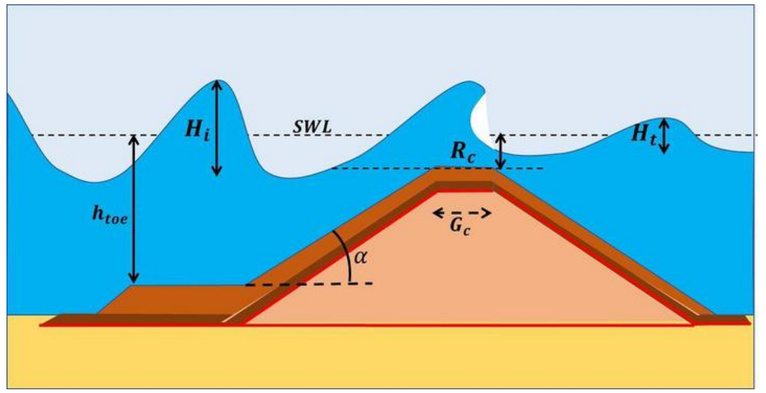
Bamboo fend

How effective are these construction in costal erosion prevention?

Background

Transmission Coefficient (T)

$$T = \frac{H_t}{H_i}$$



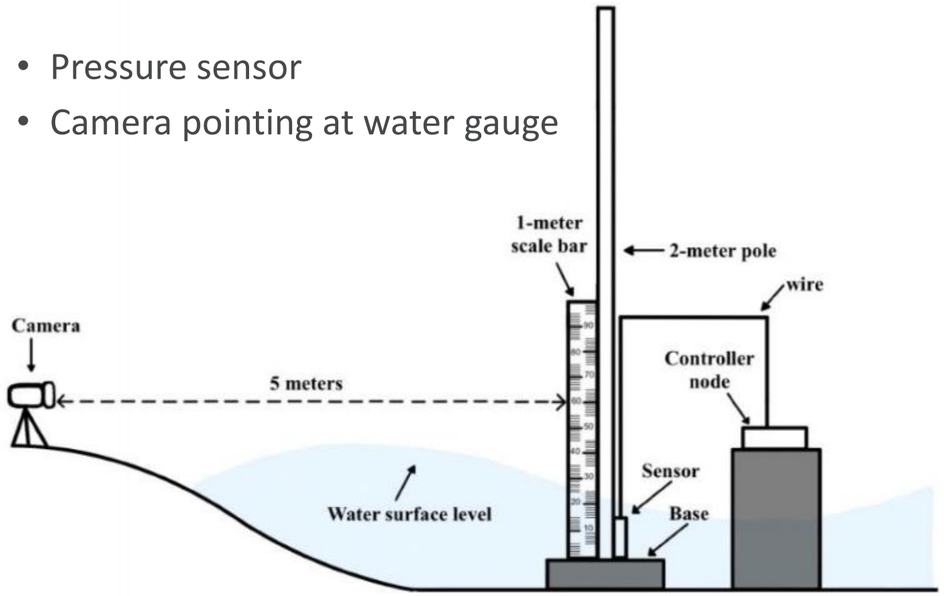
H_t = wave height after passing through or around the breakwater

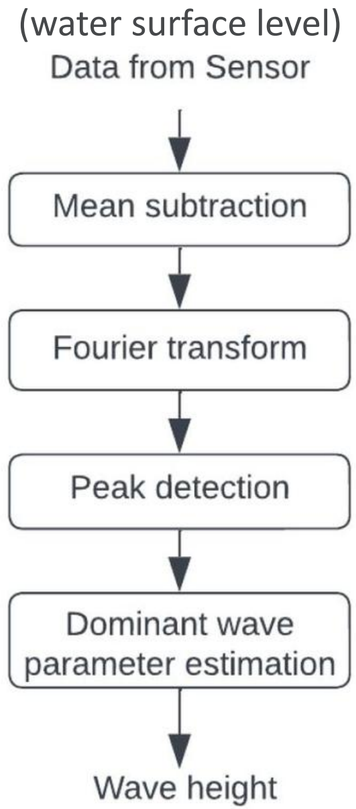
H_i = wave height before hitting the breakwater

Hence, being able to estimate precise wave height is very crucial in measuring the effectiveness of the breakwater barrier

Previous Experiment Setup to Find the Wave Height

- Pressure sensor
- Camera pointing at water gauge





In the previous setup, to compare the sensor data and the ground truth data from the video camera we need to manually labeled each frame by hand

Background

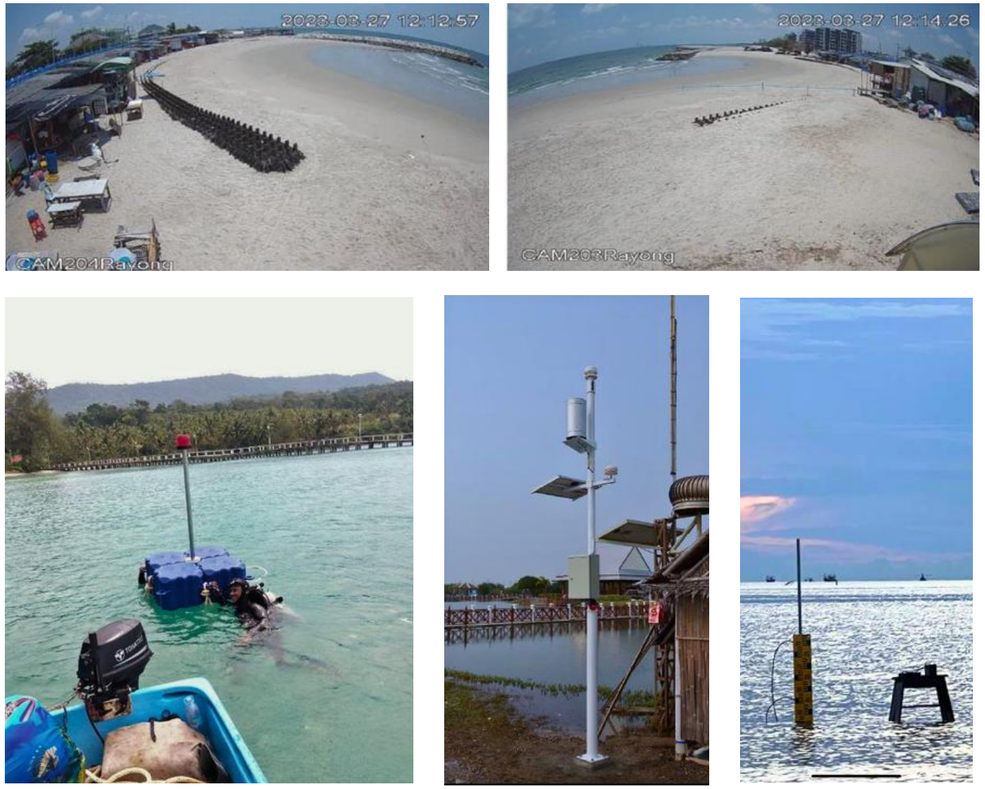
Currently, there is no research to estimate the wave height of flexible low-crested breakwaters in the shore area

Objective: Develop a method to automatically calculate the wave height at the shore area using time-series data

Background

Our Impact

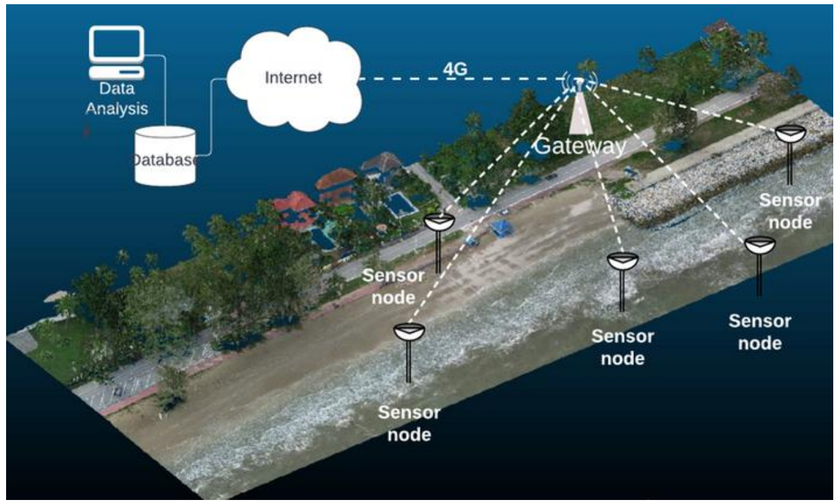
1. Site without sensor but have camera could implement our method
2. Site with existing sensor could use our method to verify/calibrate the sensor
3. Use our method to automate the process of obtaining ground truth



Background

Sensor Node Development: A project of ASEAN IVO 2024

Global ICT R&D alliance in the ASEAN region and Japan.



Coastal Erosion Monitoring Platform Based on Wireless Sensor Networks and 3D Point Clouds from Airborne LiDAR

Collaborate between 4 countries to study changes in coastal area.

Background

Location

Moonlight Beach (Seang Chan Beach)
Rayong province, Thailand

Background

We need a segmentation model
to segment the water gauge from the video frame

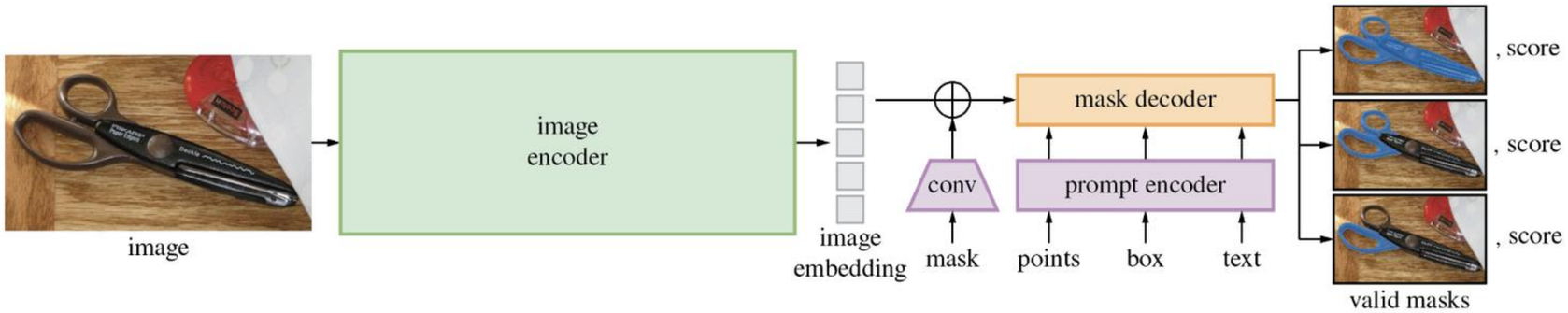
Requirements

- Near real-time speed for segmentation
- High accuracy with less artifact
- Resource efficient

⟵ Our target water gauge,
is just a square fixed in place

Background

Candidate: SAM (Segment Anything Model)



Model	Size (MB)	Parameters (M)	Speed (CPU) (ms/im)
Meta SAM-b	358	94.7	51096
MobileSAM	40.7	10.1	46122
FastSAM-s with YOLOv8 backbone	23.7	11.8	115

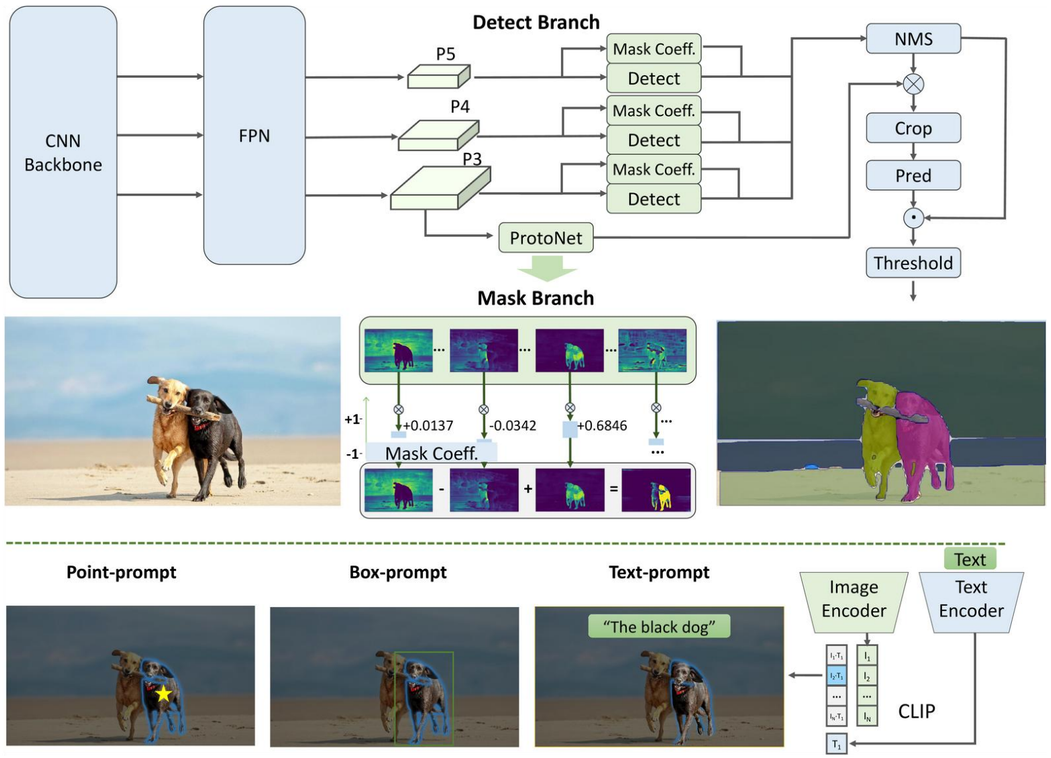
- Produce great result
- Take couple of seconds to process each frame using SAM on our RTX4060 laptop GPU

Source: https://docs.ultralytics.com/models/sam/

Source: https://blog.roboflow.com/segment-anything-breakdown/

Background

Candidate: FastSAM



Source: CASIA-IVA-Lab. "FastSAM Overview." GitHub, 2023.

- Produce similar result as SAM (sometimes a little better in our case)
- Process really fast (milliseconds) using RTX4060 laptop GPU

Background

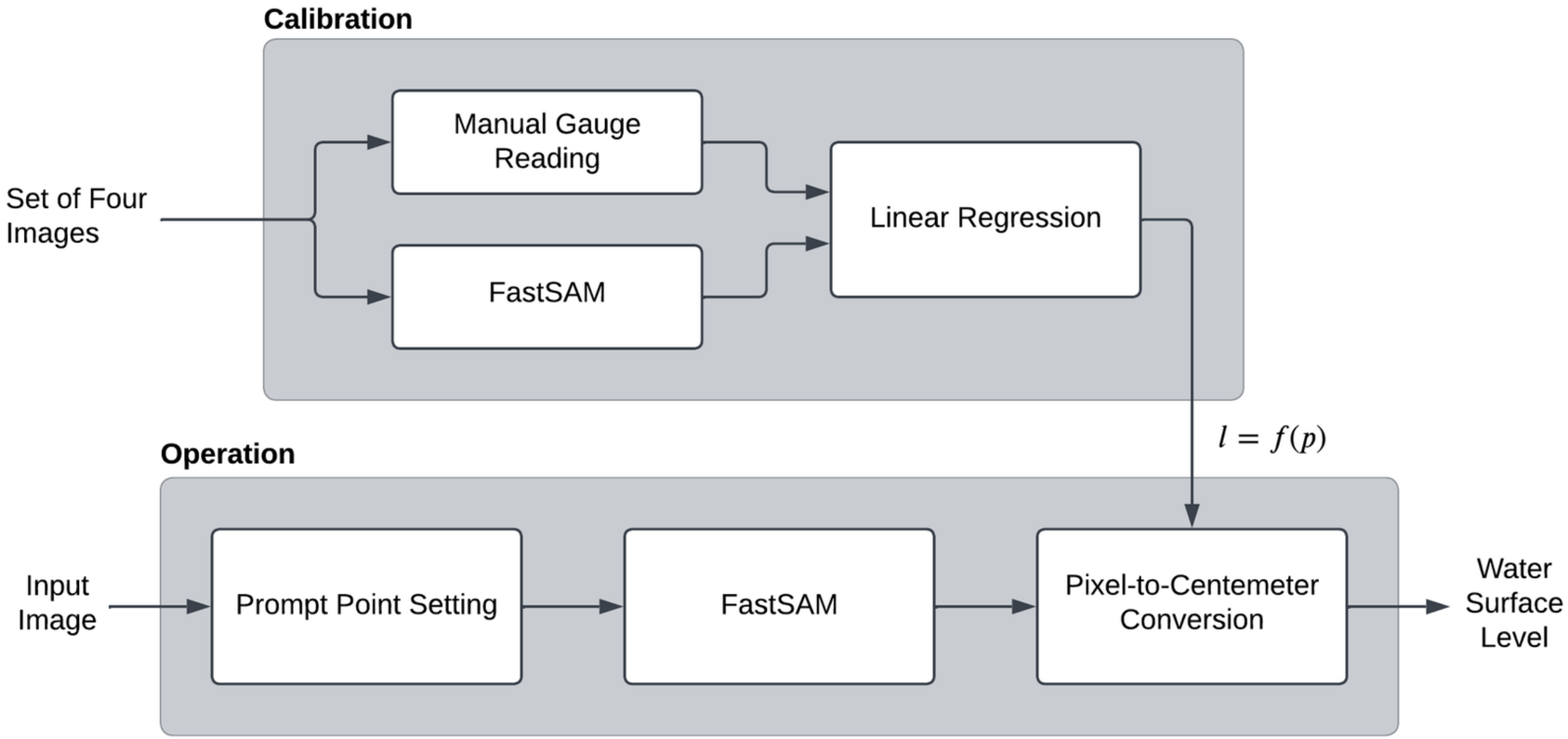
Performance Analysis: FastSAM-x vs FastSAM-s

Features \ Models	**FastSAM-x** (72.2M parameters)	**FastSAM-s** (11.8M parameters)
Artifact Produce*	More Artifact	Less Artifact
Computational Resource Used	More resource	Less resource

*When apply to our data FastSAM-x (larger model) sometimes overshooting the water gauge segmentation boundary while FastSAM-s doesn't have this issue

Proposed Method

Framework

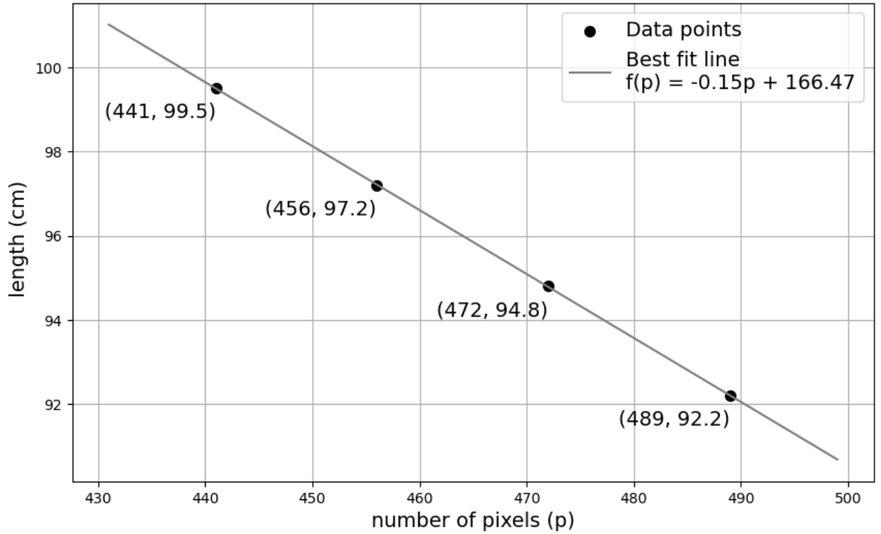


Proposed Method

Framework

4 Random Frames from the video

Manual Observation



FastSAM

Mask obtain through a point prompted FastSAM

Proposed Method

From what we observed in the real data the deviation observed is negligible enough to use linear equation.

$$f(x,\theta) = e_0 \left(\frac{x \sin\left(\theta + \frac{\pi}{2}\right)}{fov + d + x\cos\left(\theta + \frac{\pi}{2}\right)} \right) d + bias$$

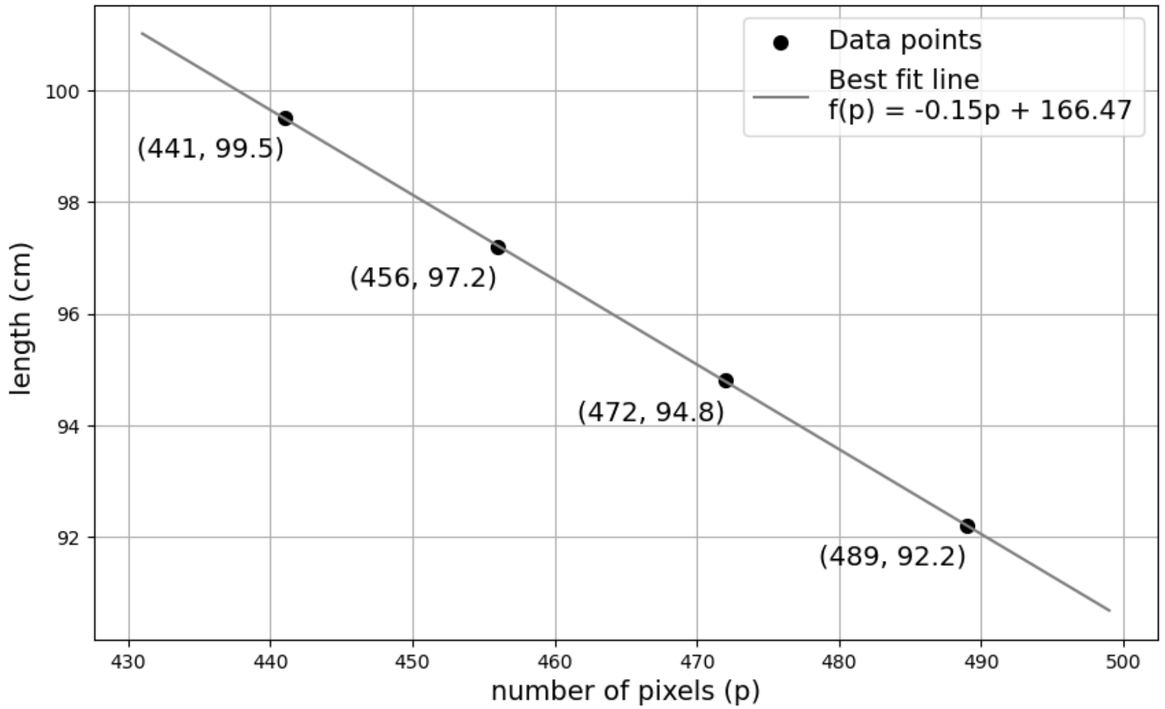
True Relation: Hyperbola Equation

$$\lim_{\theta \to 0} f(x,\theta) \approx f(x) = e_1 x + bias$$

Simplified Relation: Linear Equation

Proposed Method

Linear Equation



$$f(p) = mp + c$$

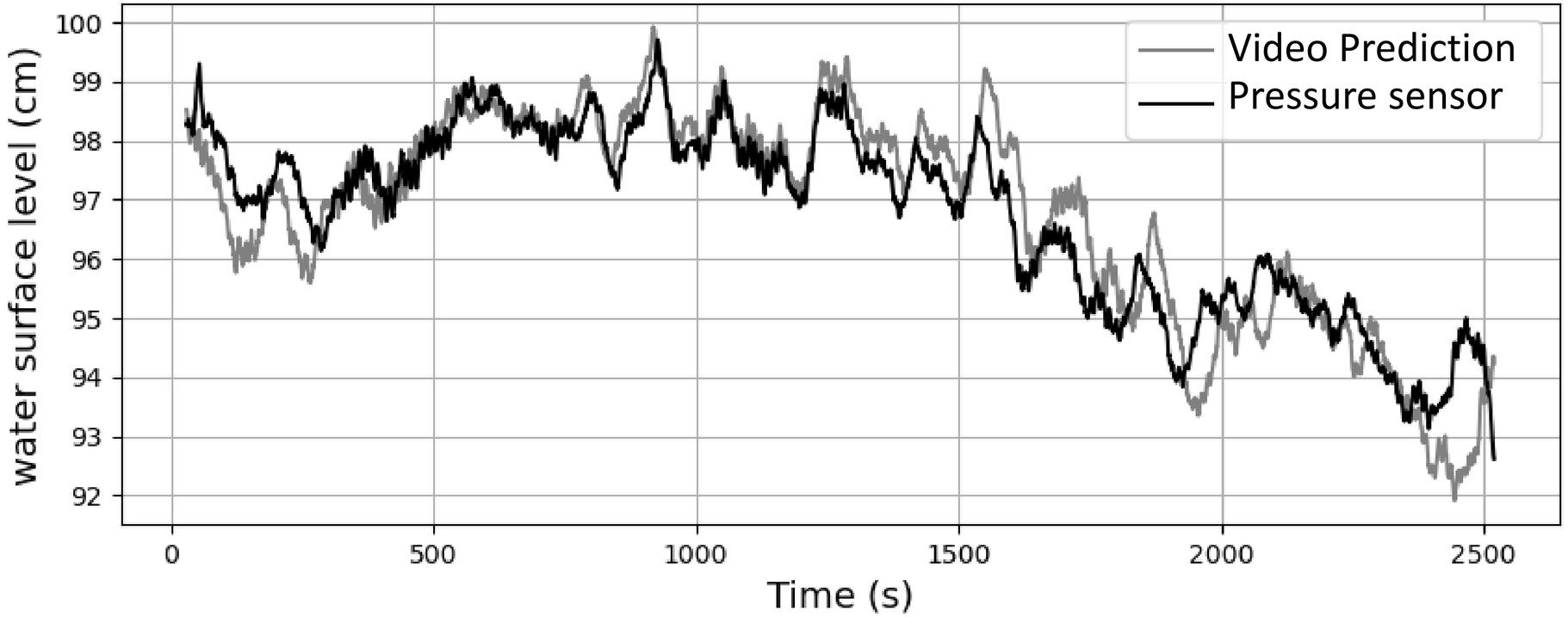
$f(p)$ = True Height

p = Pixel Height

c = Constant from linear regression

Experiment, Result, and Evaluation

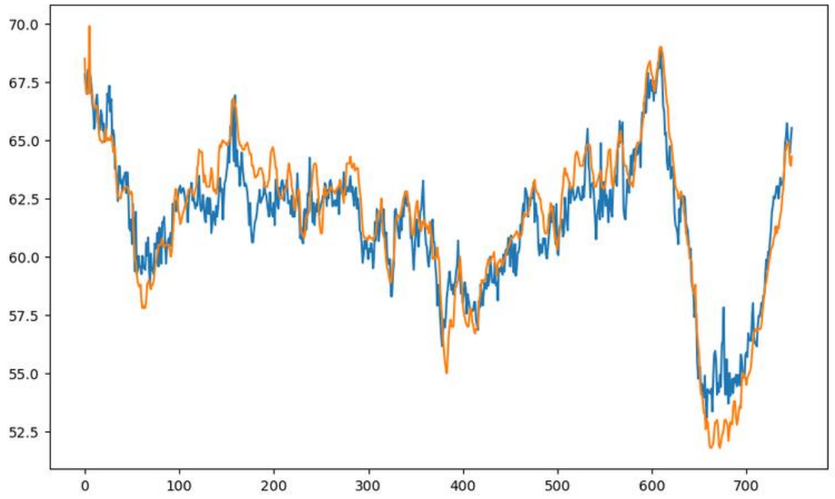
Correlation between Our method and sensor ground truth



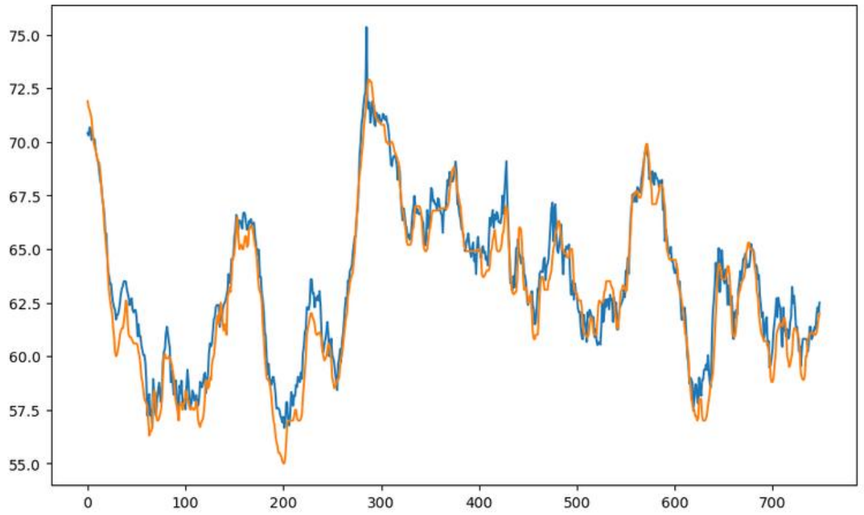
linear correlation = 0.92 RMSE = 1.0 cm

Discussion and Conclusion

Human Manual label prediction



RMSE = 1.39 cm Correlation 0.957



RMSE = 1.02 cm Correlation 0.974

Comparison between data from haman manually
labeling each data point frame-by-frame and our method prediction

Discussion and Conclusion

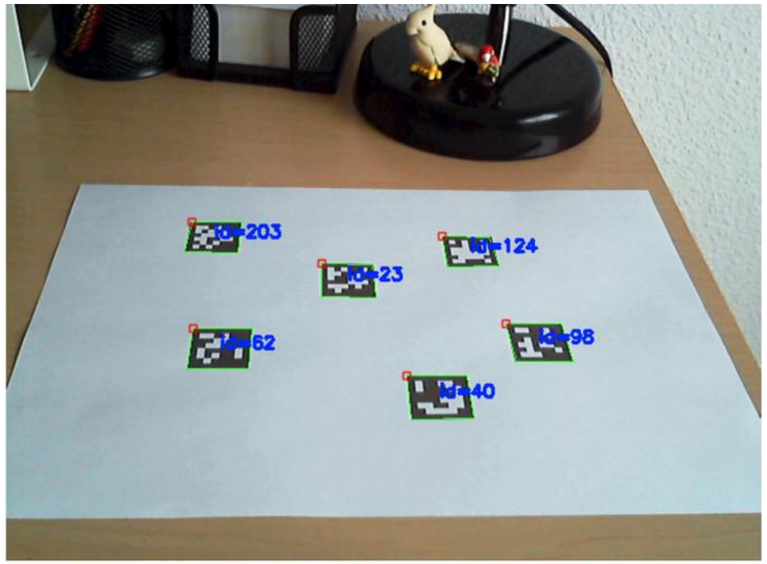
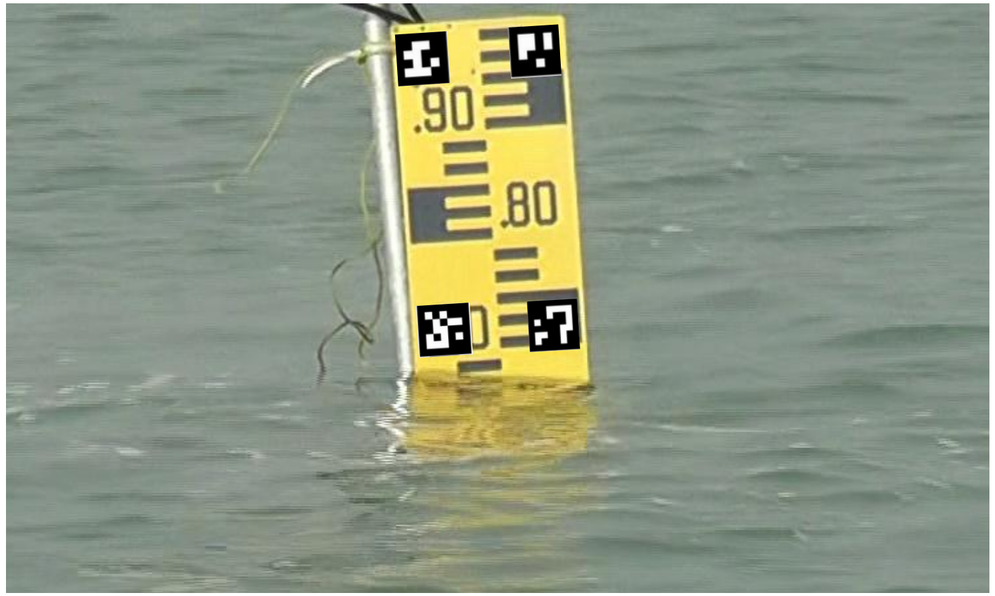


Image with detected markers

https://github.com/okalachev/arucogen/issues/3



Automation of the Calibration Phase

The study demonstrates the effectiveness of a water surface level estimation method using the FastSAM model, achieving high accuracy, and suggests future improvements through automation with Aruco markers and near-infrared imaging for enhanced reliability.