Vision Based Underwater Docking Station Detection and Pose Estimation for Autonomous Underwater Vehicles (AUVs)

– PRESENTED BY –

Bishal Hazarika (200101034)

Dhruba Jyoti Sarma (200101003)

Under the Supervision of

Prof. Kandarpa Kumar Sarma and Dr. Anjan Kumar Talukdar

and

Under the Co-guidance of

Dr. Surajit Deka

Department of Electronics and Communication Engineering,

Gauhati University, Assam

OUTLINE

- INTRODUCTION
- MOTIVATION
- LITERATURE REVIEW
- PROBLEMS FORMULATED
- UNDERWATER DOCKING STATION DETECTION
- POSE ESTIMATION OF DOCKING STATION
- METHODOLOGY
- WORK DONE AND RESULTS
- CONCLUSION
- PERT CHART
- FUTURE DIRECTION
- REFERENCES

INTRODUCTION

- Autonomous Underwater Vehicles
- Underwater Docking
- Underwater Challenges
- Drawbacks of Traditional Method
- Advantages of Vision-Based Approach
- Pose Estimation For AUV Guidance

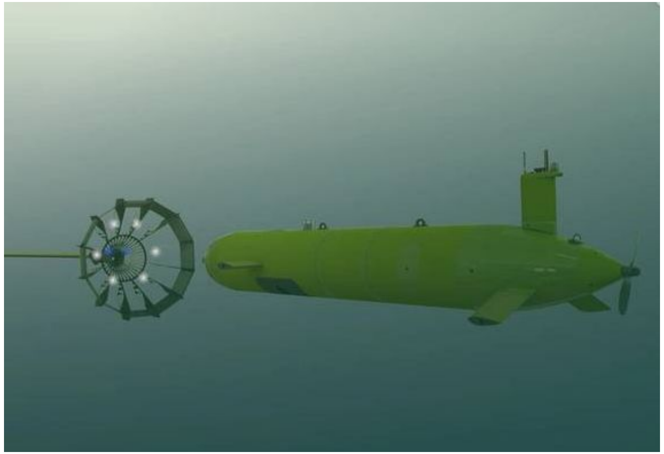


Figure 1: Docking of an AUV

MOTIVATION

In response to the challenges of operating in the deep ocean, our project is motivated by the urgent need for efficient underwater docking solutions.

- ❑ Improvement of efficiency and safety of underwater docking operations
- ❑ Increment of the operational range of AUVs
- ❑ Minimization of reliance on human intervention
- ❑ Enabling support for innovative underwater applications

LITERATURE REVIEW

SL No	PAPER TITLE	AUTHORS	TECHNIQUES USED	RESULTS	DRAWBACKS (if any)
1	YOLO Object Detection Using OPENCV [1]	Akshara Gupta, Aditya Verma,Aditya Yadav,Arvidhan M	CNN , YOLO	This paper gives a efficient approach for image detection using YOLO in OpenCV	Yolo is a good detection algorithm but the accuracy in complex environment like underwater condition may get drastically hampered
2	Underwater Object Detection and Tracking [2]	Divya Priyadarshini, MaheshKumar H. Kolekar	Object Detection, Computer Vision	The proposed methodology in this paper achieves higher precision compared to traditional techniques, regardless of image or video frame resolution and clarity.	Algorithm cannot read RGB image. Image necessarily needs to be a gray image for detecting the object.
3	Underwater Object Classification and Detection [3]	Andre Jesus, Claudio Zito, Claudio Tortorici, Eloy Roura, Giulia De Masi	Yolo V3, Faster RCNN	This paper's key contribution is to analyze and quantify the shortcomings of conventional state-of-the-art algorithms for object detection in underwater environments.	Underwater prediction may deteriorate on harsh and muddy water.

contd...

SL No	PAPER TITLE	AUTHORS	TECHNIQUES USED	RESULTS	DRAWBACKS (if any)
4	Estimation of Positions and Poses of Autonomous Underwater Vehicle Relative to Docking Station Based on Adaptive Extraction of Visual Guidance Features	Fengtian Lv, Huixi Xu, Kai shi, Xiaohui Wang	YOLO, Faster RCNN, Docking Neural Network (DoNN)	Experimental results demonstrated less than 10% absolute estimation error for each degree of freedom in the PPARD.The new extraction method achieved an 87.99% success rate, surpassing classical methods.	For real time underwater scenarios, the output may get hampered.
5	Detection and Pose Estimation for Short-Range Vision-Based Underwater Docking	SHUANG LIU , METE OZAY , TAKAYUKI OKATANI, HONGLI XU, KAI SUN, YANG LIN	CNN, YOLO, R-CNN, Fast-RCNN, Faster R-CNN	For robust and credible detection of docking stations, a CNN called docking neural network (DoNN)is used. For accurate pose estimation, a perspective-n-point algorithm is integrated into the framework	The limitations of this research include the framework's sensitivity to strong artificial noise, untested performance in diverse real-world underwater conditions.
6	Pose estimation for the case of prolonged under ice based AUV	D Frolov , S Polovko	Computer vision, Control System.	Provides a system for determining the relative position based on cameras and active-light markers. A system equation and a complete mathematical modeling for the positioning system is performed.	The absence of empirical testing in authentic under-ice conditions hinders the assessment of the system's practical viability and robustness.

PROBLEMS FORMULATED

01

Phase 01

Efficient Underwater Docking Station Detection with limited dataset using Transformer based object detection.

02

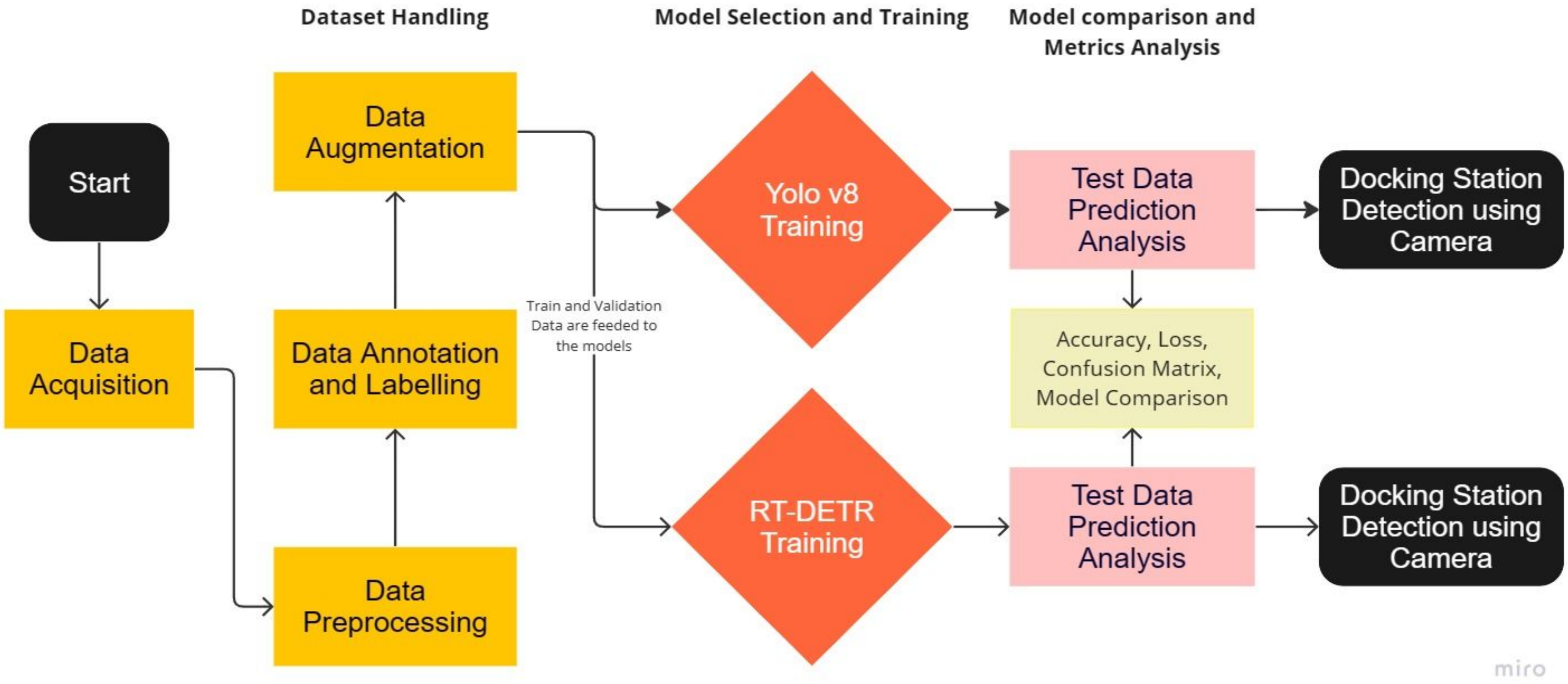
Phase 02

Pose Estimation of the Docking Station for proper and accurate docking of the Autonomous Underwater Vehicle (AUV).

PHASE 1

UNDERWATER DOCKING STATION DETECTION

BLOCK DIAGRAM
Underwater Docking Station Detection



METHODOLOGY(contd…)

Underwater Docking Station Detection

YOLO v8 :

- YOLO (You Only Look Once) stands out for its speed and accuracy.

- YOLO directly predicts bounding boxes and class probabilities from an image, bypassing the complex two-stage architecture of traditional object detection methods.

- YOLO version 8 is faster Compared to R-CNN, SSD, Faster R-CNN and earlier versions of Yolo

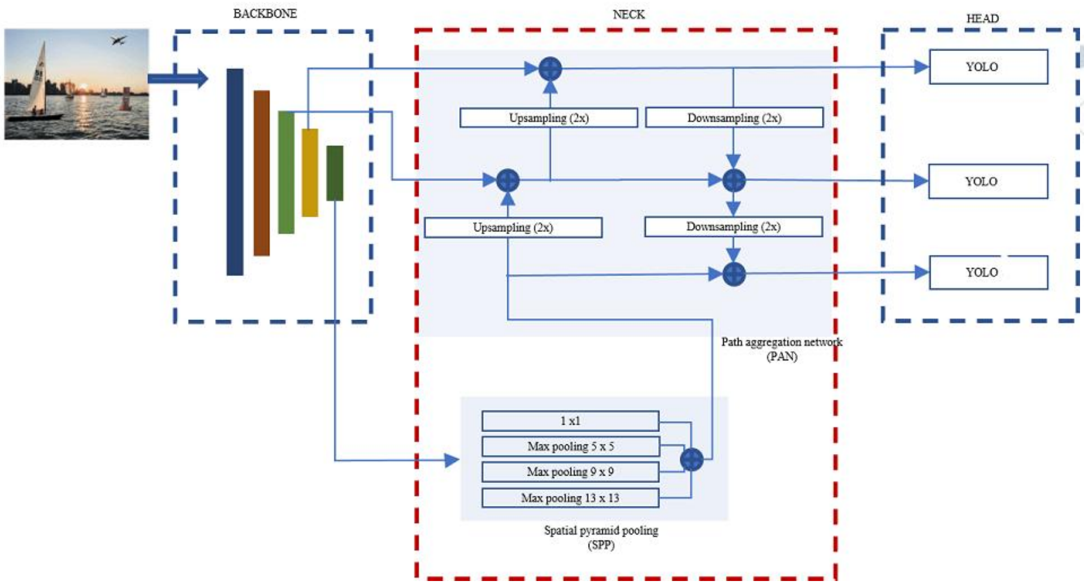


Figure 4: Structure of Yolo

METHODOLOGY(contd…)
Underwater Docking Station Detection

RT - DETR :

- Real-Time Detection Transformer (RT-DETR) is a state-of-the-art object detection algorithm that leverages the power of transformers in the field of Object Detection.
- Future Proof Technology
- Beats most of the state of the art technologies like YOLO in terms of accuracy.

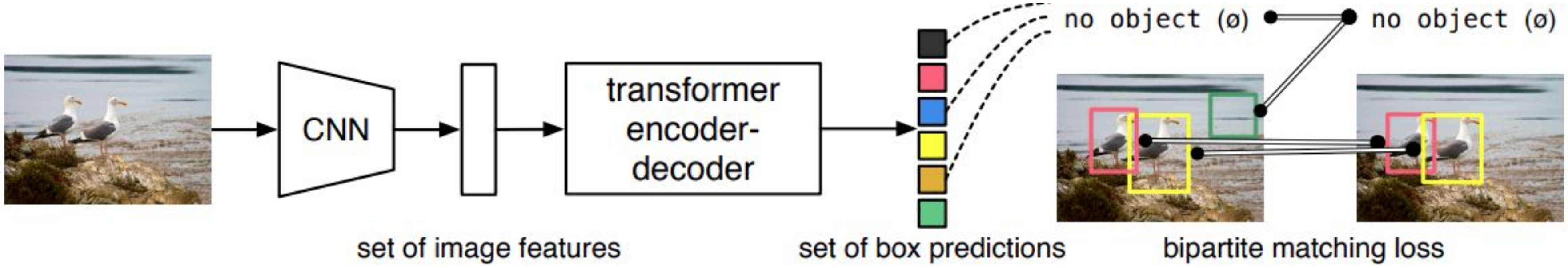
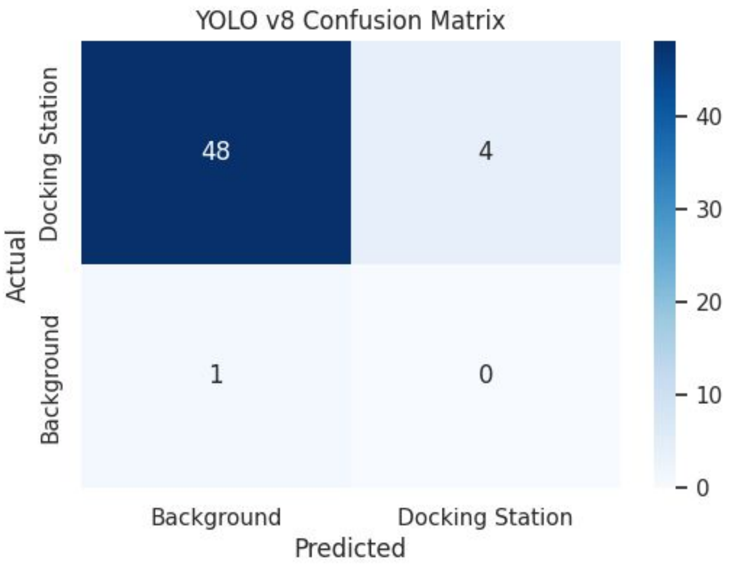
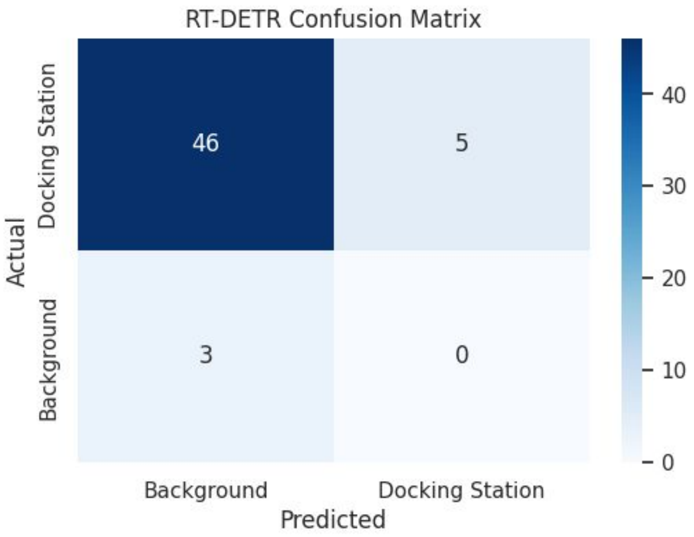


Figure 5: Structure of Detection Transformer

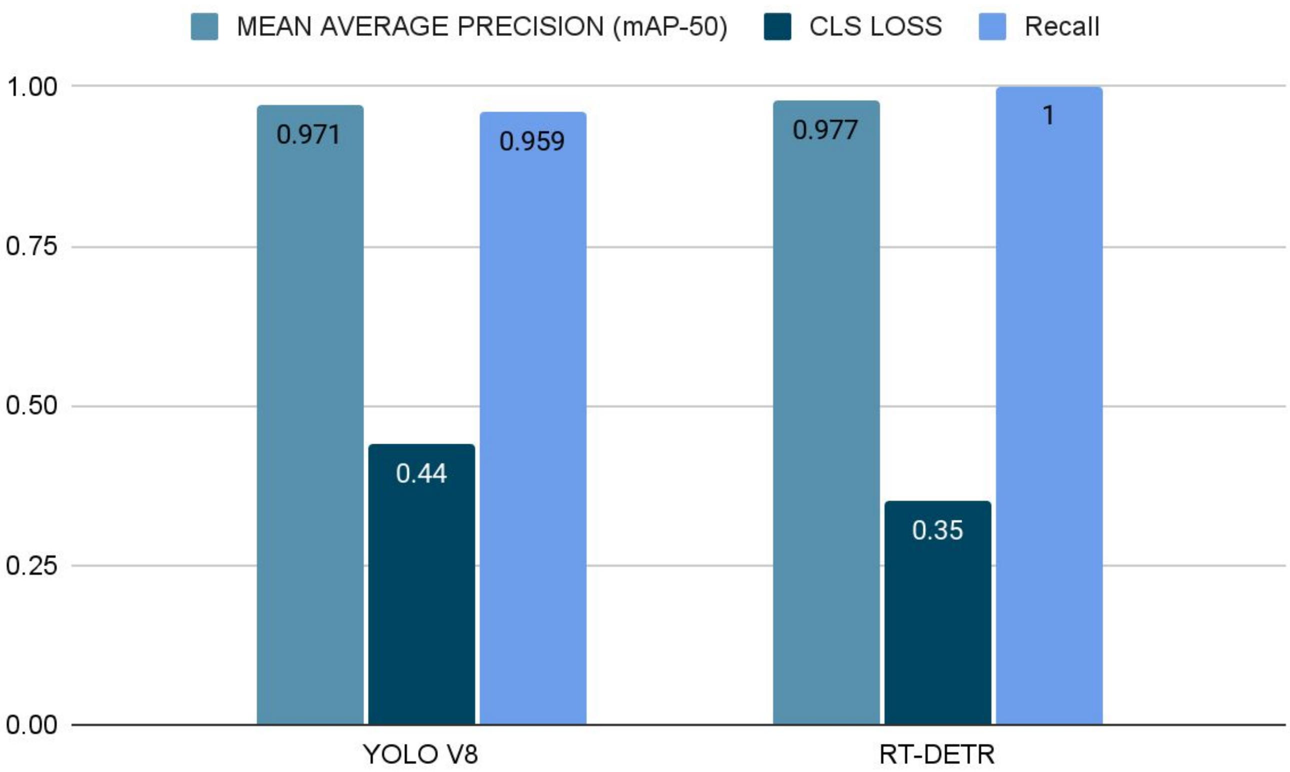
WORK DONE AND RESULTS(contd…)

YOLO v8	RT-DETR
❑ The model is trained for 50 epochs	❑ The model is trained for 50 epochs
❑ Class Loss : 0.4425	❑ Class Loss : 0.3566
❑ Recall : 0.959	❑ Recall : 1
❑ mAP50 (Mean Average Precision at IoU threshold 0.5): 0.971	❑ mAP50 (Mean Average Precision at IoU threshold 0.5): 0.978
❑ mAP50-95 (Mean Average Precision over IoU thresholds 0.5 to 0.95): 0.661	❑ mAP50-95 (Mean Average Precision over IoU thresholds 0.5 to 0.95): 0.653

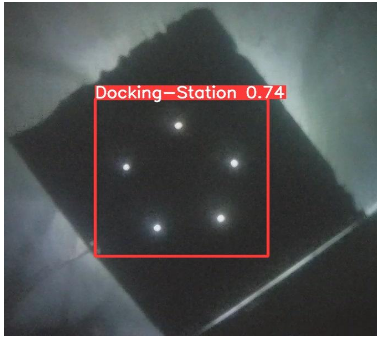
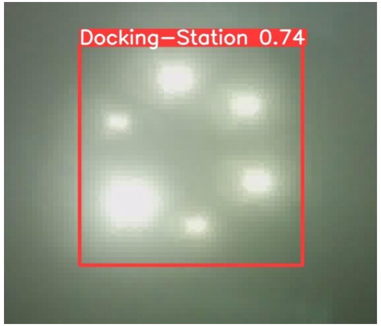
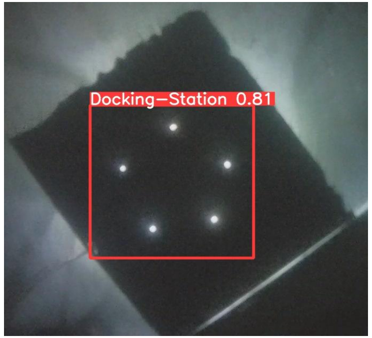
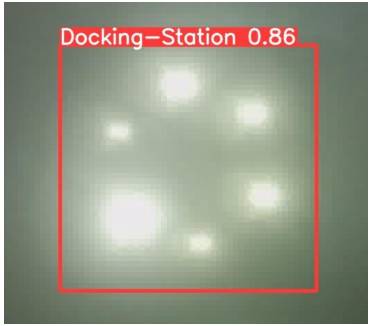
WORK DONE AND RESULTS(contd…)

YOLO v8	RT-DETR
	

WORK DONE AND RESULTS(contd...)



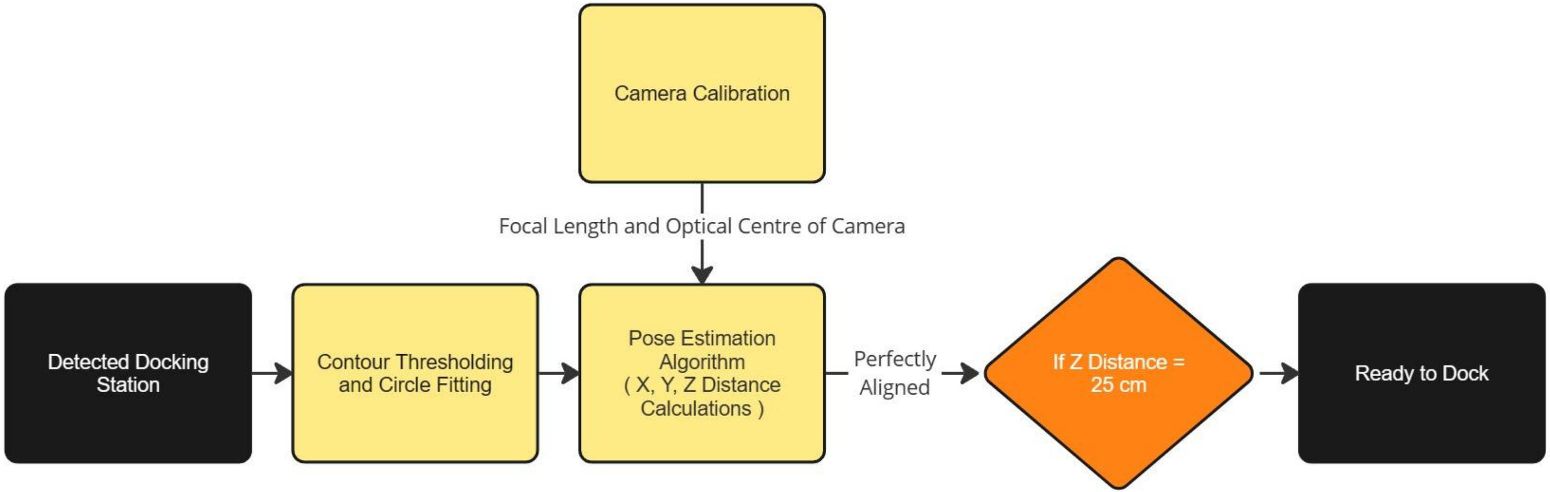
WORK DONE AND RESULTS(contd...)

YOLO v8	RT-DETR
● Real Time Prediction Result :  	● Real Time Prediction Result :  

PHASE 2

POSE ESTIMATION OF THE DOCKING STATION

BLOCK DIAGRAM
Pose Estimation



Pose Estimation

- ❏ Pose Estimation
- ❏ Importance of Pose Estimation
- ❏ Common Pose Estimation Techniques
- ❏ Benefits of accurate Pose Estimation
- ❏ Challenges in underwater Pose Estimation

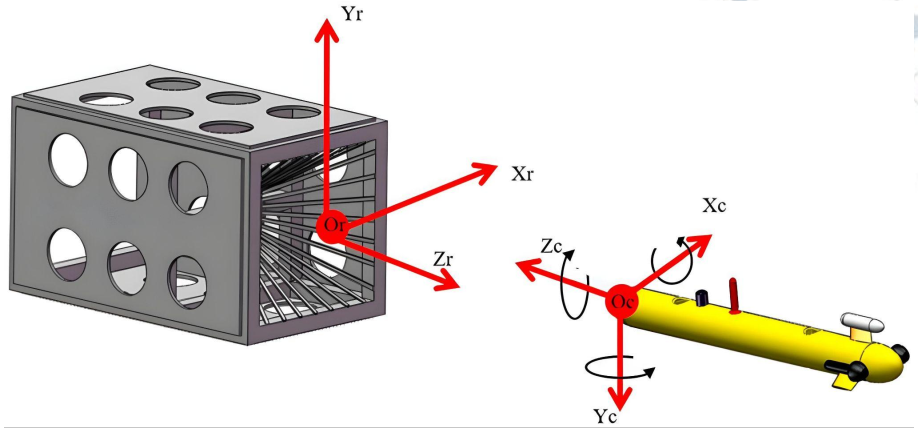


Figure 7: AUV calculating the center of the docking station

METHODOLOGY(contd...)

STEP 1 : Camera Calibration

- Used to find intrinsic and extrinsic properties (**focal length, optical centre**, etc) of the camera.
- Using these properties for **distance measurement**, distortion removal and other purposes.
- **Checkerboard pattern** used for Camera Calibration.
- Thus focal length and Optical Centre of the camera is determined.

Figure 8: Checkerboard pattern

METHODOLOGY(contd…)

STEP 1 : Camera Calibration

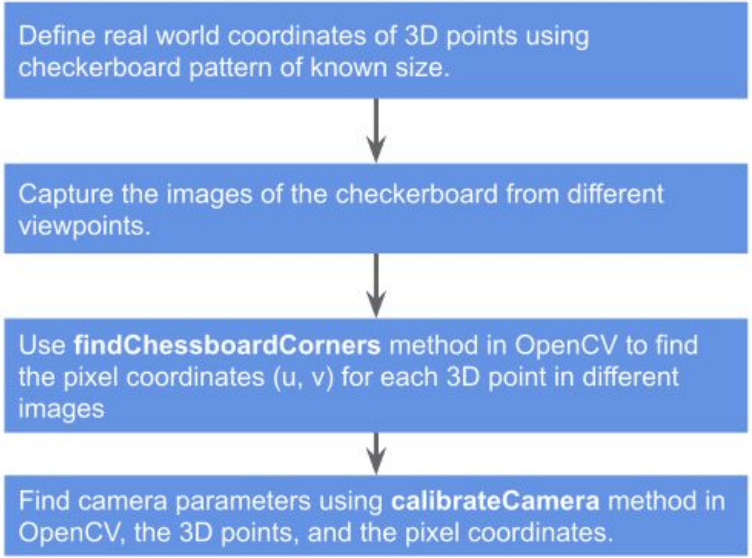


Figure 9: Flowchart of camera calibration

METHODOLOGY(contd...)

STEP 2 : Implementation of pose estimation algorithm

- Thresholding and Contour Detection
- Circle Fitting over the contours
- Calculating Z distance (in meters):

  *Z_distance = (focal length * actual_diameter) / perceived_diameter*

- Calculating X and Y distance (in meters):

  *X_distance = (X_distance in pixel * actual diameter) / perceived_diameter*

  *Y_distance = (Y_distance in pixel * actual diameter) / perceived_diameter*

- Visualization and Guidance
- Recommendation about docking status

WORK DONE AND RESULTS(contd…)

- Calculated Focal Length = **657** pixels

Thresholding /Contour Detection

Circle Fitting

X, Y, Z distances

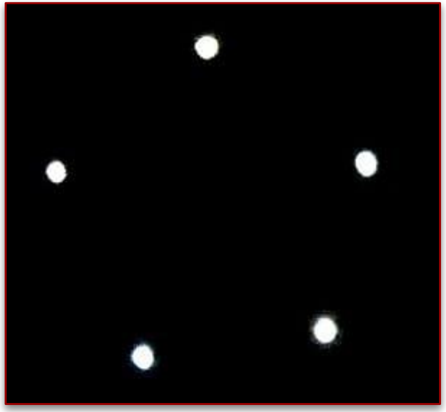


Figure 10: Contour detection

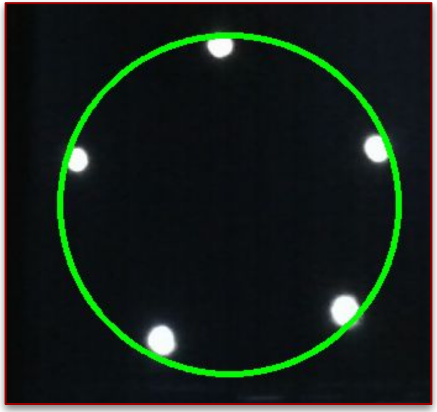


Figure 11: Circle fitting over the contour

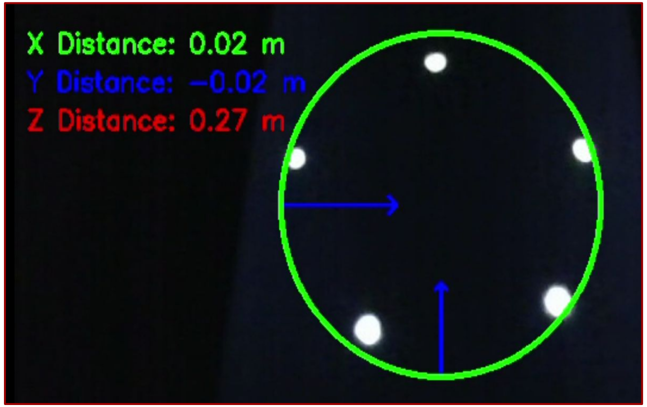


Figure 12: Displaying X,Y and Z distances

WORK DONE AND RESULTS(contd…)

When Optical Centre is Perpendicular to the Centre of the Docking station

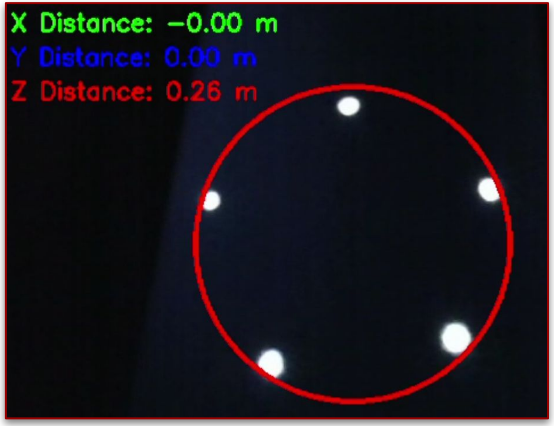


Figure 13: Perfectly aligned

Ready to Dock at a distance equal to 0.25 m

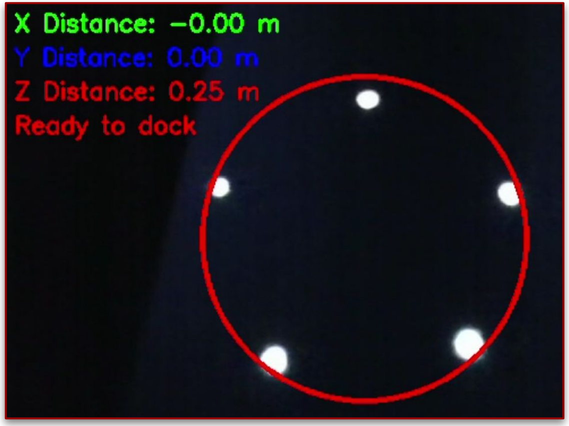


Figure 14: Ready to dock

WORK DONE AND RESULTS(contd...)

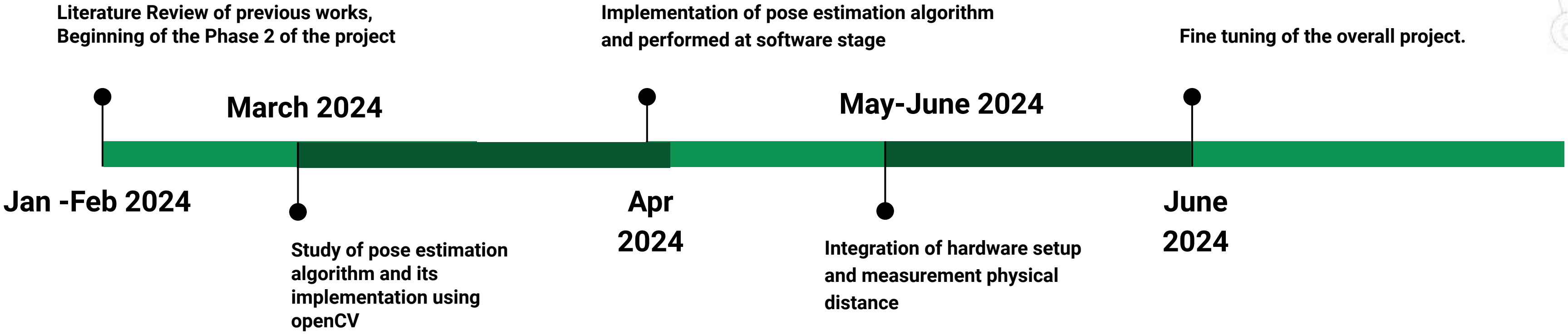
Axis	Actual Distance (cm)	Calculated Distance (cm)	Percentage Error (cm)
X	2.5	3	20
	3.5	4	14
	4.5	5	11
Y	2.7	3	11
	3.7	4	8
	4.7	5	6
Z	24	25	4
	25	26	4
	26	27	3.8

*Percentage error = (actual distance - calculated distance)/actual distance * 100%*

WORK DONE AND RESULTS

- VIDEO DEMONSTRATION

PERT CHART


Literature Review of previous works,
Beginning of the Phase 2 of the project
Implementation of pose estimation algorithm
and performed at software stage
Fine tuning of the overall project.
March 2024
May-June 2024
Jan -Feb 2024
Apr
2024
June
2024
Study of pose estimation
algorithm and its
implementation using
openCV
Integration of hardware setup
and measurement physical
distance

CONCLUSION

- RT-DETR Model exceeds over YOLO v8 in terms of Recall and Precision.
- Real Time Detection of the Docking Station with good accuracy.
- Implementation of pose estimation algorithm.
- Achieved guidance about movement of AUV for perfect docking.
- Achieved recommendation about docking status.
- An average error of 2% can be observed in distance measurement.

FUTURE DIRECTION

- ❑ Integration of Hardware Setup.
- ❑ Optimization of the models used for better performance.
- ❑ Expansion of training dataset in varied environments.
- ❑ The Pose Estimation Algorithm is currently tested above water. Next work will be focused on underwater conditions.
- ❑ Optimisation of the pose estimation algorithm for error reduction.

REFERENCES

[1] Gupta, Akshara, Aditya Verma, and A. Yadav. "YOLO OBJECT DETECTION USING OPENCV." International Journal of Engineering Applied Sciences and Technology 5.10, 2021.

[2] D. Priyadarshni, M. Kolekar. "Underwater Object Detection and Tracking," , pp. 837-846, 2020.

[3] J. Redmon, S. K. Divvala, R. B. Girshick, and A. Farhadi, “You only look once: Unified, real-time object detection,” CoRR, vol. abs/1506.02640, 2015.

[4] N. Carion, F. Massa, G. Synnaeve, N. Usunier, A. Kirillov, and S. Zagoruyko, “End-to-end object detection with transformers,” 2020.

[5] W. Lv, S. Xu, Y. Zhao, G. Wang, J. Wei, C. Cui, Y. Du, Q. Dang, and Y. Liu, “Detrs beat yolos on real-time object detection,” arXiv preprint arXiv:2304.08069, 2023.

[6] S. Liu, M. Ozay, T. Okatani, H. Xu, K. Sun and Y. Lin, "Detection and Pose Estimation for Short-Range Vision-Based Underwater Docking," in *IEEE Access*, vol. 7, pp. 2720-2749, 2019

[7] v, Fengtian, Huixi Xu, Kai Shi, and Xiaohui Wang. 2022. "Estimation of Positions and Poses of Autonomous Underwater Vehicle Relative to Docking Station Based on Adaptive Extraction of Visual Guidance Features" *Machines* 10, no. 7: 571

[8] K. Yamashita *et al.*, "Improvement of 3D Pose Estimation Abilities by Light-Emitting-3D Marker for AUV Docking,"

THANK YOU