Obstacle Detection in USVs

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Content / Outlines

Introduction and Motivation

- Unmanned Surface Vessels(USVs) are generally used in perimeter monitoring and surveillance tasks.
- USVs can be navigated either through manual control or autonomously following a trajectory.
- They come in various dimensions but usually less than 2 meters.
- They are portable and can be easily navigated in narrow marinas.
- In the majority of applications, they are required to navigate along a pre-determined path.
- May be required to perform some tasks autonomously.

Fig. 1

Image credits: https://www.defenceprocurementinternational.com/features/maritime/are-unmanned-surface-vehicles-a-paradigm-shift-in-naval-warfare

Introduction and Motivation

- An autonomous system necessitates the use of an obstacle detection system and requires excessive computation.
- Computation can be performed either at the ground station or via an onboard computing device.
- Performing computation on the ground station and information transfer using telemetry limits the range of the USV.
- For autonomous navigation, variety of sensors are used such as LiDAR, Sonar, Radar, Camera etc.
- The compact size of the USVs constraints the power consumption and payload capacity which limits the use of sensors.

Fig. 2

Image credits: https://defense.info/defense-systems/unmanned-surface-vehicles-in-support-of-the-sustainment-mission/

Introduction and Motivation

- USV needs situational awareness to identify obstructions.
- General obstructions in USVs scenarios are other vessels, people (Scuba divers), objects such as trash and most importantly the shoreline or water-edge line.
- In certain instances (particularly those beyond India), satellite provides seashore maps[3]
- When combined with a GPS, enable the management of seashore obstacles.
- No publicly available datasets of USVs for Indian Scenarios

Fig-3a
Image credits: https://danandholly.com/2021/01/indian-fishing-boats/

Fig-3b
Image taken from MODS dataset[21]

Literature Review and Literature Gap

- Obstacle detection was previously addressed in the field of Unmanned Ground Vehicles (UGVs).
- The research for it in USVs is still in the early stages.
- Methods designed for UGVs cannot be easily applied to USVs for the following reasons:
  - They depend on estimating the ground plane. Not applicable to the underwater environment of USVs.
  - Maritime environment exhibit greater diversity as even a little submerged object pose a risk.
- A lot of methods for detecting obstacles in marine environments is the use of range sensors like Radar, Sonar or LiDAR. Size and power restrictions.
- Therefore, cameras combined with computer vision algorithms may be a promising alternative.

Literature Review and Literature Gap

Authors	Contribution
Larson et al.[4] (2007)	• Used a monocular camera and Estimated horizon using trigonometric calculations and nautical charts.
Gal, O.[5] (2011)	• Used edge detection approach to detect the horizon line. • Assumed sea-edge as a straight line.
Wang et al.[6] (2011)	• Used pixel profile analysis and RANSAC regressor to estimate sea-sky line. • Created a real-time obstacle detection system for a monocular and stereo camera system based on saliency detection

- Most of these approaches approximate the edge of water by the horizon line.
- In coastal scenarios, water-edge doesn't align with the horizon.

Literature Review and Literature Gap

Authors	Contribution
Kristan et al.[7] (2015)	• Introduced a graphical model for monocular obstacle detection by constrained semantic segmentation • Partitions an image into three distinct and approximately parallel regions: sky, ground and water. • Does not presume a straight water edge and operates in real-time • Constructed the first large annotated dataset - MODD
Bovcon et al.[8, 9] (2018, 2019)	• Included sensor data like roll and pitch value from the Inertial Measurement Unit(IMU). • Improved the segmentation model by introducing stereo verification. • Constructed a new dataset with time-synchronizatized data streams – MODD2. • Proposed another dataset MaSTr1325 which was per-pixel semantically labelled and a data augmentation protocol
Bovcon et al.[10] (2022)	• Proposed a large unified dataset – MODS for obstacle detection and estimate depth maps.

Literature Review and Literature Gap

Authors	Contribution
Ahmed et al.[11] (2023)	• Used a generative adversarial network(GAN) model for image de-hazing and de-noising. • YOLOv5 based object detection system to detect objects from enhanced images.

- Majority of approaches used are segmentation based and cannot give real time inference on Embedded GPUs.
- Accuracy of the existing approaches will significantly vary when implemented in Indian Scenarios.
- Deep learning-based object detectors have a significant potential for real-time obstacle detection.
- There is no publicly available dataset for USVs that cater to Indian scenarios.

Objectives and Methodology

With this research, we plan to complete the following objectives:

1. To manufacture a USV equipped with a camera, LiDAR and IMU sensor synchronization.
2. To explore and experiment existing approaches in Indian scenarios.
3. To create a large annotated dataset for Indian waters to boost the research in this field.
4. To develop a robust obstacle detection system that can work on an Embedded GPU.

Objectives and Methodology

Methodology to be followed:

- Experimentation with a multi-modal approach for obstacle detection. Semantic segmentation for detecting the water-edge and an object detection model to detect obstacles.
- Exploring multiple segmentation and object detection models to test their real-time performance.
- Since the USV in under development, we plan to experiment on the MODS[10] dataset.
- Developing an IMU – camera calibration system and employing an Embedded GPU. Testing the USV on various water-bodies.
- Construct a dataset with visual and sensor data, and experiment with the models created.

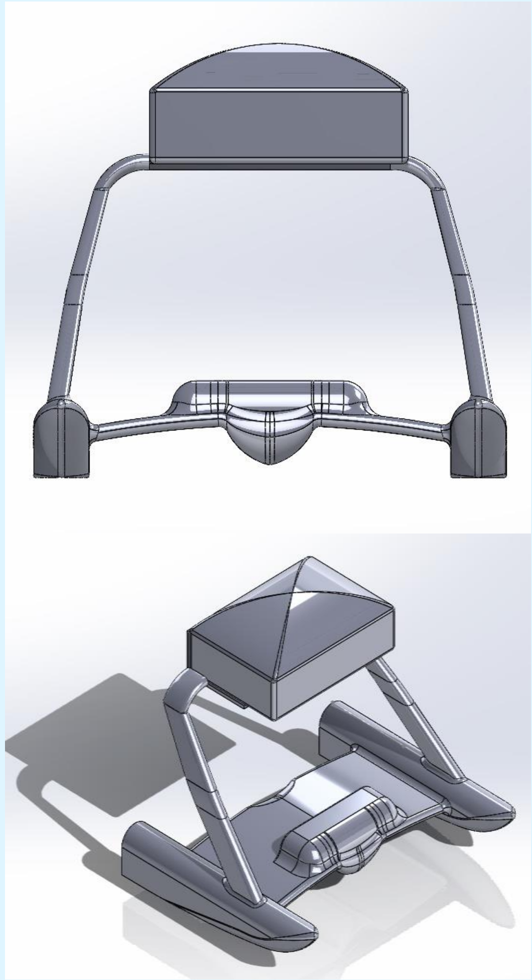


Fig. 4: CAD Model

Experimentation Details and Model Description

Dataset Modification

- The MODS dataset contained annotations in JSON format.
- The dataset was modified for water-edge segmentation task and contains 8175 images.
- Binary Masks of the images were created using OpenCV library.
- The images were resized to 640 x 640 pixels for training.

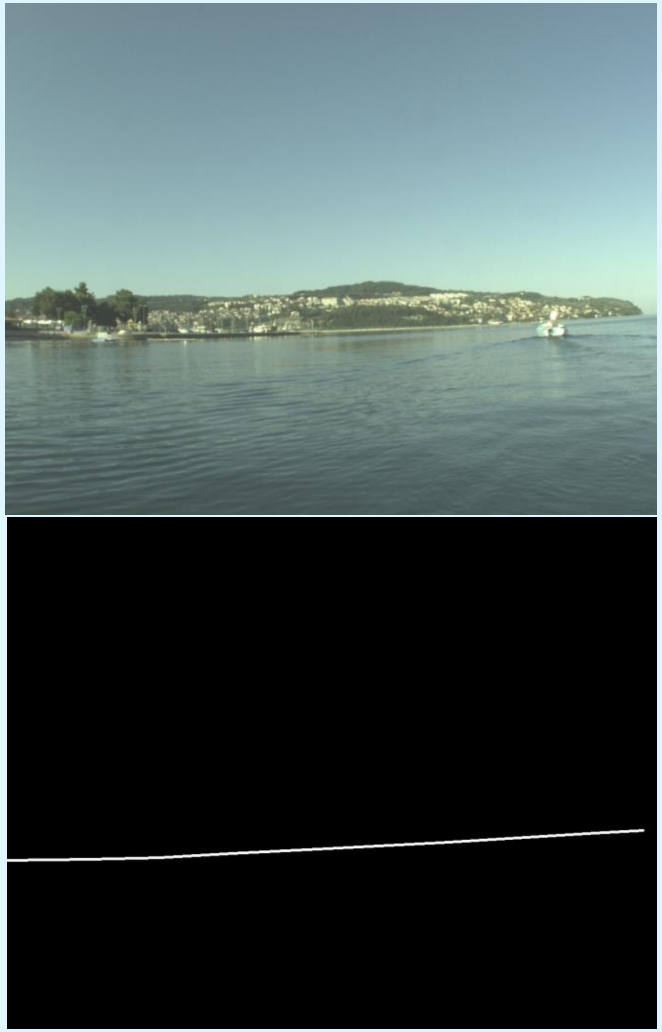


Fig. 5: Image and its mask

Experimentation Details and Model Description

Model Description

- The model used for the segmentation task is a modified U-Net Architecture[12].
- An input size of 640 is used instead of 572.
- Batch Normalization layers are included to prevent overfitting.
- Model was created using the PyTorch library and Python Programming language.
- The final model contains 118,577,922 trainable parameters.

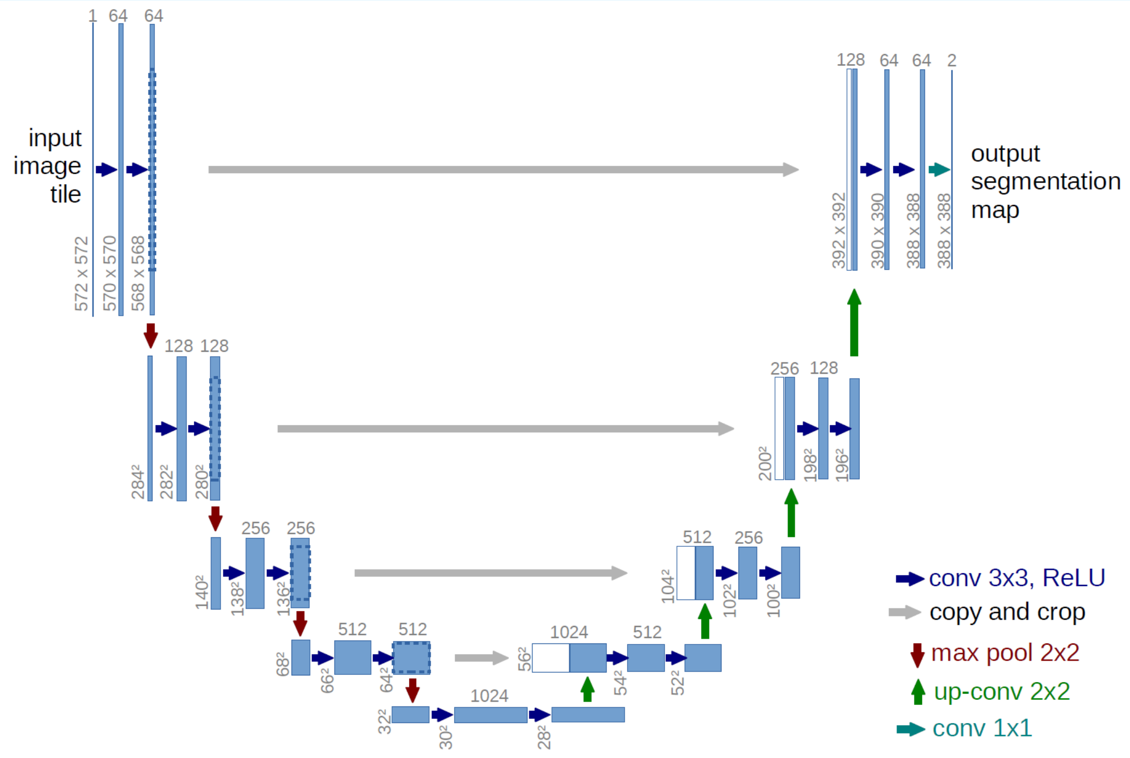


Fig. 6: U-Net Architecture[12]

Experimentation Details and Model Description

Experimentation Details

- Model was trained for 4 hours and in total 25 Epochs.
- Two NVIDIA T4 GPUs provided by kaggle are used parallelly.
- The loss-function used in Binary cross entropy with logits loss.
- Optimizer used is the Adam Optimizer.
- The learning rate schedule can be seen in table-1
- Data Augmentations were applied using the albumentations library.

Epoch No.	Learning Rate
1-10	0.001
11-15	0.0001
16-20	0.00001
21-25	0.000001

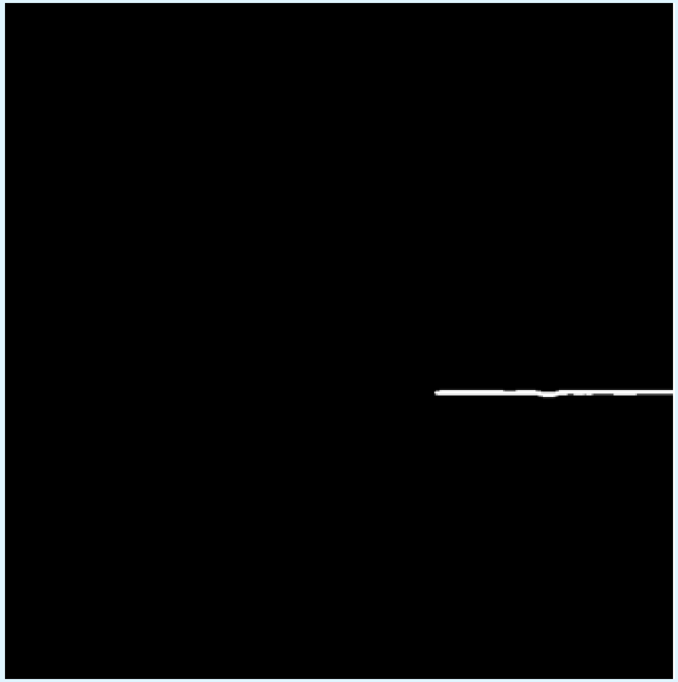
Table-1: Learning Rate Schedule

Results and Discussions

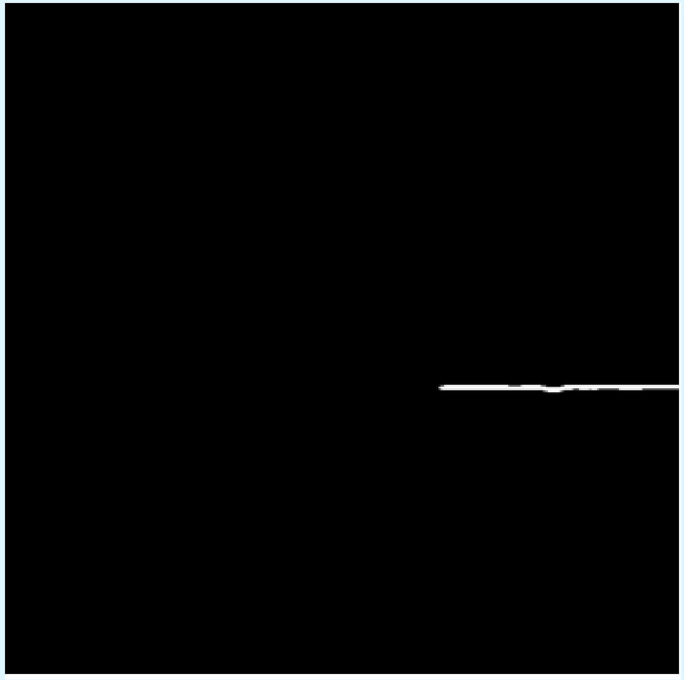
- Model achieved 99.5 % accuracy and a dice score of 0.68
- We observed that the accuracy and dice score increases as we reduce the learning rate
- Accuracy is misleading due to unbalanced dataset. Therefore, considering only dice score as a metric.
- Dice score > 0.8, considered good.
- Can be further improved by pre-training on a large dataset.
- The input image, ground truth mask, and predicted mask is shown in the next slides

Results and Discussion

Input Image



Ground Truth Mask



Predicted Mask

Fig. 7a: Results

Results and Discussion

Input Image Ground Truth Mask Predicted Mask

Fig. 7b: Results

Conclusion and Future Scope

- The segmentation performed using U-Net was successful.
- Further experimentation can be done by using modern segmentation models like other models like SegFormer
- Performance can be improved by using sensor data
- Sophisticated loss-functions can be used to increase water-obstacle separation
- Construction of an Indian dataset is extremely necessary
- For object detection, the following approaches can be used:
    - A completely different model
    - Use the segmentation features learnt, and train only a detection head

References

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THANK YOU