

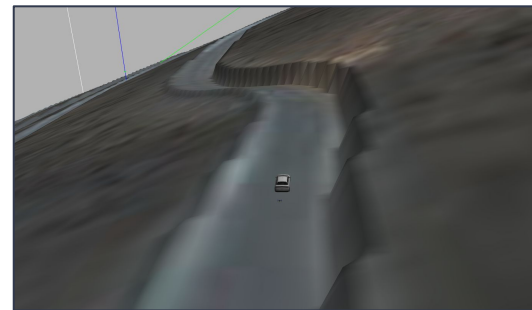
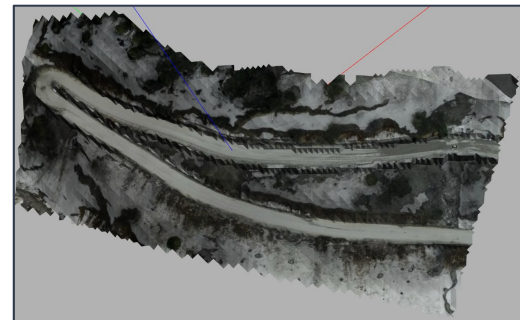
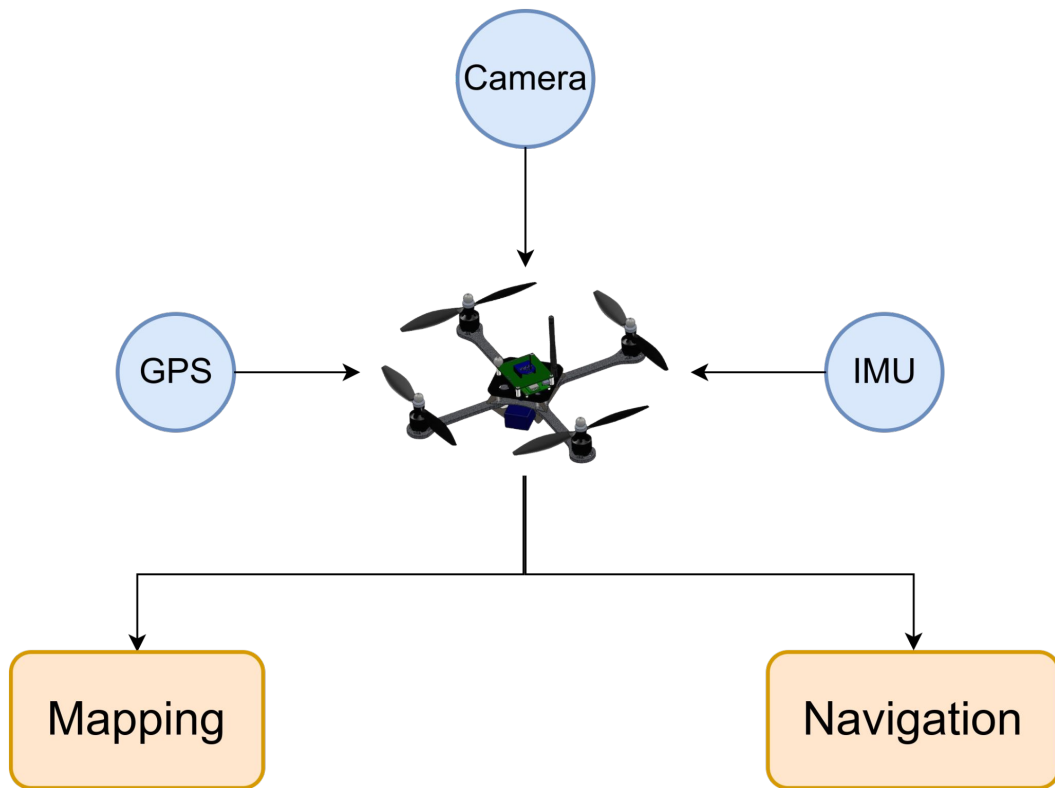
Inter IIT Tech Meet 10.0



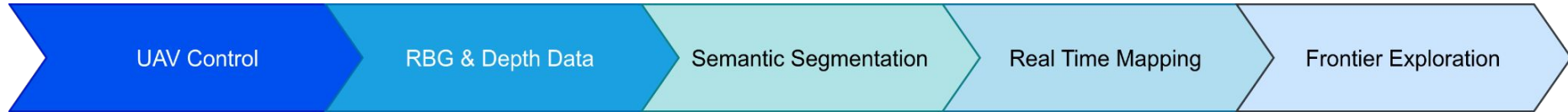
DRDO's UAV Guided UGV Navigation Challenge

- Team 14

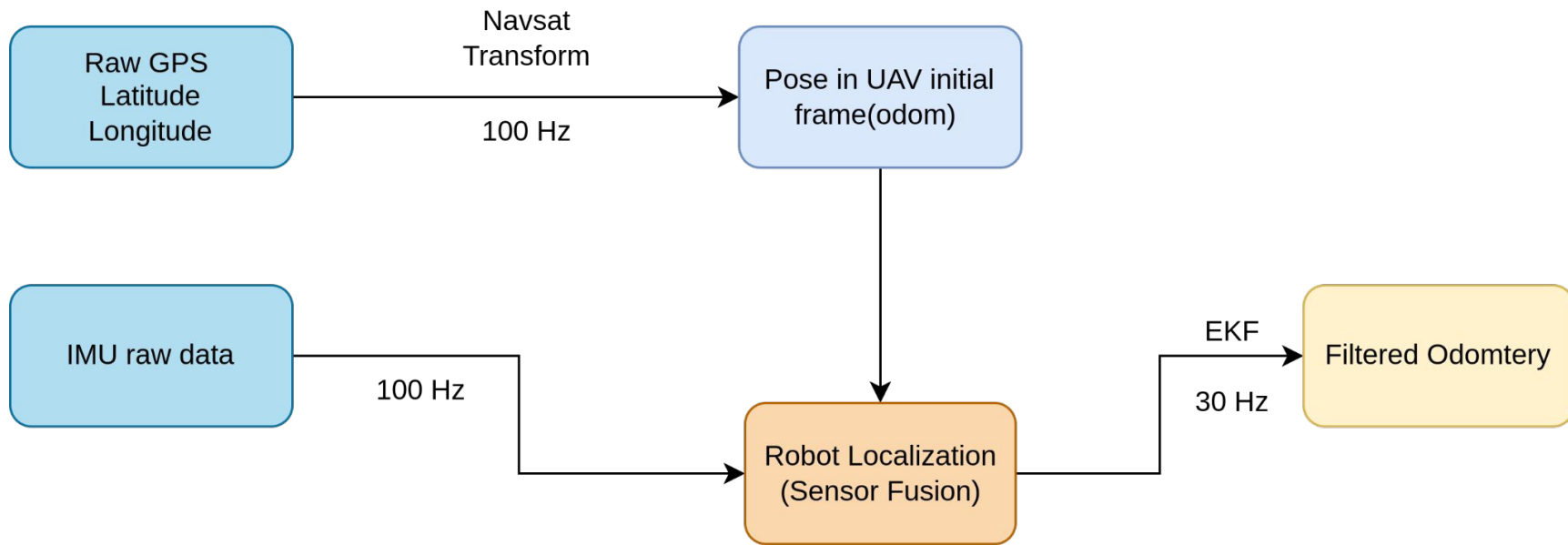
Task



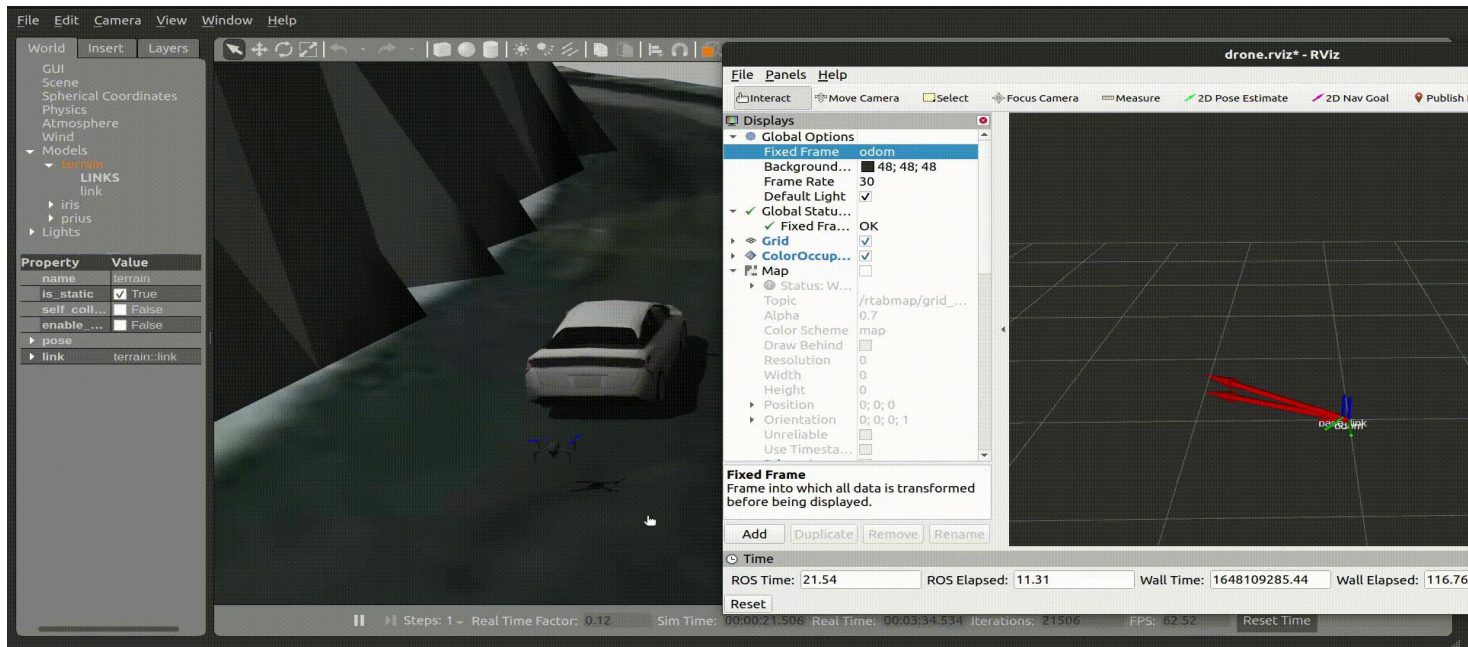
Phase - I : Mapping



UAV Localization



UAV Localization



Accuracy Report

- Maximum observed error after multiple-goal points turned out to be ± 0.5 meters in all three axes
- Calculated the error by transforming the actual location of the UAV as reported by Gazebo to the initial start position of the drone that is the Odom frame.

UAV Control

Goal Pose

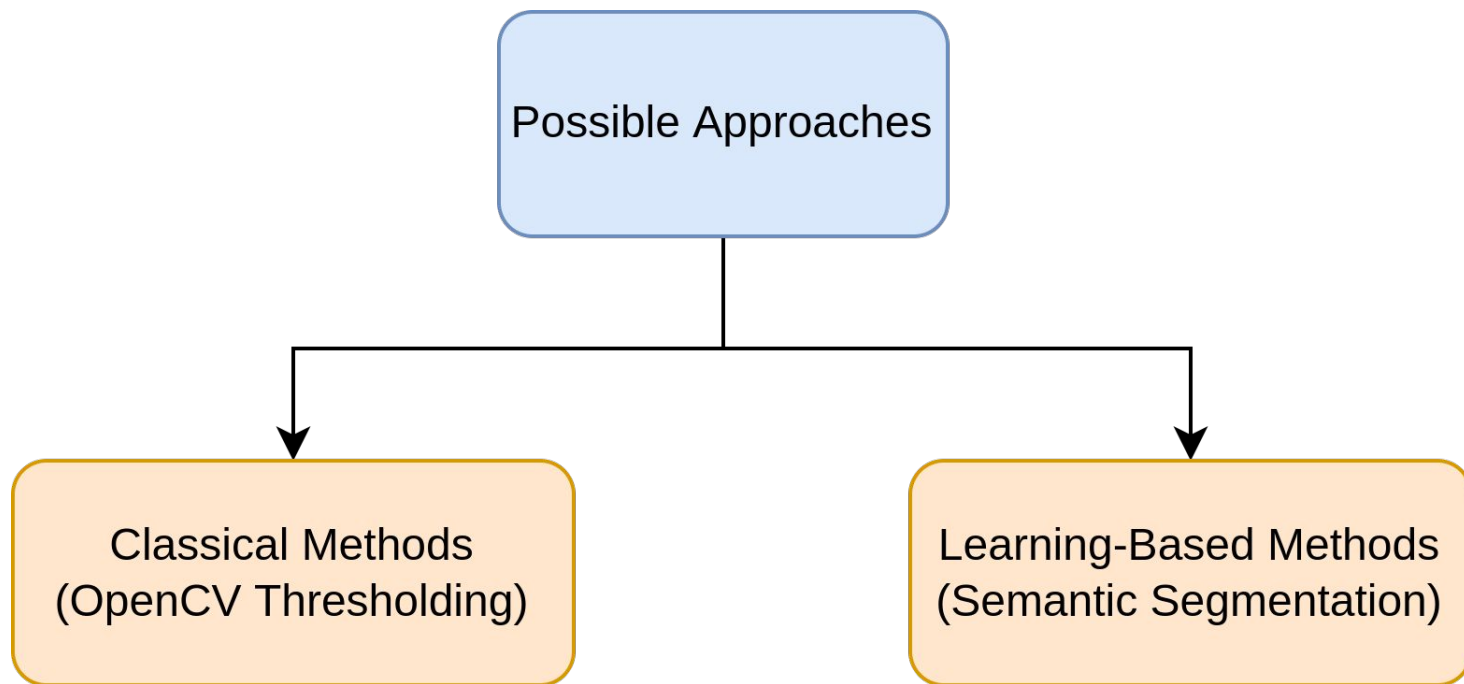
(rosmmsg geographic_msgs/GeoPoseStamped



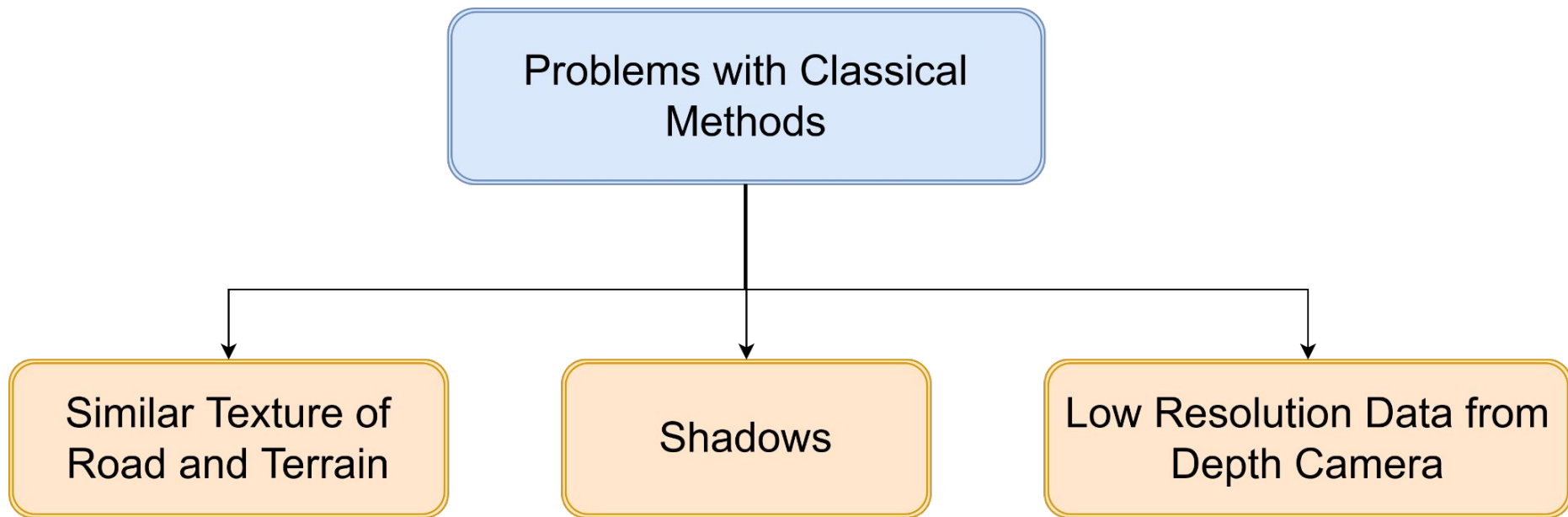
rostopic /mavros/setpoint_position/global



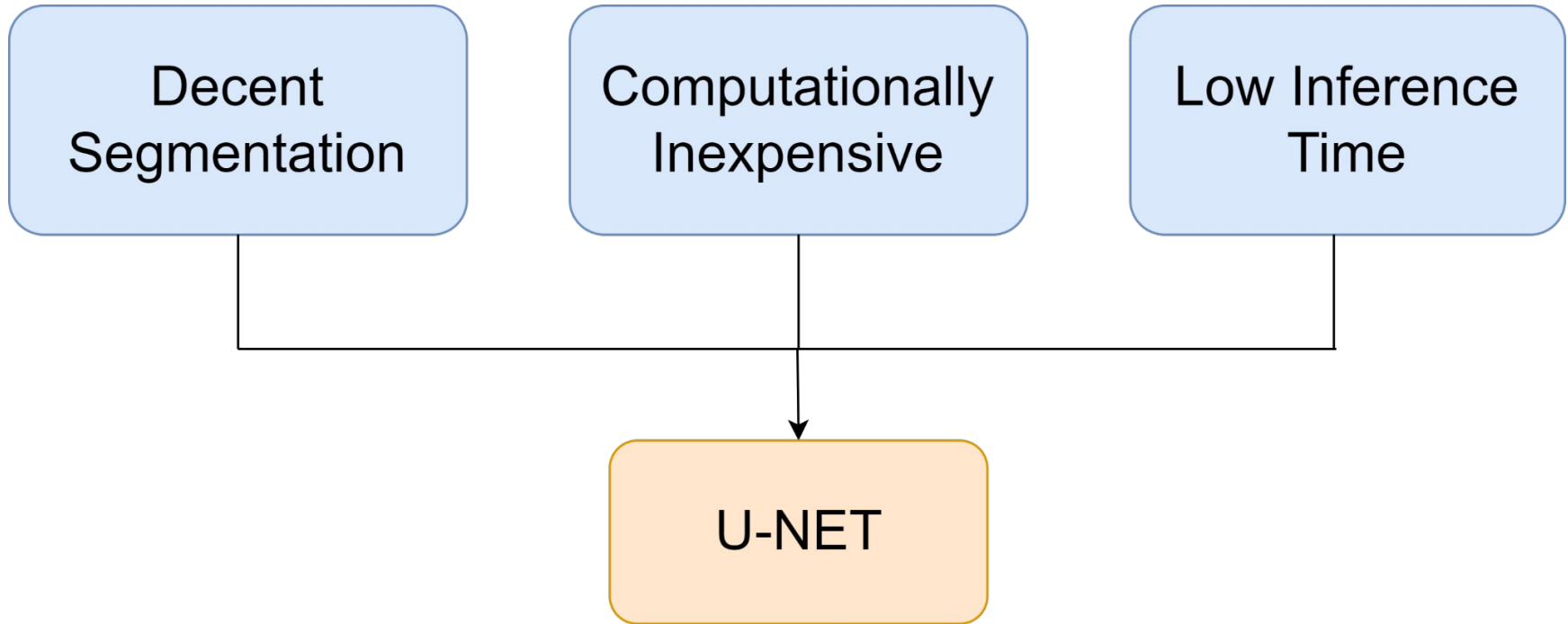
Road Segmentation : Approach Selection



Road Segmentation : Approach Selection



Semantic Segmentation : Model Selection



Dataset Generation and Annotation

Image from Gazebo world captured by the UAV



Annotated using the CVAT online tool



Augmenting the Data

Need for augmentation:

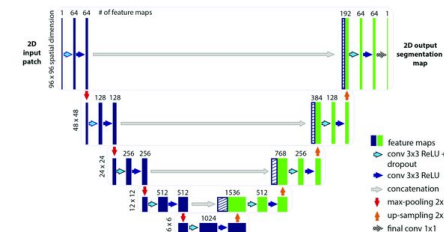
- Only 95 images as training data.
- Augmentation generates more Data.

Augmentations used :

- Rotation with limit 60 degrees and probability 0.6
- Horizontal Flip with probability 0.5
- Vertical Flip with probability 0.5

```
train_transforms = A.Compose(  
    [  
        A.Resize(height=128, width=128),  
        A.Rotate(limit=60, p=0.6),  
        A.HorizontalFlip(p=0.5),  
        A.VerticalFlip(p=0.5),  
        A.Normalize(  
            mean=0.0,  
            std=1.0,  
            max_pixel_value=255.0,  
        ),  
        ToTensorV2(),  
    ],  
)
```

Training U-Net



Optimizer

Adam with learning
rates 2e-3 to 5e-8

Loss Function

BCE with logits

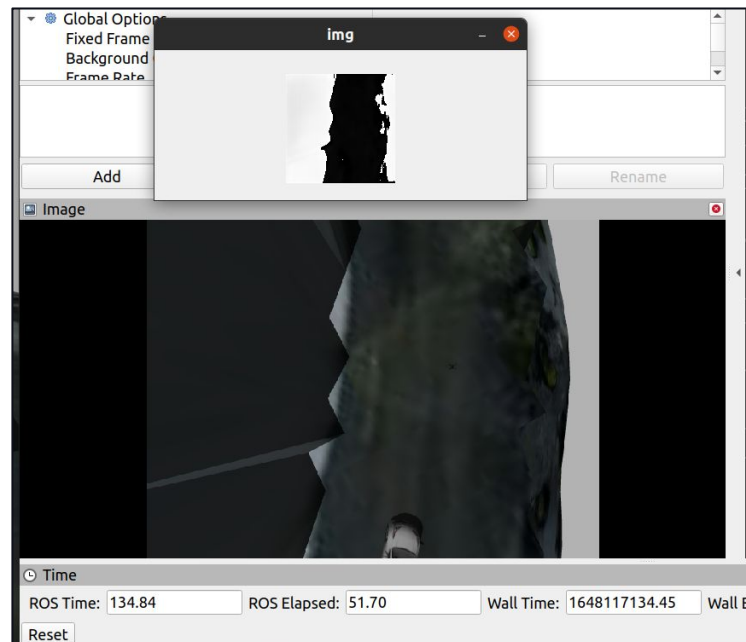
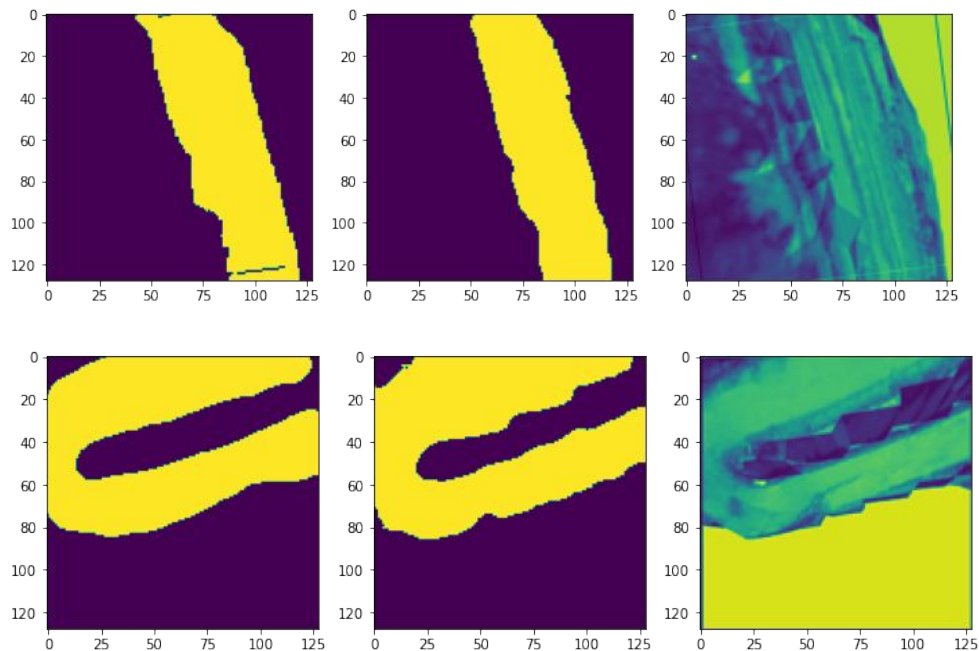
Epochs

10000

Road Segmentation Results

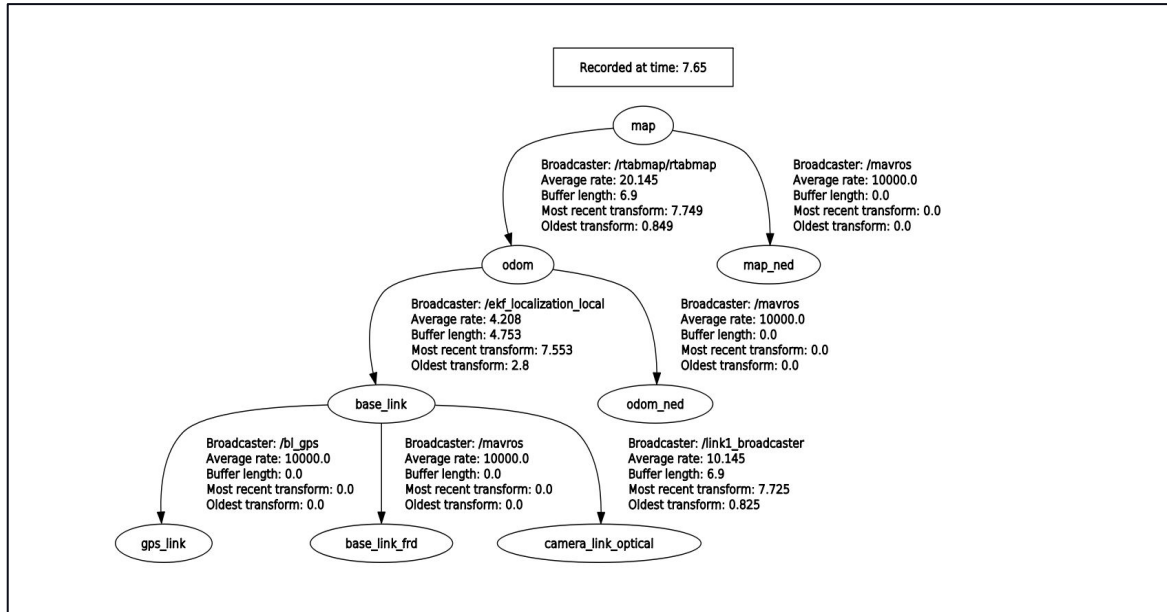
Accuracy on Test Data – 96.4%

Inference time = 170ms

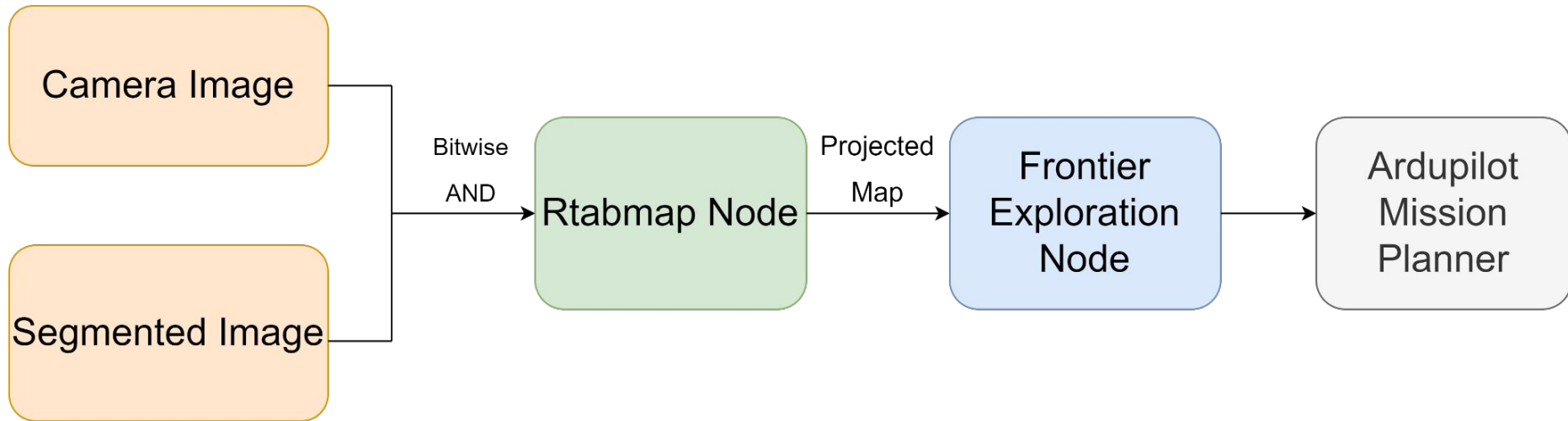


Fixes In TF Tree

Static_transform_publisher between the base_link and camera_link_optical with a transformation of (0 0.01 -0.07 1.57 3.14 0)



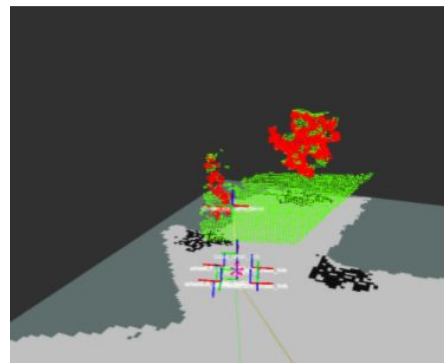
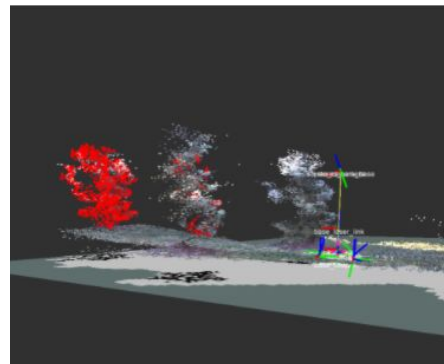
Mapping and Exploration



Mapping and Exploration

RTAB-Map (Real-Time Appearance-Based Mapping)

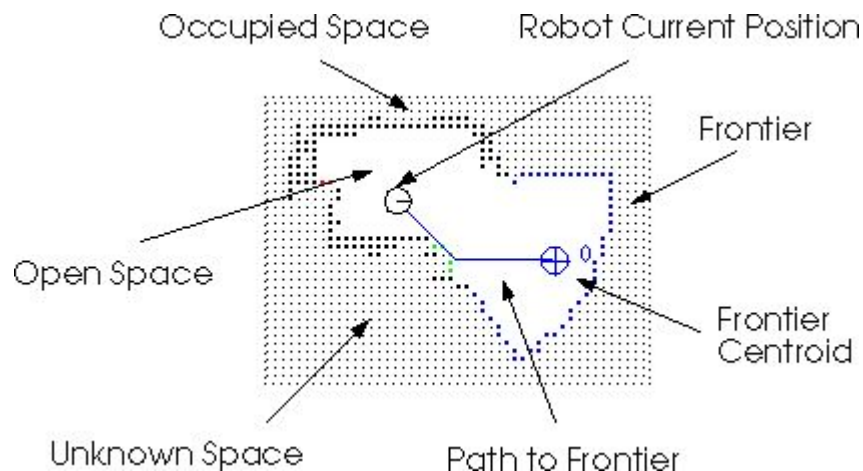
- RTAB-Map is a RGB-D SLAM approach based on an incremental appearance-based loop closure detector.
- The algorithm uses data collected from vision sensors to localize the robot and map the environment.
- A process called loop closures is used to determine whether the robot has seen a location before. As the robot travels to new areas in its environment, the map is expanded.



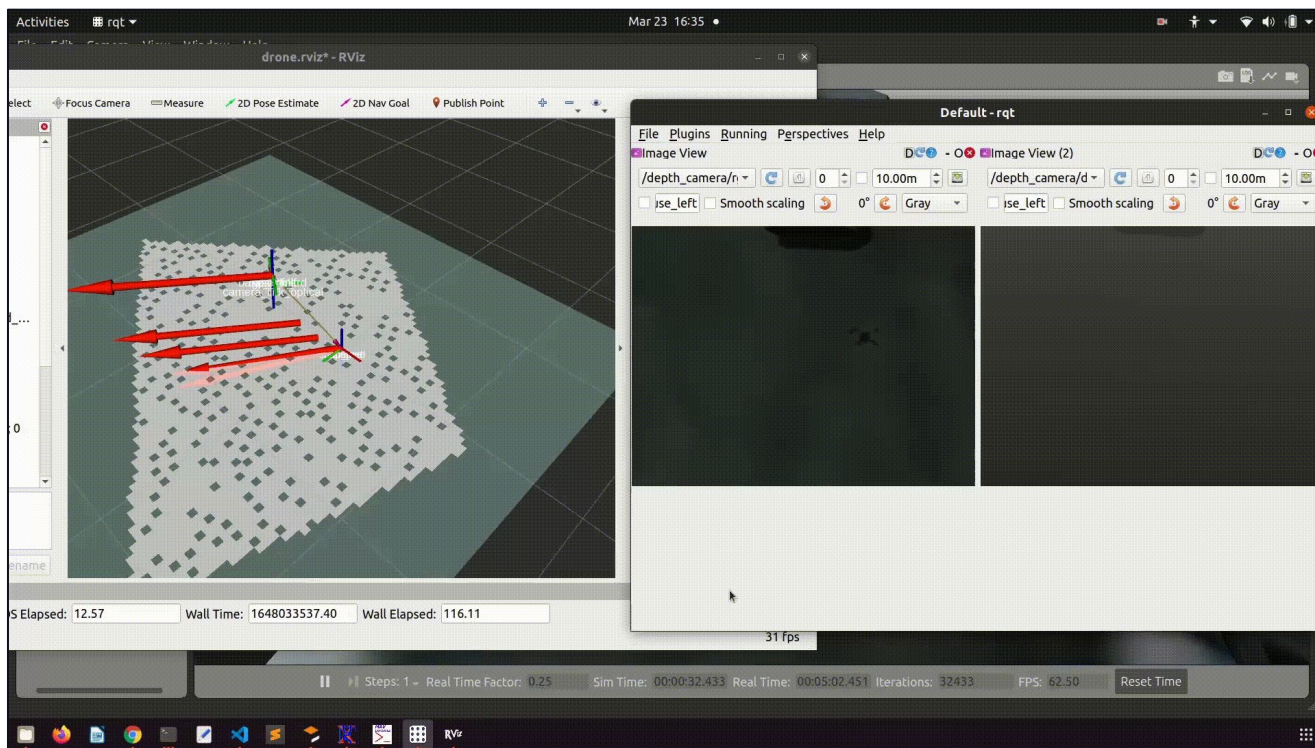
Mapping and Exploration

Frontier Exploration

- Frontiers are regions on the boundary between open space and unexplored space.
- The approach involves navigating towards these frontiers and building the map.
- By moving to a new frontier, we can keep building the map of the environment, until there are no new frontiers left to detect.



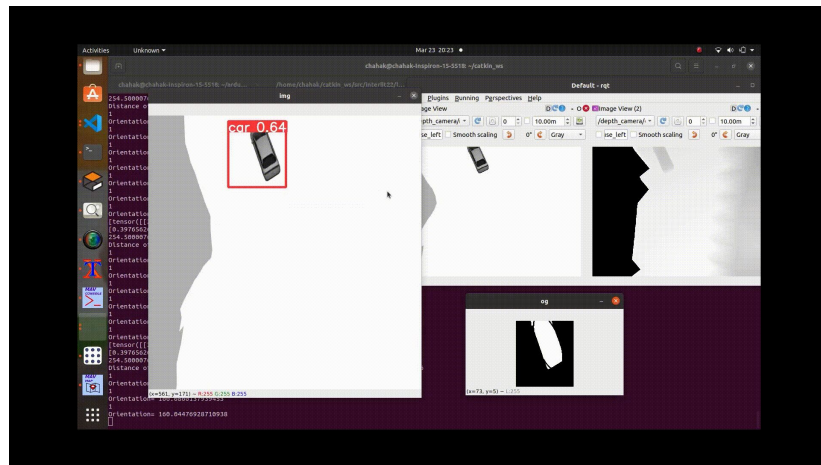
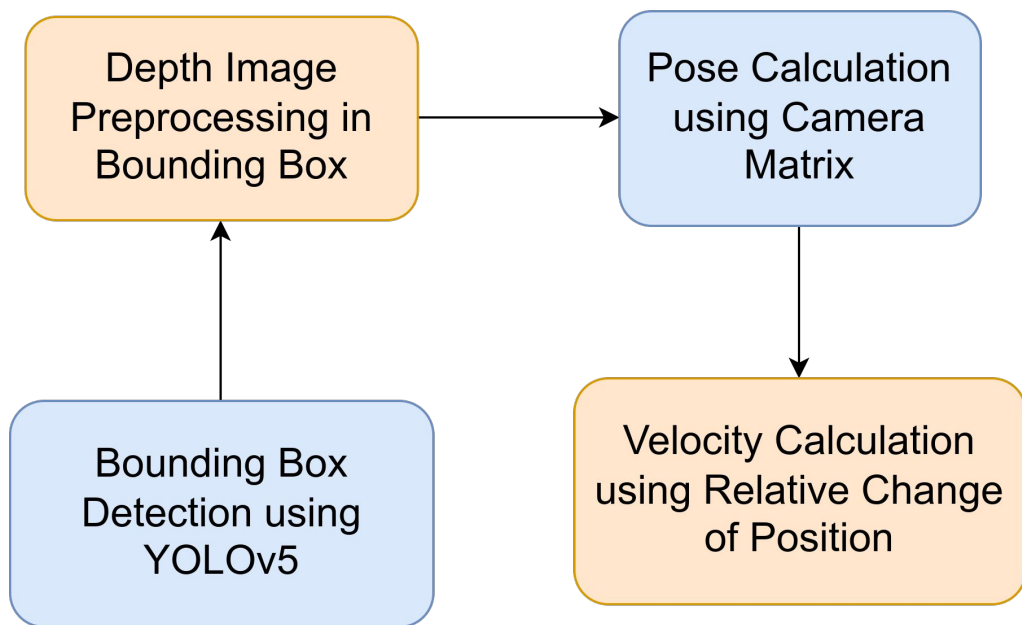
Mapping and Exploration



Phase - II : Navigation



UGV Detection and Tracking : Approach



UGV Detection using YOLOv5

Manual Collection of
RGB images from
UAV

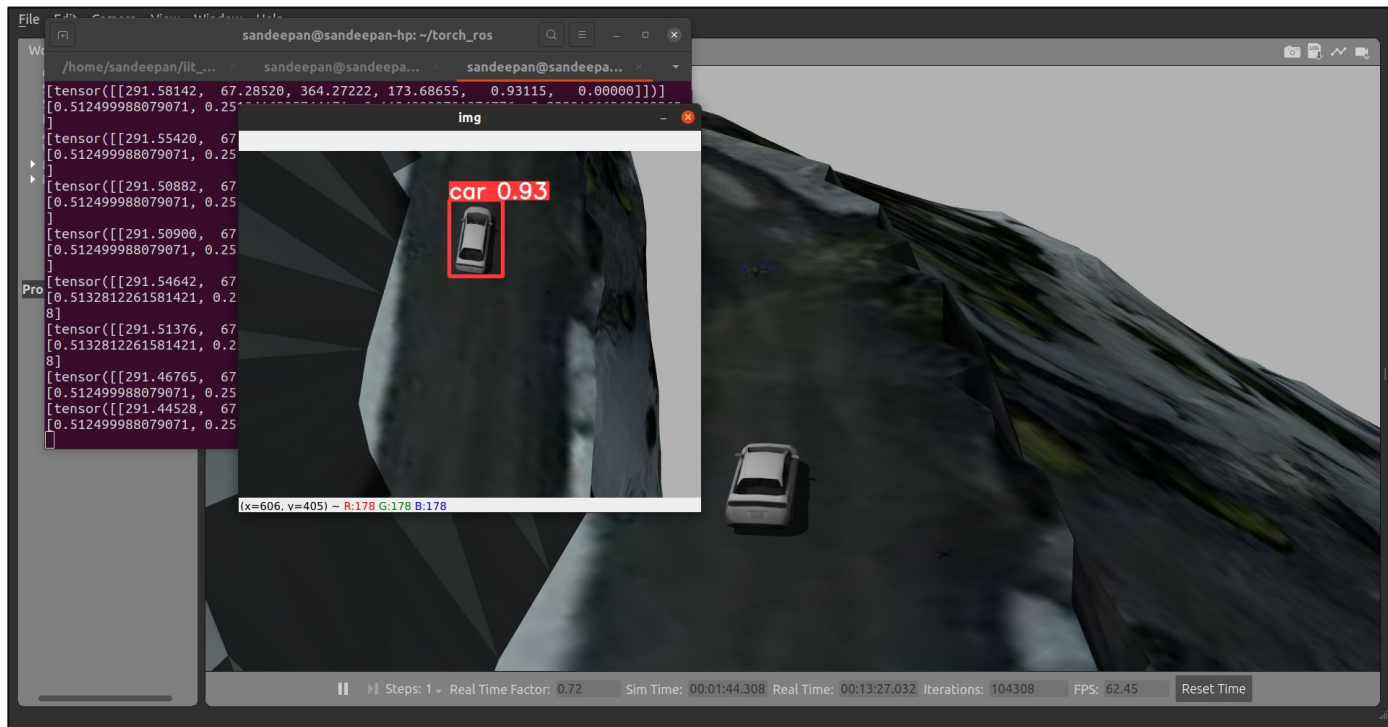
Image Augmentation
(3 times increase in
dataset)

Training on YOLOv5

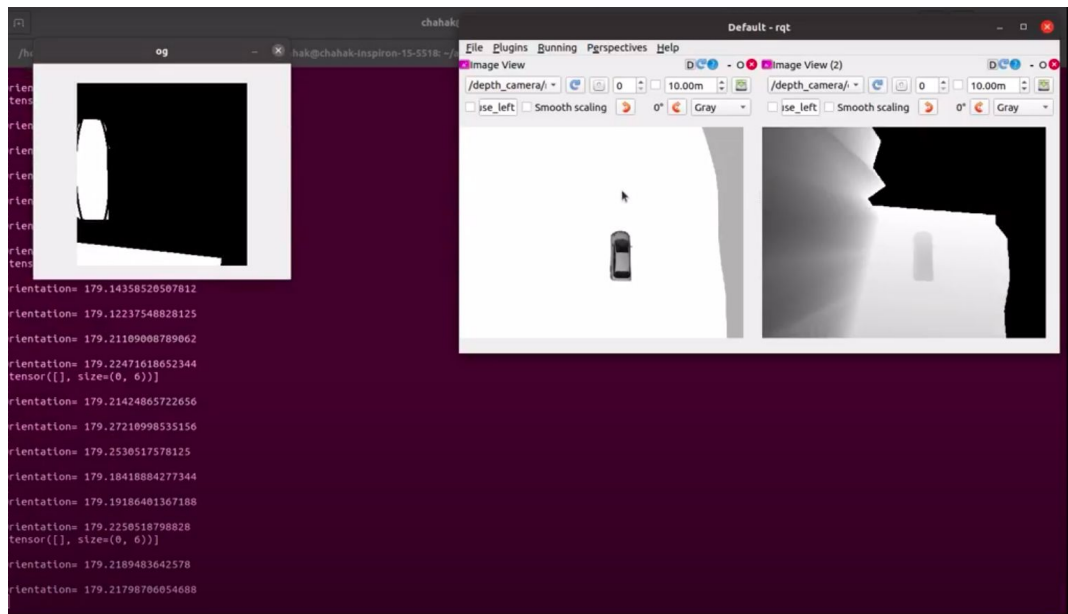
RESULTS :

mAP@0.5 scores: 0.989
mAP@0.5.:95 scores: 0.552

Yolov5 Detection

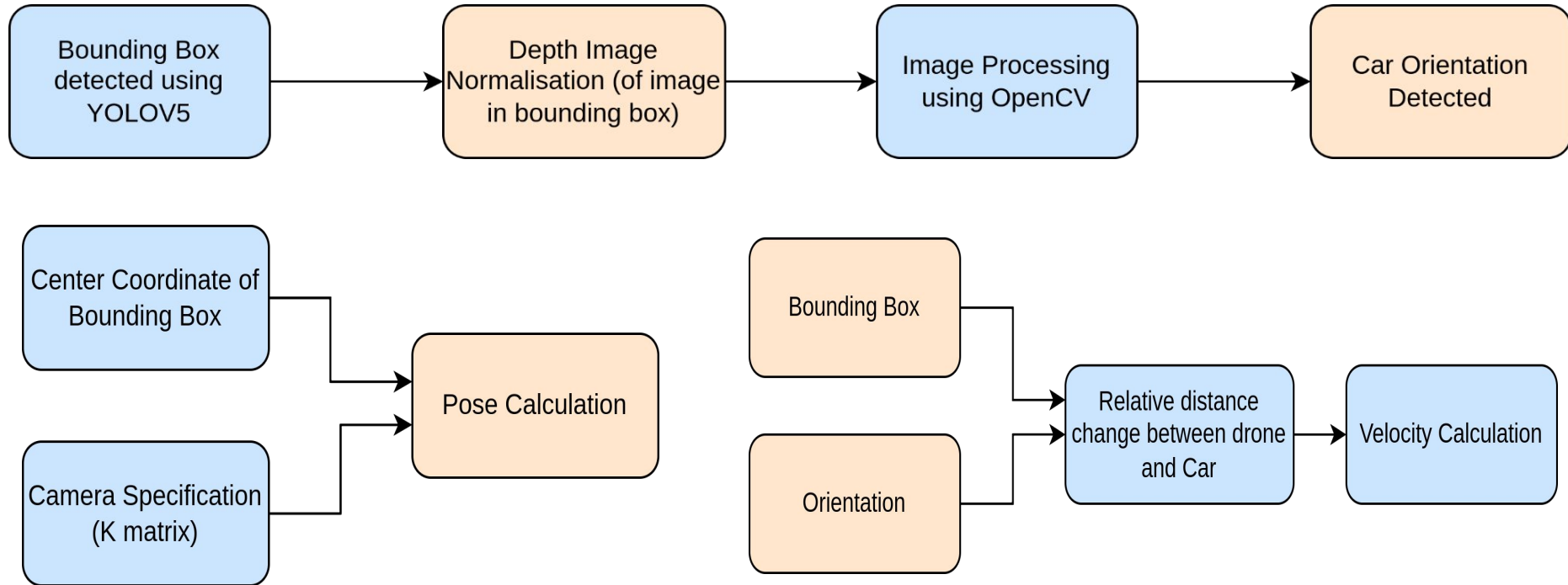


Orientation from Depth Image

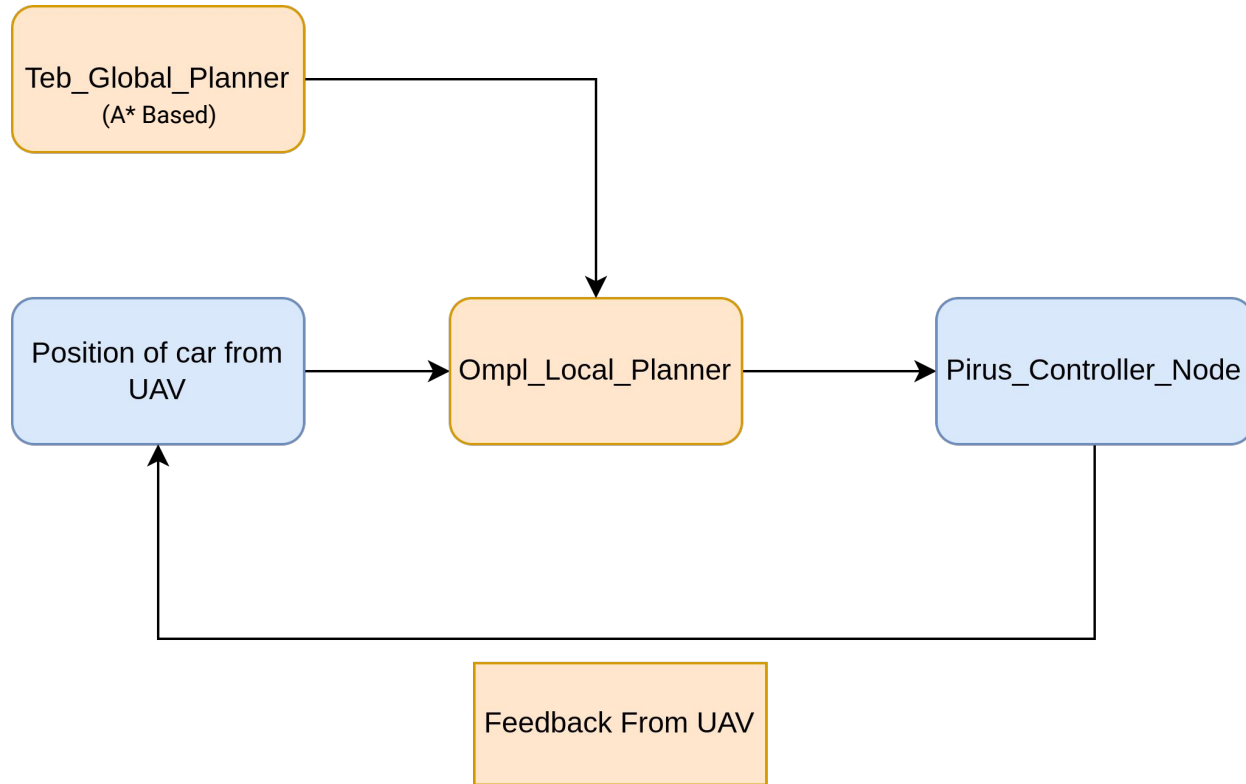


Orientation 179° as determined from Depth Image

UGV Tracking

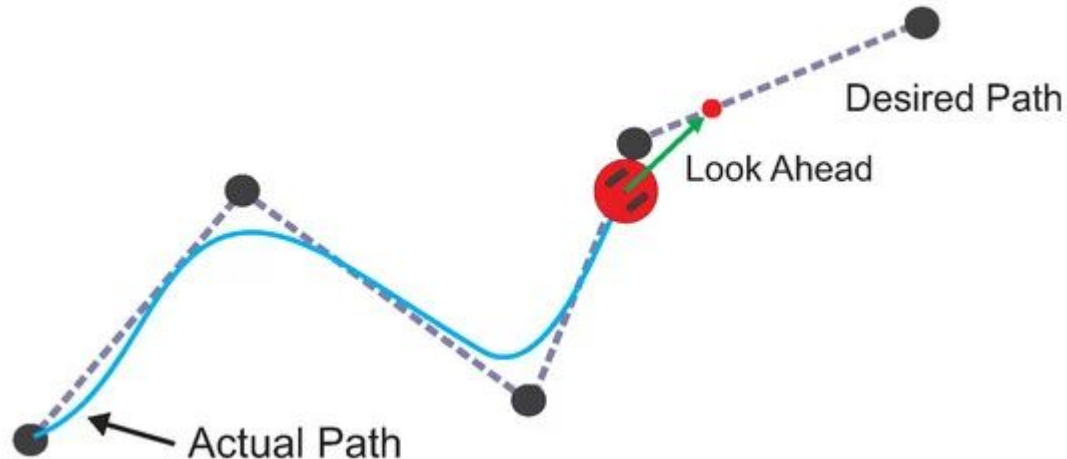


UGV Controls



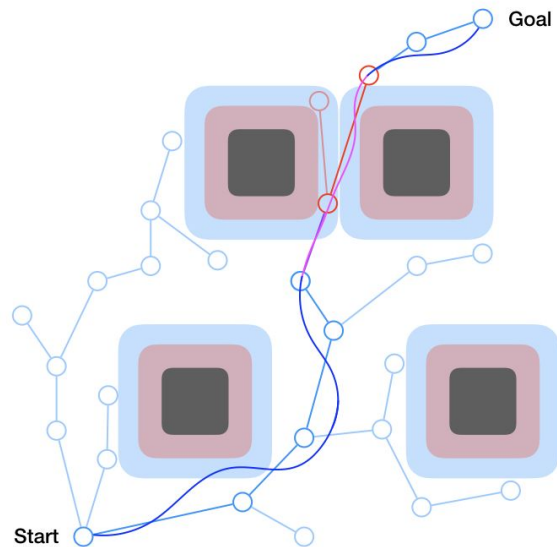
UGV Control

For UGV control Pure Pursuit Controller was used which is a path tracking algorithm. It computes the angular velocity command that moves the robot from its current position to reach some look-ahead point in front of the robot.



UGV Path Planning

- Local Planner-OMPL(Open Motion Planning Library) which is a collection of state-of-the-art sampling-based motion planning algorithms.
- Global Planner-TEB(Timed Elastic Band) is used which locally optimizes the robot's trajectory with respect to trajectory execution time, separation from obstacles and compliance with kinodynamic constraints at runtime.



Challenges Faced

- Configuring the UAV IMU axis for accurately fusing the IMU data while localizing.
- Height optimization while mapping the terrain autonomously as the depth data is lost at a height greater than 15 metres above the road.
- Noise in the output image provided by the U-Net model along with the latency provided new challenges in the mapping phase.
- Low camera update rate.
- Insufficient hardware specs as we averaged around 0.1 RTF.
- Scarcity of time for integrating the individual sub-parts.

Scope of Improvement

- Road segmentation can be enhanced by much larger dataset and better camera sensor.
- Mapping could be done autonomously by choosing frontiers on distance-based metric.
- Reducing the inference time of the U-Net model and processing the filtered image before feeding it to RTabMap.
- More accurate tracking of UGV using object tracking and optical flow methods.

Performance Analysis(Phase-I)

Computation	Cost(approx)
Gazebo	2 cores
Ardupilot	0.085 cores
RTabMap + UAV Localization	0.3 cores
Road segmentation	4 cores

Performance Analysis(Phase-II)

Computation	Cost(approx)
Gazebo	2 cores
Ardupilot	0.085 cores
UAV + UGV Localization	2 cores
UGV Control	0.5 cores

System Specifications

OS	Ubuntu 20.04
Processor	11th Gen Intel(R) Core(TM) i5-1135G7 @ 2.40GHz
Graphics	GeForce MX350

Thank You