



TEXAS TECH UNIVERSITY SYSTEM™



Autonomous Navigation with Unitree Go1 Quadrupe Robot

Implementation of SLAM, Object Detection plus tracking, and Path Planning

Graduate Project Lab
Week 6

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October 15, 2024



1. SLAM Basics

Mathematical Foundations

•Core Components:

- **State Estimation:** Estimating the robot's pose (position and orientation)
- **Map Building:** Creating a representation of the environment

•Key Mathematical Concepts:

- **Probability Theory:** Handling uncertainty
- **Bayesian Filters:** Recursive estimation (e.g., Kalman Filter, Particle Filter)
- **Linear Algebra:** Transformations and coordinate frames

The SLAM Problem Formulation

•State Vector ($\{x\}$):

- Robot pose and map features

•Observations ($\{z\}$):

- Sensor measurements (e.g., LiDAR scans)

•Controls ($\{u\}$):

- Robot motion commands

•Objective:

- Estimate the posterior $P(x|z_{1:t}, u_{1:t})$

2. Bayesian Approach to SLAM



Bayesian Approach to SLAM

- **Recursive Bayesian Estimation:**

- **Prediction Step:**

- $\hat{\mathbf{x}}_t = f(\mathbf{x}_{t-1}, \mathbf{u}_t) + \mathbf{w}_t$
 - \mathbf{w}_t : Process noise

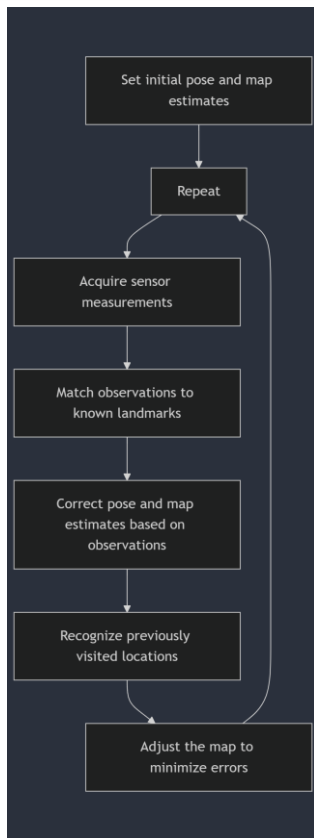
- **Update Step:**

- $\mathbf{x}_t = \hat{\mathbf{x}}_t + K_t(\mathbf{z}_t - h(\hat{\mathbf{x}}_t))$
 - K_t : Kalman Gain
 - $h(\hat{\mathbf{x}}_t)$: Measurement model

- **Assumptions:**

- Markov property
 - Gaussian noise (for EKF SLAM)

3. SLAM Algorithm Flowchart



- **Step 1: Initialization**
 - Set $\mathbf{x}_0 = [x_0, y_0, \theta_0]$
 - Empty map \mathcal{M}
- **Step 2: Motion Prediction**
 - $\hat{\mathbf{x}}_t = f(\mathbf{x}_{t-1}, \mathbf{u}_t)$
- **Step 3: Sensor Measurement**
 - Obtain \mathbf{z}_t
- **Step 4: Data Association**
 - Match \mathbf{z}_t to landmarks in \mathcal{M}
- **Step 5: State Update**
 - Compute \mathbf{x}_t and update \mathcal{M}
- **Step 6: Map Optimization**
 - Adjust map to minimize residual errors

```
initialize(x_0, M)
for t in 1...T:
    # Motion Prediction
    x_pred = predict_motion(x_{t-1}, u_t)

    # Sensor Measurement
    z_t = get_sensor_data()

    # Data Association
    associations = associate_data(z_t, M)

    # State and Map Update
    x_t, M = update_state_map(x_pred, z_t, associations)

    # Map Optimization (if necessary)
    M = optimize_map(M)

return go(f, seed, [])
}
```

4. Setting up SLAM for Software Development



Installation and Setup

- **Step 1: Install ROS 2 Humble**

- Update system packages
- Add ROS 2 repository and keys
- Install ROS 2 desktop packages

- **Step 2: Create ROS 2 Workspace**

- `mkdir -p ~/ros2_ws/src`
- Initialize workspace with `colcon build`

- **Step 3: Clone Necessary Packages**

- `turtlebot3`, `turtlebot3_msgs`, `turtlebot3_simulations`
- Use compatible branches (e.g., `humble-devel`)

Installing Dependencies

- **Use `rosdep` to Install Dependencies**

- `rosdep update`
- `rosdep install --from-paths src --ignore-src -r -y`

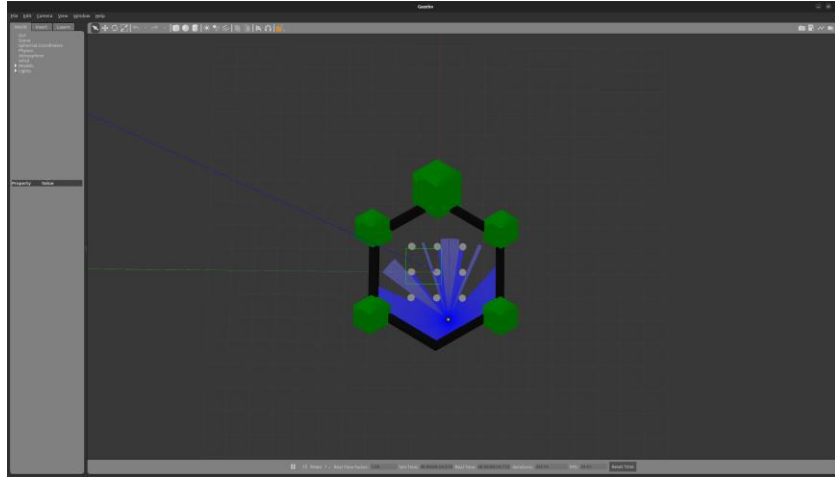
- **Build the Workspace**

- `colcon build --symlink-install`

- **Source the Workspace**

- `source ~/ros2_ws/install/setup.bash`
- Add to `~/ .bashrc` for automatic sourcing

5. Launching SLAM



Gazebo: Simulates the robot and environment

- **Set the Robot Model Environment Variable**

- `export TURTLEBOT3_MODEL=burger`

- **Terminal 1: Launch Gazebo Simulation**

- `ros2 launch turtlebot3_gazebo turtlebot3_world.launch.py`

- **Terminal 2: Launch Cartographer SLAM Node**

- `ros2 launch turtlebot3_cartographer cartographer.launch.py use_sim_time:=True`

6. Visualization in Real Time

- **Visualizing with RViz:**

- `rviz2 -d ~/ros2_ws/src/turtlebot3_cartographer/rviz/turtlebot3_cartographer.rviz`

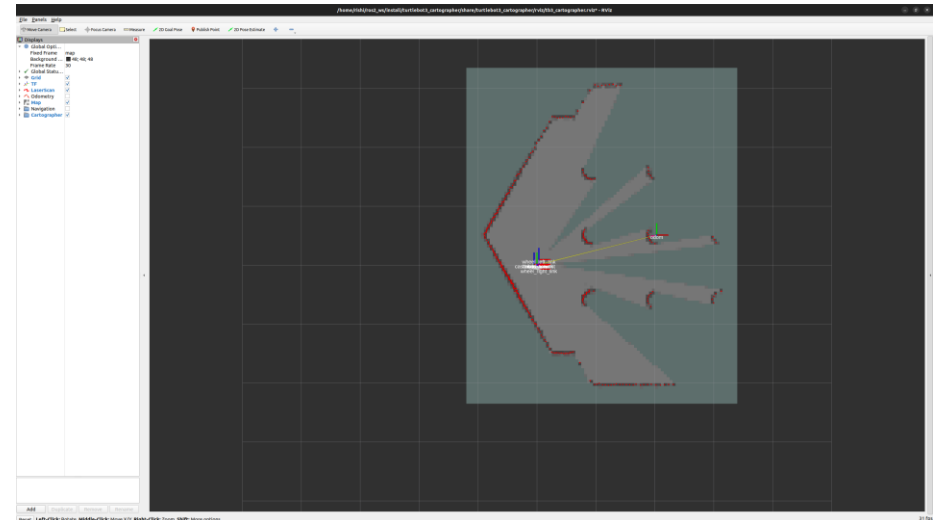
- **RViz Displays:**

- **Robot Model:** Visual representation of TurtleBot3
- **Map:** 2D occupancy grid map being built in real-time
- **Laser Scan:** Sensor data visualization

- **Interacting with RViz:**

- Zoom, pan, and rotate the view
- Add or remove display elements

RViz: Visualizes the robot's pose and the map being built



7. COCO DATASET



What is COCO?



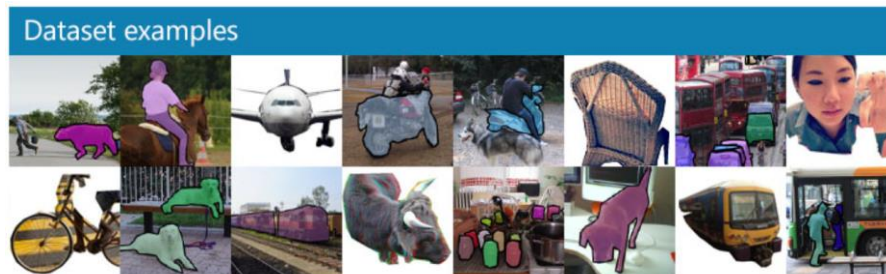
COCO is a large-scale object detection, segmentation, and captioning dataset. COCO has several features:

Over 100 Classes:

- Humans
- Animals
- Vehicles
- Household Items etc.

Over 200,000 Images

Very Large when trained for object detection (80 MB)



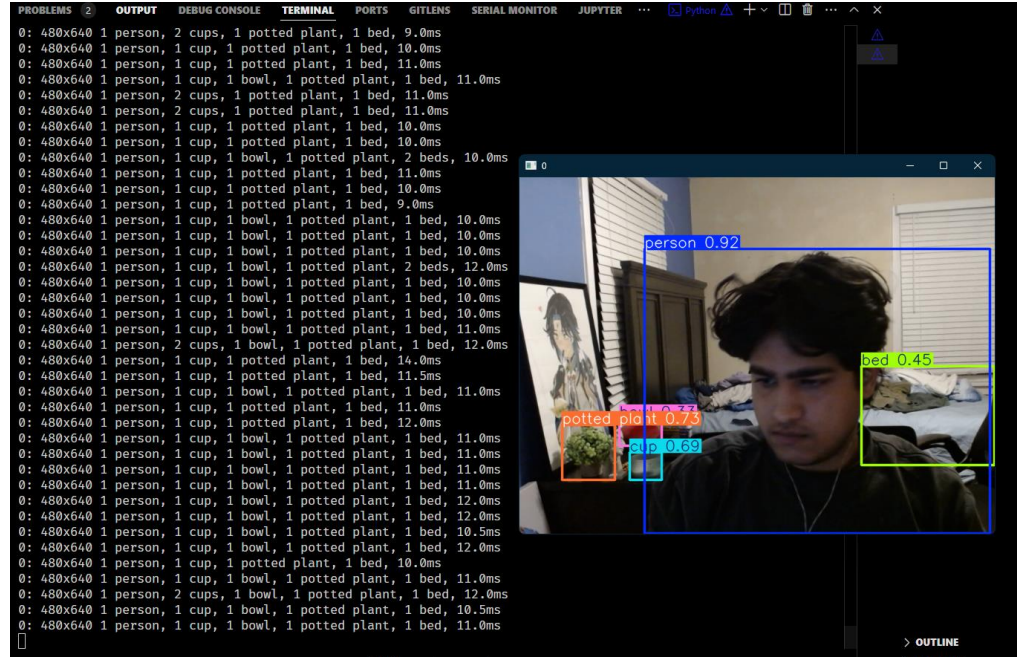
8. YOLOV8 Object Detection

Inference with a Pre-Built Model

```
from ultralytics import YOLO

# Load model
model = YOLO("yolov8s.pt")

# Inference
results = model(source=0, show=True)
```



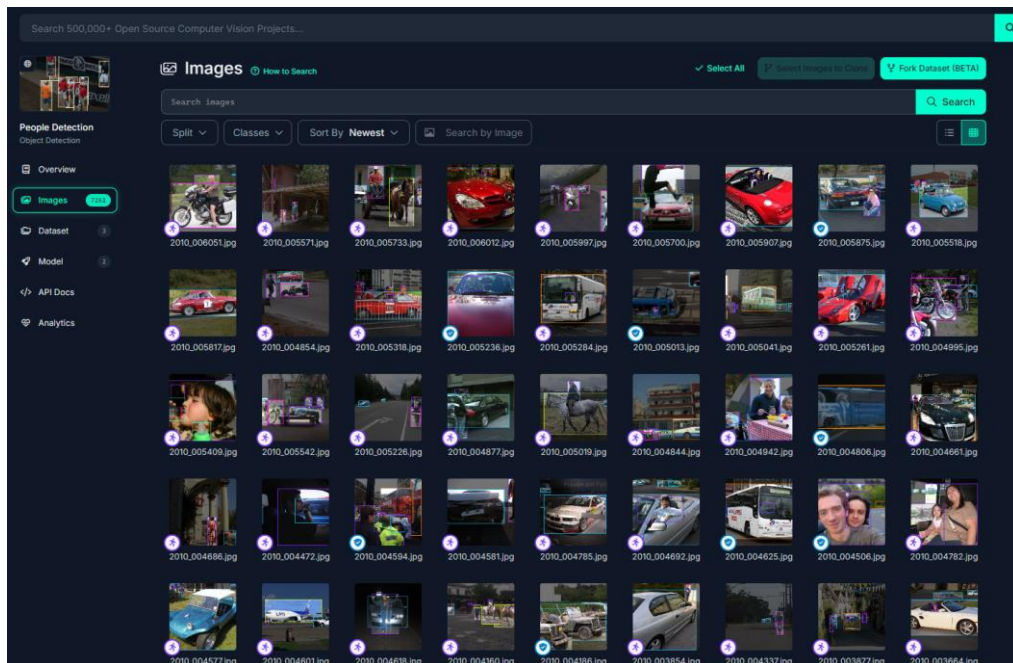
The screenshot displays the Jupyter Notebook interface with the following components:

- Terminal Output:** A list of 480x640 images with detected objects and their confidence scores. The objects include 'person', 'cup', 'potted plant', 'bed', and 'bowl'.
- Video Frame:** A video frame showing a person, a potted plant, a cup, and a bed. Bounding boxes and confidence scores are overlaid on the frame:
 - person: 0.92
 - potted plant: 0.73
 - cup: 0.69
 - bed: 0.45

9. Training an Object Detection Model from Scratch



Roboflow: Open-Source Image Annotation and Dataset Library



```
!pip install roboflow

from roboflow import Roboflow
rf = Roboflow(api_key="3Xj3eINZEW8xa3RNGle1")
project = rf.workspace("leo-ueno").project("people-detection-o4rdr")
version = project.version(8)
dataset = version.download("yolov8")
```

10. Training Results



```
if __name__ == '__main__':
    # Train the model
    results = model.train(data="D:\Documents\Object_Training\data.yaml", epochs=100, imgs2=640)

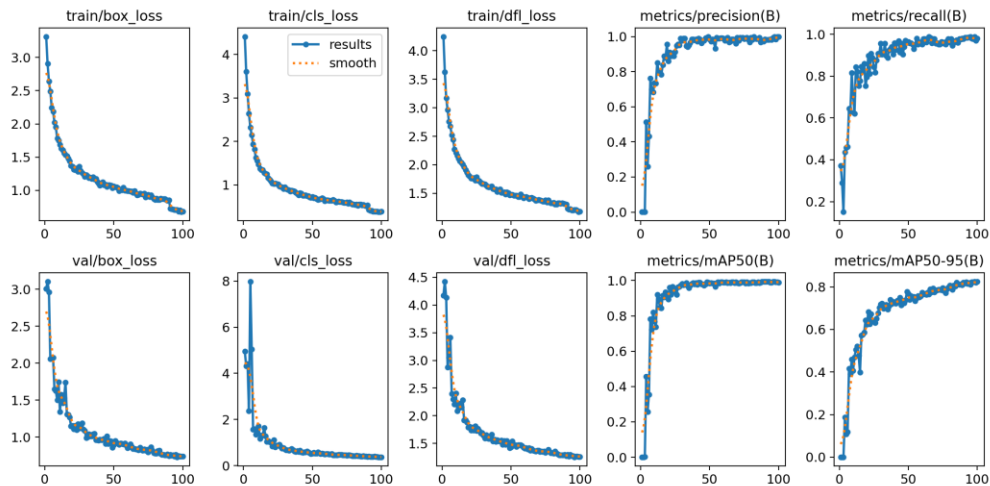
Python

New https://pytorch.org/project/ultralytics/8.2.72 available. Update with 'pip install -U ultralytics'
Ultralytics YOLOv8.2.68 Python-3.9.5 torch-2.0.0+cu117 CUDA:0 (NVIDIA GeForce RTX 2070, 8192MiB)
engine\trainer: task=detect, mode=train, model=yolov8n.yaml, data=D:\Documents\Object_Training\data.yaml, epo
Overriding model.yaml nc=80 with nc=1
```

	from	n	params	module	arguments
0	-1	1	464	ultralytics.nn.modules.conv.Conv	[3, 16, 3, 2]
1	-1	1	4672	ultralytics.nn.modules.conv.Conv	[16, 32, 3, 2]
2	-1	1	7360	ultralytics.nn.modules.block.C2f	[32, 32, 1, True]
3	-1	1	18560	ultralytics.nn.modules.conv.Conv	[32, 64, 3, 2]
4	-1	2	49664	ultralytics.nn.modules.block.C2f	[64, 64, 2, True]
5	-1	1	73984	ultralytics.nn.modules.conv.Conv	[64, 128, 3, 2]
6	-1	2	197632	ultralytics.nn.modules.block.C2f	[128, 128, 2, True]
7	-1	1	295424	ultralytics.nn.modules.conv.Conv	[128, 256, 3, 2]
8	-1	1	460288	ultralytics.nn.modules.block.C2f	[256, 256, 1, True]
9	-1	1	164608	ultralytics.nn.modules.block.SPPF	[256, 256, 5]
10	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2, 'nearest']
11	[-1, 6]	1	0	ultralytics.nn.modules.conv.Concat	[1]
12	-1	1	148224	ultralytics.nn.modules.block.C2f	[384, 128, 1]
13	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2, 'nearest']
14	[-1, 4]	1	0	ultralytics.nn.modules.conv.Concat	[1]
15	-1	1	37248	ultralytics.nn.modules.block.C2f	[192, 64, 1]
16	-1	1	36992	ultralytics.nn.modules.conv.Conv	[64, 64, 3, 2]
17	[-1, 12]	1	0	ultralytics.nn.modules.conv.Concat	[1]
18	-1	1	123648	ultralytics.nn.modules.block.C2f	[192, 128, 1]

TensorBoard: Start with 'tensorboard --logdir runs\detect\train12', view at <http://localhost:6006/>
 Freezing layer 'model.22.dfl.conv.weight'
 AMP: running Automatic Mixed Precision (AMP) checks with YOLOv8n ...
 AMP: checks passed
 Output is truncated. View as a [scrollable element](#) or open in a [text editor](#). Adjust cell output [settings](#) ...
 train: Scanning D:\Documents\Object_Training\dataset\RGB\train\labels.cache... 652 images, 0 backgrounds, 0 c
 augmentations: Blur(p=0.01, blur_limit=(3, 7)), MedianBlur(p=0.01, blur_limit=(3, 7)), ToGray(p=0.01), CLAHE
 val: Scanning D:\Documents\Object_Training\dataset\RGB\valid\labels.cache... 186 images, 0 backgrounds, 0 cor
 Plotting labels to runs\detect\train12\labels.jpg ...
 optimizer: 'optimizer-auto' found, ignoring 'lr=0.01' and 'momentum=0.937' and determining best 'optimizer',
 optimizer: AdamW(lr=0.002, momentum=0.9) with parameter groups 57 weight(decay=0.0), 64 weight(decay=0.0005),
 TensorBoard: model graph visualization added
 Image sizes 640 train, 640 val
 Using 8 dataloader workers
 Logging results to runs\detect\train12
 Starting training for 100 epochs ...

Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
1/100	2.34G	3.312	4.414	4.248	33	640: 100% 41/41 [00:07c
	Class	Images	Instances	Box(P	R	mAP50 mAP50-95): 100% 6/
	all	186	186	0.00124	0.371	0.000862 0.00026



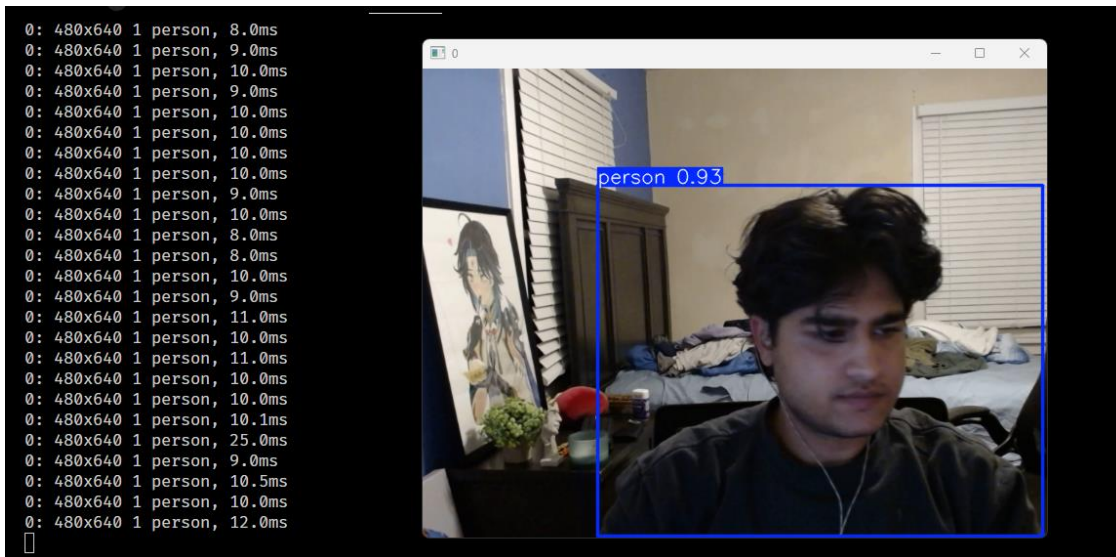
Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
98/100	2.31G	0.703	0.3785	1.201	12	640: 100% 41/41 [00:05c
	Class	Images	Instances	Box(P	R	mAP50 mAP50-95): 100% 6/
	all	186	186	0.984	0.988	0.991 0.825

Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
99/100	2.31G	0.6771	0.3779	1.174	12	640: 100% 41/41 [00:05c
	Class	Images	Instances	Box(P	R	mAP50 mAP50-95): 100% 6/
	all	186	186	1	0.971	0.99 0.821

Epoch	GPU_mem	box_loss	cls_loss	dfl_loss	Instances	Size
100/100	2.32G	0.6845	0.3845	1.182	12	640: 100% 41/41 [00:05c
	Class	Images	Instances	Box(P	R	mAP50 mAP50-95): 100% 6/
	all	186	186	1	0.981	0.988 0.825

100 epochs completed in 0.211 hours.
 Optimizer stripped from runs\detect\train12\weights\last.pt, 6.3MB
 Optimizer stripped from runs\detect\train12\weights\best.pt, 6.3MB

11. New Light Weight Model!!





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