



# MODULE 5: TECHNICAL FUNDAMENTALS – IN-DEPTH TECHNOLOGIES AND BASICS OF SIMULATION & ANALYSIS FOR AUTONOMOUS VEHICLES

Nicholas Ho  
Institute of System Science, NUS



# Contents



1. Self-driving cars' perception and decision-making
2. Basics of Simulation & Analysis
3. Workshop: Introduction to software pertaining to topics on Simulation & Analysis for Autonomous Vehicles

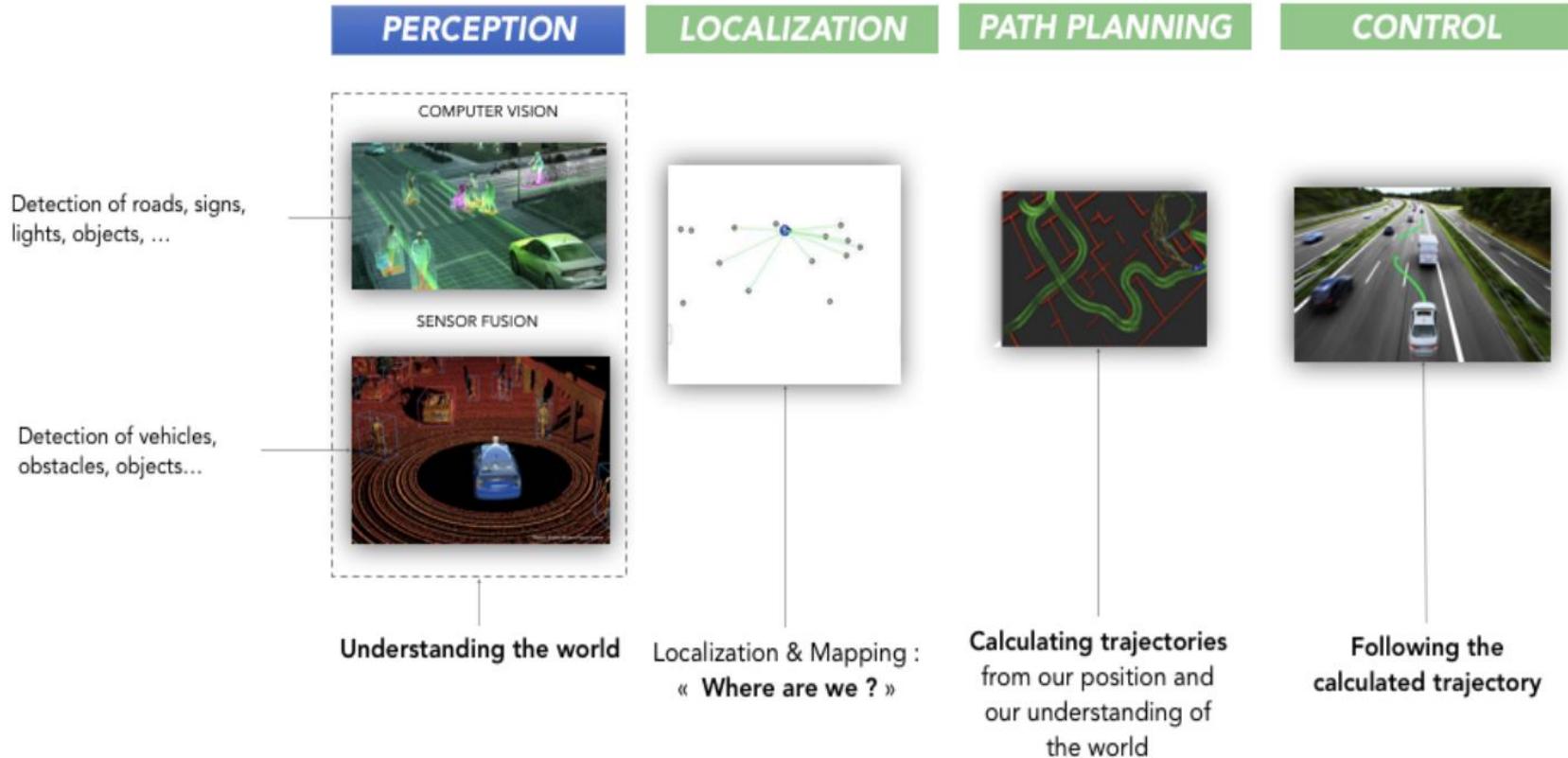


# CHAPTER 1: **SELF-DRIVING CARS' PERCEPTION AND DECISION-MAKING**





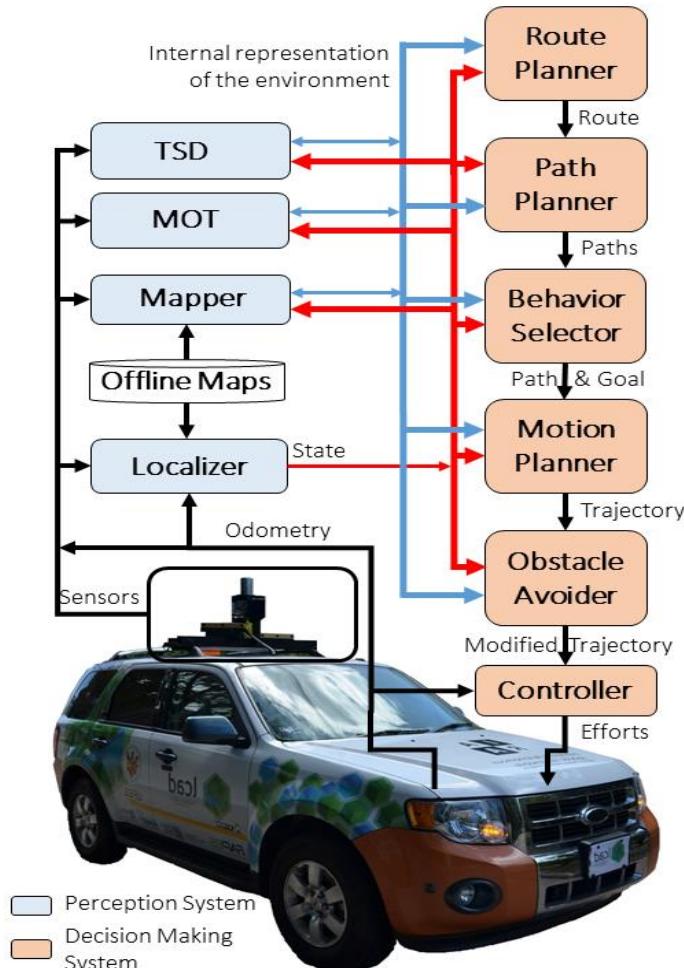
# RECAP: How AV Work?





# 1. AV PERCEPTION

# Typical Architecture of Self-Driving Cars

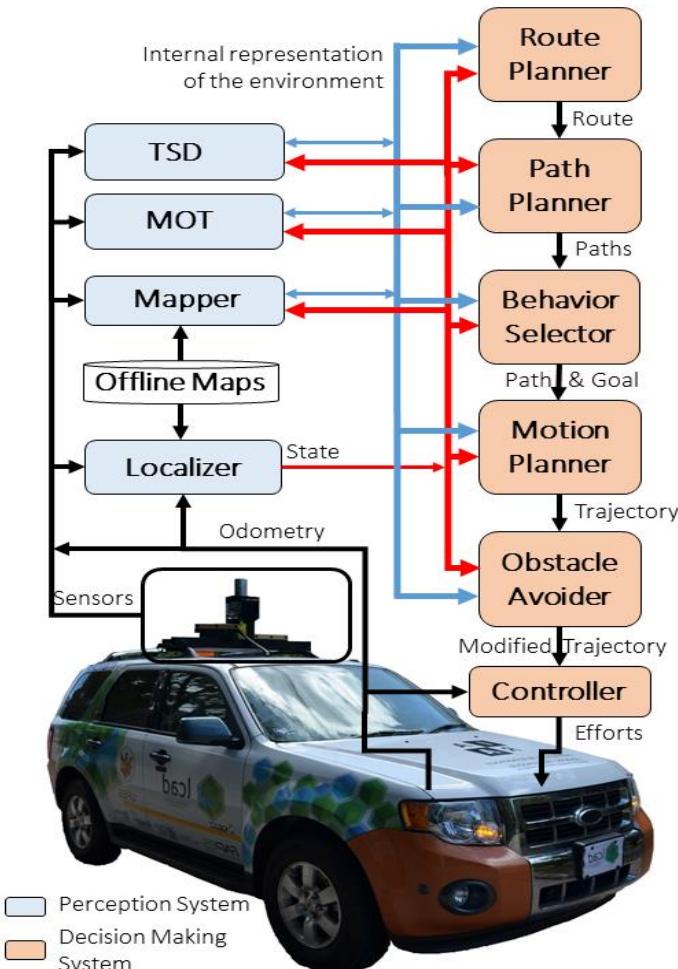


## The Perception Subsystems:

- The Localizer subsystem is responsible for **estimating the car's State (pose, linear velocities, angular velocities, etc.) in relation to static maps of the environment**
- Receives inputs from the Offline Maps, Sensors' data and Odometry
- Outputs the State of the car
  - ❖ Offline Maps (i.e. static maps) are **computed automatically before the autonomous operation**, typically using the sensors of the self-driving car itself; manual annotations or editions may be required



# Typical Architecture of Self-Driving Cars

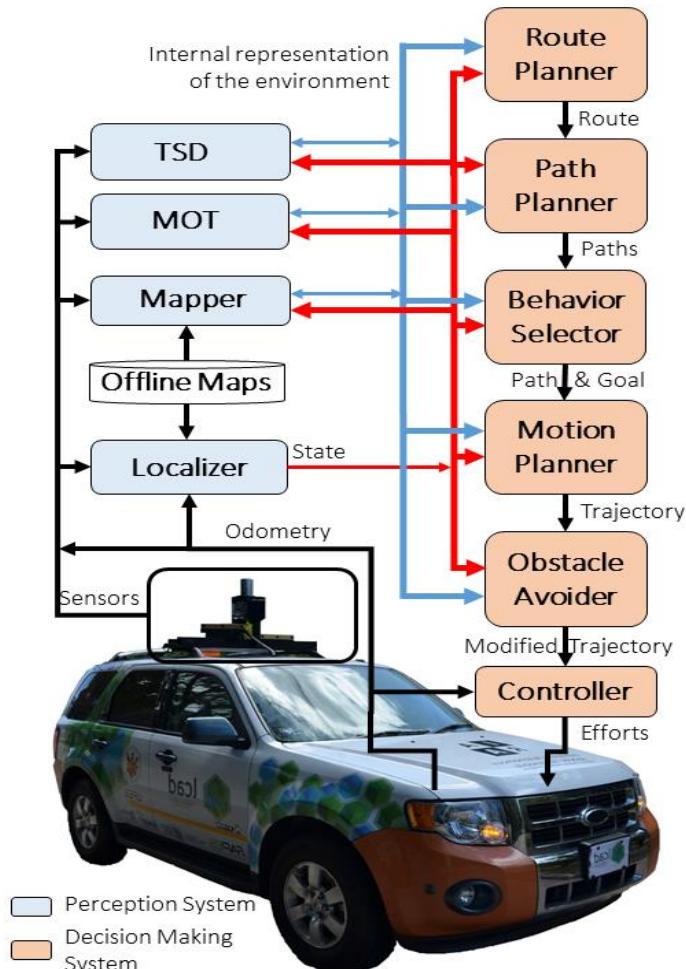


## The Perception Subsystems:

- The **Mapper subsystem** receives the inputs from the **Offline Maps** database and the self-driving car's **State**, and generates the **online map** (i.e. **real-time maps**) as **output**
- The **Moving Objects Tracker subsystem (i.e. MOT)** receives the inputs from the **Offline Maps** and the self-driving car's **State**, and **detects and tracks** (i.e. calculates the pose and velocity of) **the nearest moving obstacles** (e.g. other vehicles, lamp posts, pedestrians)



# Typical Architecture of Self-Driving Cars



## The Perception Subsystems:

- **The Traffic Signalization Detector subsystem (i.e. TSD)** is responsible for the **detection and recognition of traffic signalization**;
  - ❖ Receives the Sensors' data and the car's State, and detects the position of traffic signalizations and recognizes their class or status



# Fusion of Various Sensory Systems



Source: <https://www.youtube.com/watch?v=gEy91PGGLR0>



# Fusion of Various Sensory Systems

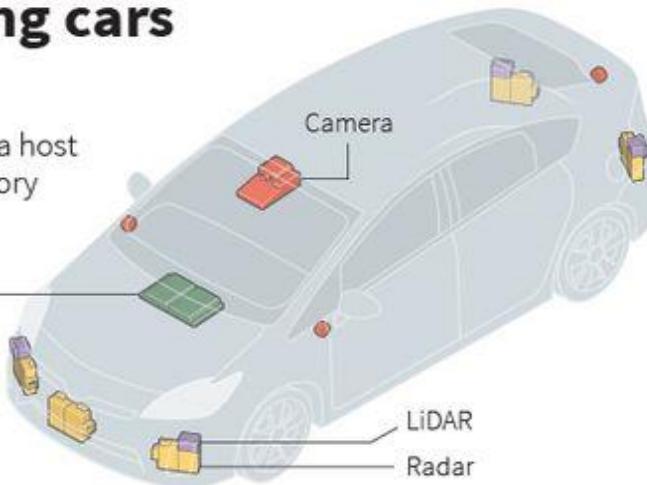


## How self-driving cars see the road

Autonomous vehicles rely on a host of sensors to plot their trajectory and avoid accidents.

- **Multi-domain controller**

Manages inputs from camera, radar, and LiDAR. With mapping and navigation data, it can confirm decisions in multiple ways.



- **Camera**

Takes images of the road that are interpreted by a computer. Limited by what the camera can "see".



- **Radar**

Radio waves are sent out and bounced off objects. Can work in all weather but cannot differentiate objects



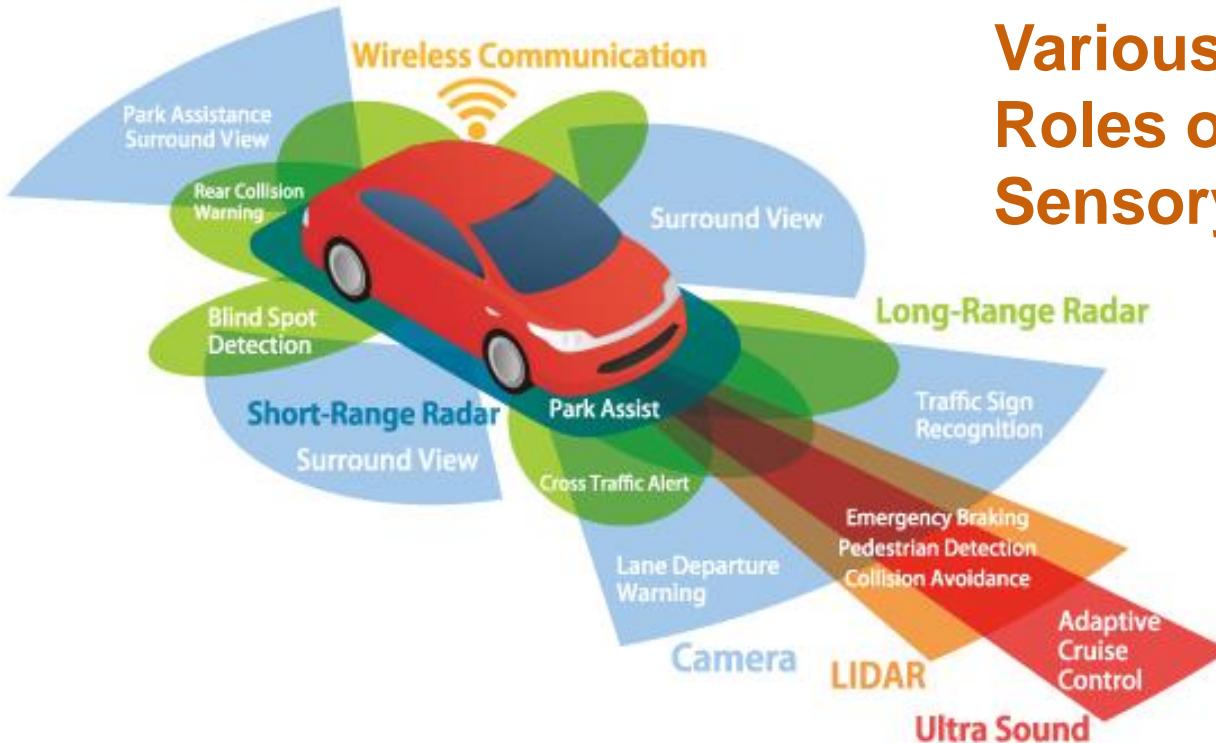
- **LiDAR**

Light pulses are sent out and reflected off objects. Can define lines on the road and works in the dark.

Source: Delphi



# Fusion of Various Sensory Systems



## Various Possible Roles of each Sensory System

- The **Camera** is a very good tool for **detecting roads, reading signs or recognizing a vehicle**
- The **Lidar** is better at accurately **estimating the position of this vehicle**
- The **Radar** is better at accurately **estimating the speed**



# Fusion of Various Sensory Systems



NUS  
National University  
of Singapore



Sensortype	Radar	Camera	Ultrasonic	Lidar (Multi-beam)	Lidar Laserscanner
Beam width	20-70°	50-70°	30-50°	10-30°	180-360°
Max. range	50-200 m	50-150 m	2-5 m	10-150 m	150-200 m
Measured variables	Distance Relative velocity	Object outline Angle	Distance	Distance Angle	Distance Angle Object outline
Environment model					



# Fusion of Various Sensory Systems

Table 1. Comparison of sensors: “✓” operate completely under specific conditions, “–” operate reasonably well under specific conditions, “✗” does not operate well.

Factors	Camera	LiDAR	RADAR	Fusion
Range	–	–	✓	✓
Resolution	✓	–	✗	
Distance Accuracy	–	✓	✓	✓
Velocity		✗	✓	✓
Color Perception	–	✗	✗	✓
Object Detection	✗		✓	✓
Object Classification	✓	✗	✗	✓
Lane Detection	✓	✗	✗	✓
Obstacle Edge Detection	✓	✓	✗	✓
Illuminations Conditions	✗	✓	✓	✓
Weather Conditions	✗	–	✓	✓

The aim of sensor fusion is to use the advantages of each to precisely understand its environment



# Fusion of Various Sensory Systems



Features	LIDAR	RADAR	Ultrasonic	Passive Visual (Camera Technology)
<b>Primary technology</b>	Light detection and ranging. It is a surveying technology that measures distance by illuminating a target with laser.	Radio detection and ranging. It is an object-detection system that uses radio waves to determine the range, angle, or velocity of objects.	It is an object detection system which emits ultrasonic sound waves and analyzes their return to determine distance.	It uses sophisticated object detection algorithms like DNN[1] to understand images visible from cameras.
<b>Proximity detection</b>	Poor	Good	Very good	Poor
<b>Range</b>	~100 m	~0.15-250 m	~5 m	250 m
<b>Resolution</b>	Good	Average	Poor	Very Good
<b>Works in dark</b>	Very good	Very good	Very good	Very poor (Almost non-existent)
<b>Works in very bright light</b>	Very Good	Very Good	Very Good	Good
<b>Works in snow/ fog/ rain</b>	Average	Very Good	Very Good	Poor
<b>Provides colour/ contrast</b>	Very Poor	Very Poor	Very Poor	Very good
<b>Detects speed</b>	Good	Very Good	Very Poor	Poor
<b>Sensor cost</b>	Costs around \$70,000 (eg: Velodyne HD64)	It is cost effective at an average price of ~\$50-\$200	Costs less than \$50	~\$100-200
<b>Sensor size</b>	Very bulky. It weighs an approx. 15 kg for the most popular Velodyne HD64.	Light & compact at ~200 grams	Very Good	Very Good
<b>Top 5 players</b>	Robert Bosch, General Motors, Daimler, Ford Global Technologies & Bayerische Motoren Werke	Toyota, Robert Bosch, Denso, Nissan & Fujitsu TEN	Denso, Honda, Nissan, Mitsubishi Electric & Robert Bosch	Denso, Panasonic Electric Works, Robert Bosch, Valeo Systemes Electriques & Hyundai Mobis



# Fusion of Various Sensory Systems



Sensors	Pros	Cons
Camera	<ul style="list-style-type: none"><li>• High-speed imaging</li><li>• Passive sensor</li><li>• Best for recognition</li><li>• No need for high power</li><li>• Inexpensive</li><li>• Infrared or thermal availability</li><li>• Interference-free</li><li>• High sensing resolution</li><li>• AI and deep learning research are very advanced</li></ul>	<ul style="list-style-type: none"><li>• Light and visibility dependent</li><li>• Easily affected by shadow or reflections</li><li>• Get dirty frequently</li><li>• Direct 3D is not possible without any stereo</li></ul>
LiDAR	<ul style="list-style-type: none"><li>• Direct 3D information</li><li>• Performed in both day and night</li><li>• Very high accuracy measurements</li><li>• High resolution</li><li>• At present, AI research is very advanced</li></ul>	<ul style="list-style-type: none"><li>• Very expensive</li><li>• No appearance information</li><li>• Ineffective under rain and fog</li><li>• Have rotating parts</li><li>• Most of LiDAR is not a deep learning base yet</li></ul>
RADAR	<ul style="list-style-type: none"><li>• Captures direct distance and velocity</li><li>• Inexpensive</li><li>• Performed both day and night</li><li>• Immunity to adverse weather</li><li>• Detect potentially long-range</li><li>• Reliable and proven technology</li><li>• Solid state</li></ul>	<ul style="list-style-type: none"><li>• Provides very noisy output</li><li>• Object boundary detection is not good</li><li>• Limited classification capability</li><li>• Poor resolution</li><li>• Unable to detect small objects</li><li>• AI research just started</li></ul>
Ultrasonic Sensor	<ul style="list-style-type: none"><li>• Has sensing capability with all material types</li><li>• Not affected by atmospheric dust, rain, snow, etc.</li><li>• Can work in all adverse conditions</li><li>• Provides good readings in sensing large-sized objects with hard surfaces</li></ul>	<ul style="list-style-type: none"><li>• Air needs to travel and is easily affected by wind</li><li>• Highly sensitive to temperature variation and vapors</li><li>• Difficulties in reading from soft, curved, thin, and small objects</li></ul>

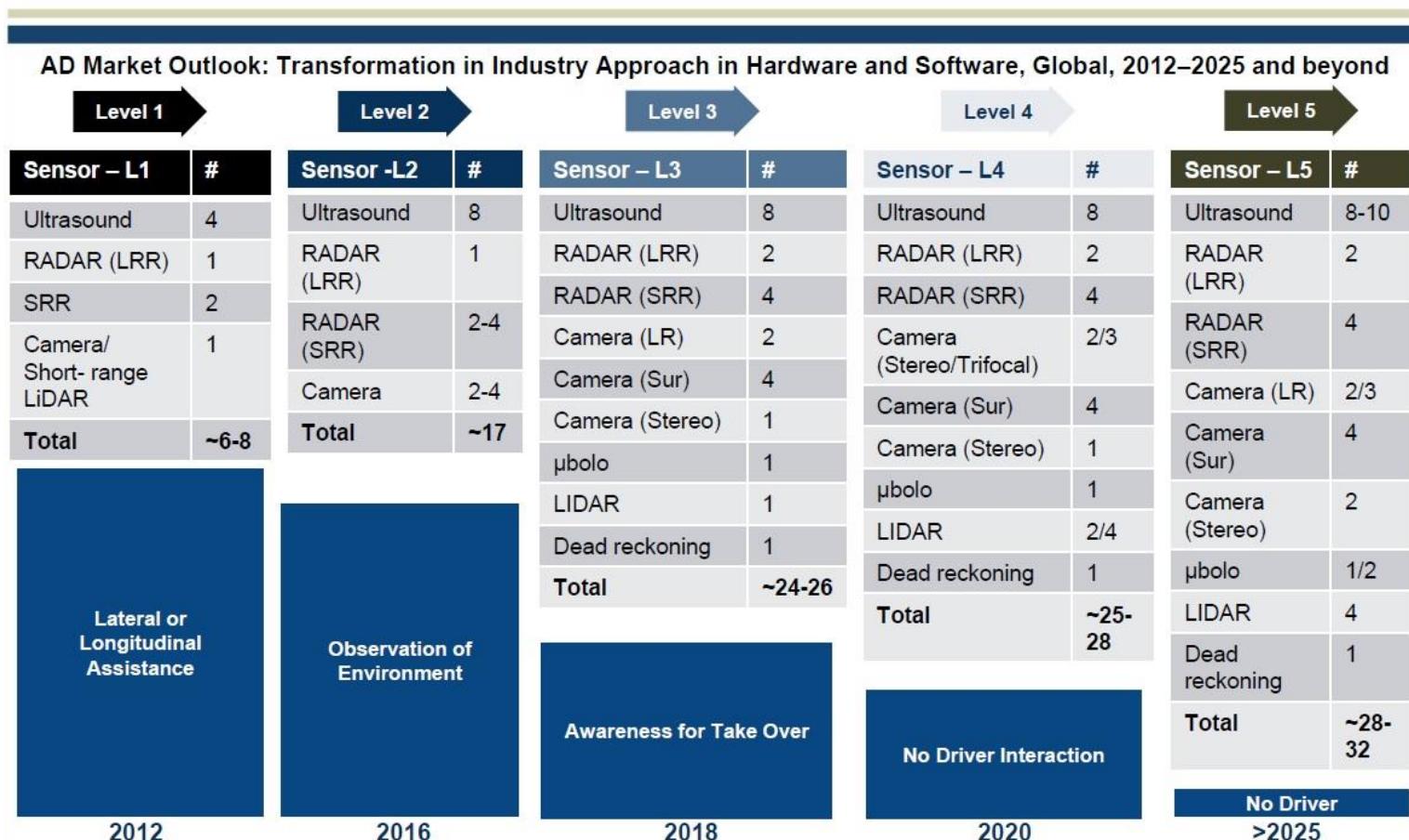


# Fusion of Various Sensory Systems



## Next Generations of Sensor Fusion

Highly automated and fully autonomous cars to have up to six radars and nine camera modules.



#: Average sensor count in respective levels; μbolo: Thermal camera/IR Sensor for Night Vision Approximation based on number of features supported

Source: Frost & Sullivan



# Fusion of Various Sensory Systems



Table 2. Comparison of Autonomous Vehicle technologies.

Company	No. of Camera	No. of LiDAR	No. of RADAR
Tesla	8	0	1
Google Waymo	12	5	6
Baidu Apollo	5	2	3
BMW Series	2	4	5
Volvo	6	3	2
Navya	2	10	2

<https://www.linkedin.com/pulse/short-survey-overview-autonomous-vehicles-sensors-lila-rana/>

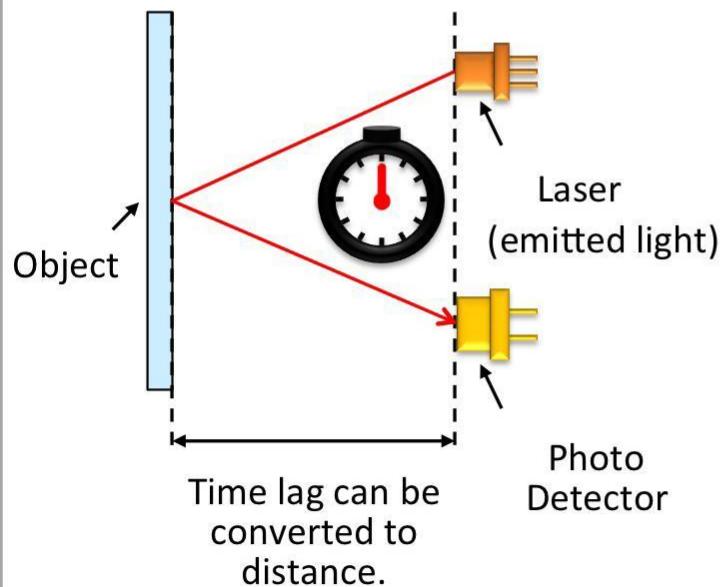


# Basics of LiDAR



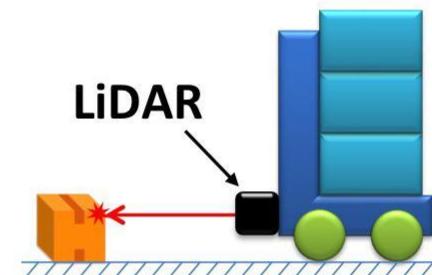
## Laser-based distance measurement sensor

### Principles of LiDAR

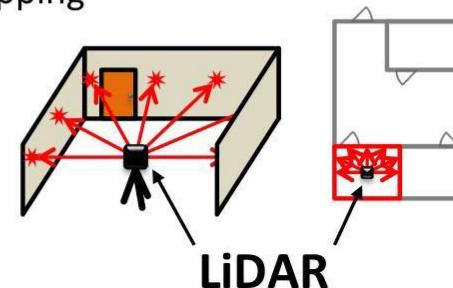


### LiDAR usage

#### Obstacle detection

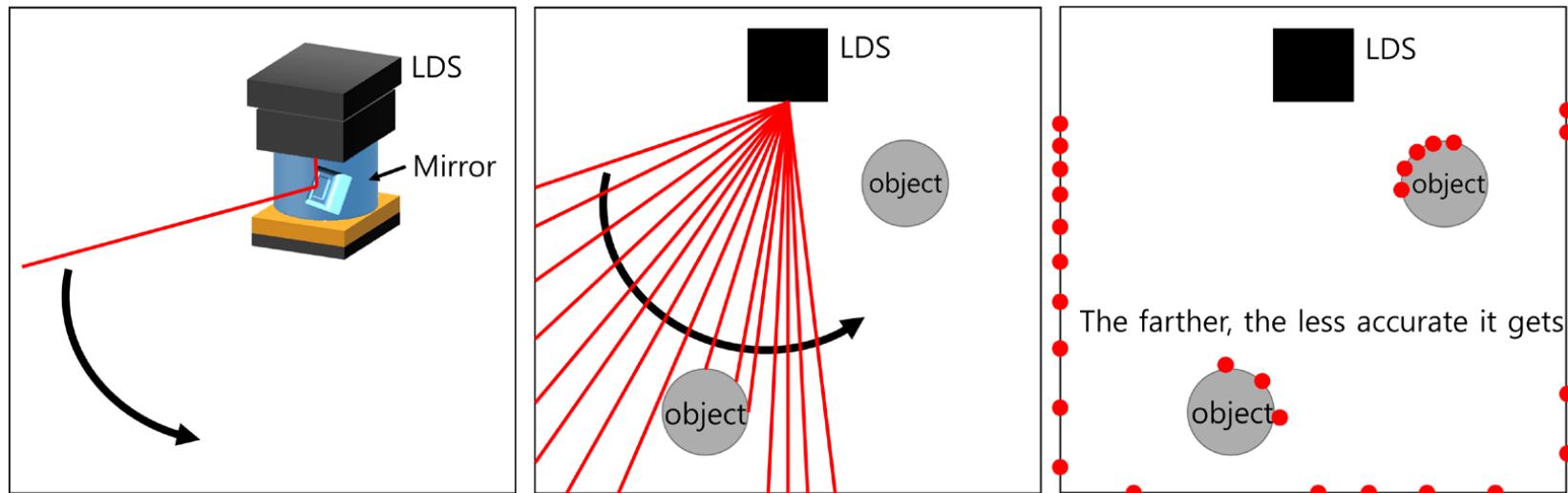


#### Spatial mapping



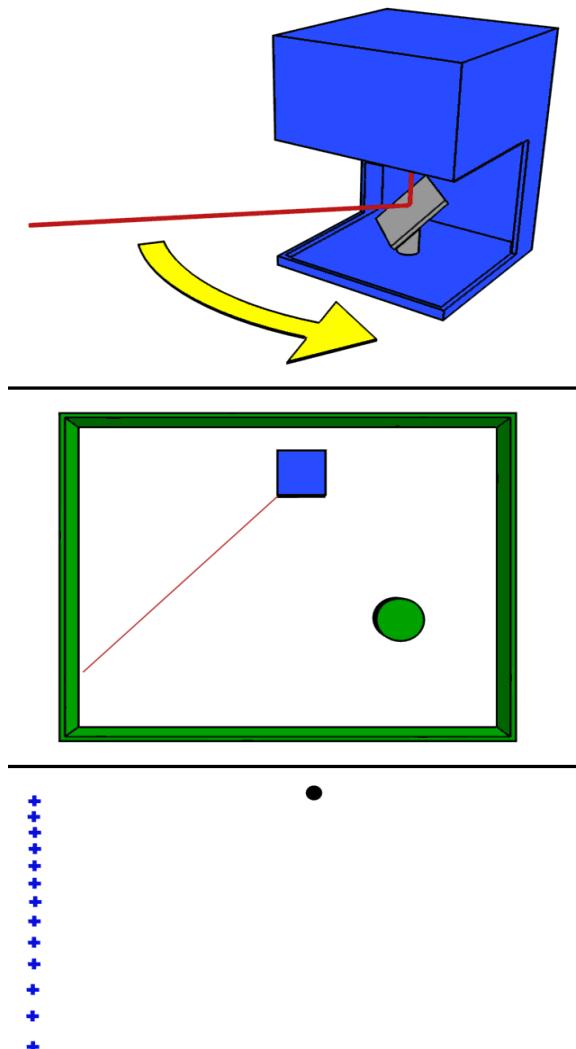


# Basics of LiDAR



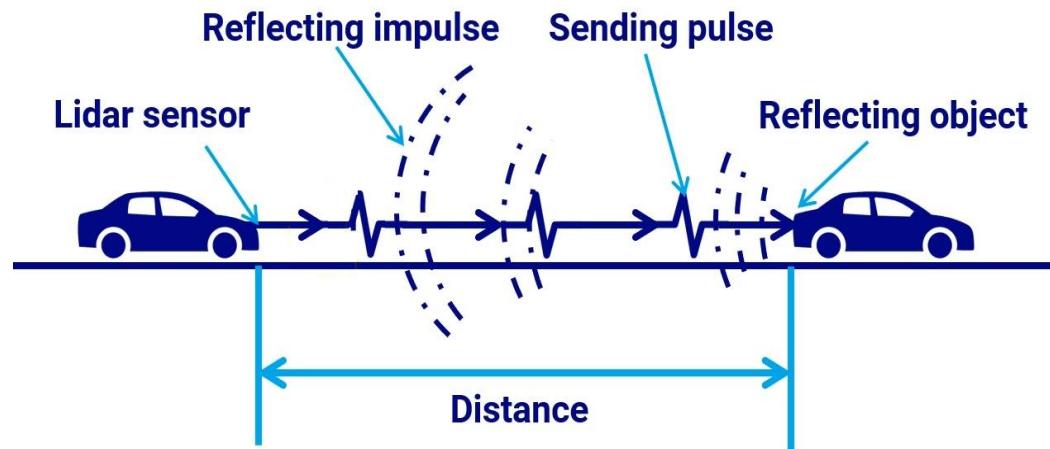


# Basics of LiDAR



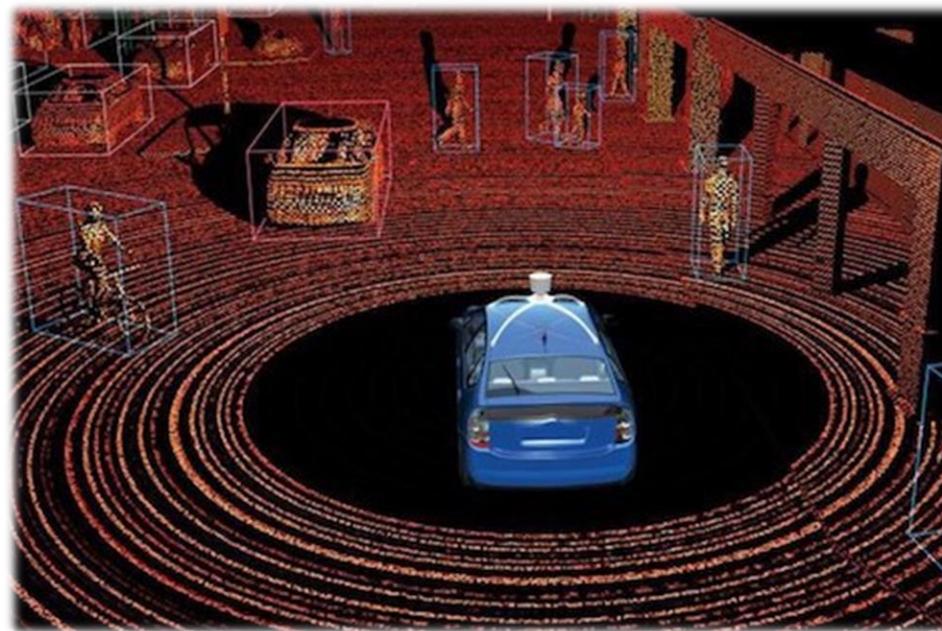
## LiDAR (Light Detection and Ranging)

- Object detection
- Distance measurement
- Similar to RADAR and SONAR but uses visual light
- Pulse propagation time method





# Basics of LiDAR





# Basics of LiDAR



## Technology: Lidar

GPS   Lidar   Radar   Video   Ultrasound

### Destructive Innovators

#### Velodyne Lidar: HDL-32E

- Cost: \$29,900 (half of HDL-64E)
- 32 laser – scanner pairs; 7000 pt/sec
- Compact size – more applications
- Range: 1-100m; accuracy < 2cm
- Distance – Reflectivity – Angle
- Internal MEMS – Motion sensing
- GPS synchronization



#### Ibeo – Valeo Joint Project

- Lidar Cost: \$250, by 2014
- Accuracy < 1.5", at 200 yd
- In any weather



## KEY FEATURES

- Dual Returns
- $\pm 2$  cm accuracy
- 1kg (plus 0.3kg for cabling)
- 32 Channels
- 80m-100m Range
- 700,000 Points per Second
- 360° Horizontal FOV
- +10° to -30° Vertical FOV
- Low Power Consumption
- Rugged Design

## PUCK™ VLP-16



## KEY FEATURES

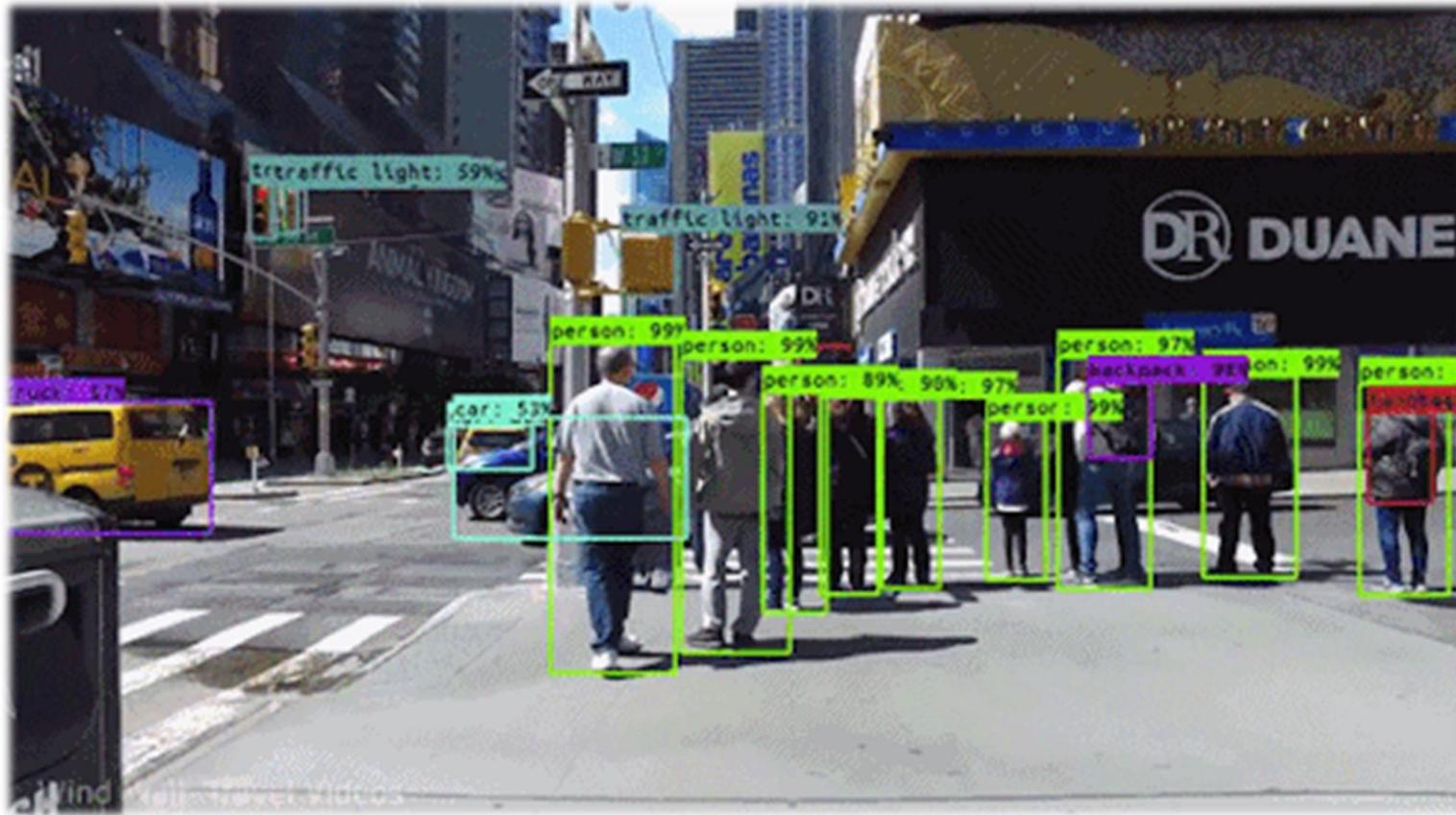
- \$7999
- Dual Returns
- 830 grams
- 16 Channels
- 100m Range
- 300,000 Points per Second
- 360° Horizontal FOV
- ± 15° Vertical FOV
- Low Power Consumption
- Protective Design

## Velodyne Puck LiDAR

<https://www.linkedin.com/pulse/short-survey-overview-autonomous-vehicles-sensors-lila-rana/>



# Machine Vision in AV: Camera with AI



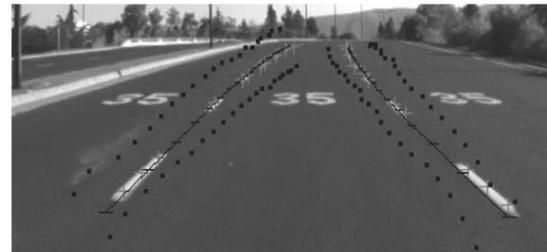
**Identifies Objects  
(i.e. roads, traffic lights, other vehicles, pedestrians, signs)**



# Machine Vision in AV: Camera with AI



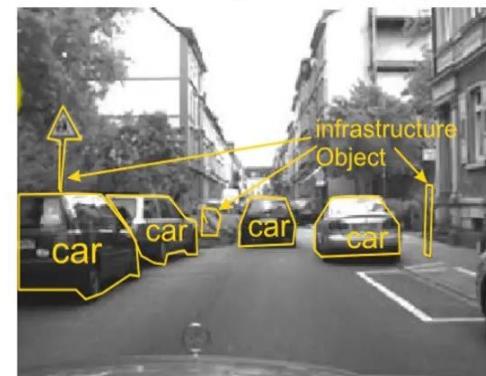
Lane detection



Classification based on characteristics



Classification based on probability database

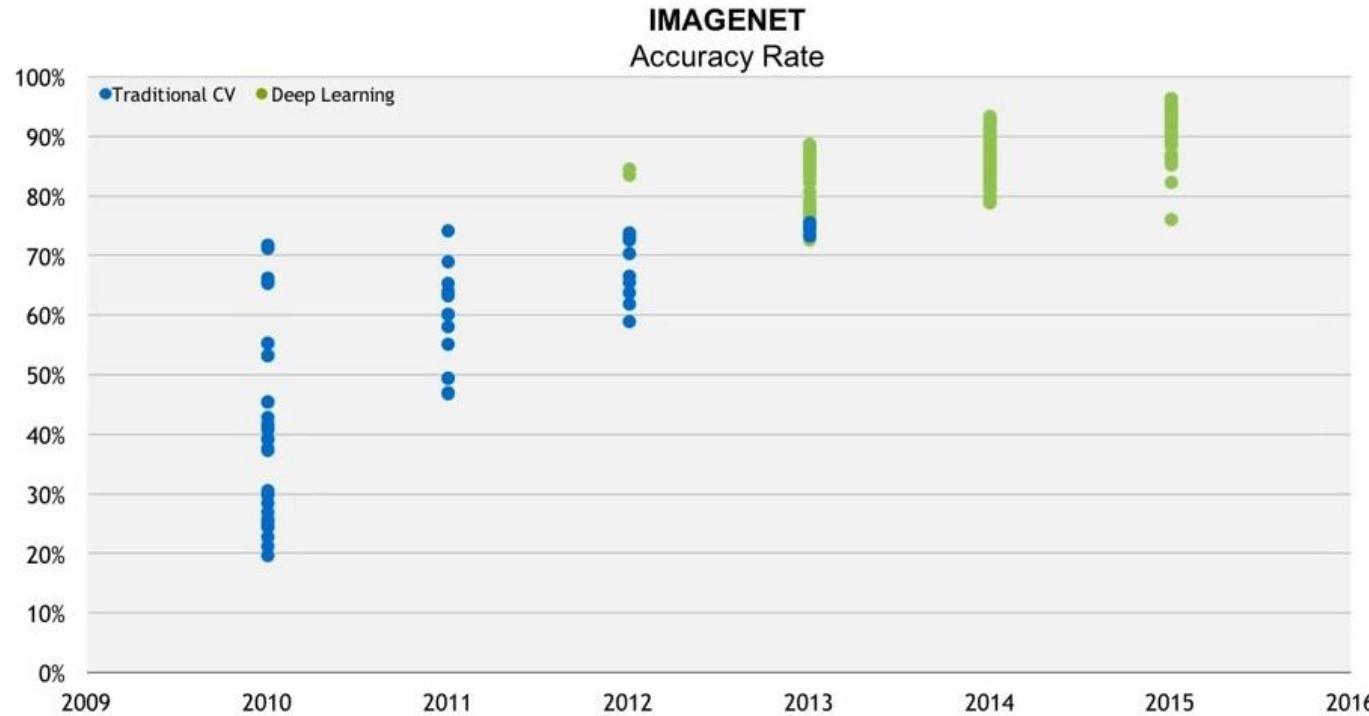




# Machine Vision in AV: Camera with AI



## Deep Learning for Visual Perception Going from strength to strength





# Is camera-only the future of self-driving cars?



If humans need only visual input to drive cars, why shouldn't computers? In the past, most self-driving car (SDC) technologies have relied on multiple signals, including cameras, lidar, radar and digital maps. But recently there's been a growing belief among some scientists and companies that autonomous driving will become possible with camera input only.

<https://www.autonomousvehicleinternational.com/features/is-camera-only-the-future-of-self-driving-cars.html>



# Tesla's perspectives



Meanwhile, Tesla's head of AI, Andrej Karpathy, recently gave some [insights into the reasoning for their decision to drop radar sensors from future Tesla models](#), instead relying only on cameras for environmental perception. There's two interesting takeaways from his statements:

Tesla claims the simultaneous use of cameras and radar produces too many perceptual conflicts, making sensor fusion and decision making problematic.

Tesla will continue to not use HD maps, because maintaining them would be a tremendous effort.

Tesla is definitely right about these problems being hard. However, the rest of the automotive industry seems to disagree with them about what the implications should be. Let's take a quick look at the first point:

<https://www.autonomousvehicleinternational.com/features/the-road-to-everywhere-are-hd-maps-for-autonomous-driving-sustainable.html>

\*\*\*HD maps (aka 3D maps) = roadmaps with inch-perfect accuracy and a high environmental fidelity – they contain information about the exact positions of pedestrian crossings, traffic lights/signs, barriers and more



# The limits of computer vision



A few stickers on  
a stop sign or  
road are enough  
to confuse AI

<https://www.autonomousvehicleinternational.com/features/is-camera-only-the-future-of-self-driving-cars.html>



# The limits of computer vision



<https://www.channelnewsasia.com/singapore/four-teenagers-arrested-sumang-walk-punggol-carpark-vandalism-vulgarities-3069661>



# Localization for AV Bosch E.g.



Source: <https://youtu.be/KvVv0kooDVU>



# Sensors that Support Localization Functions



Inertial Sensors (IMU)



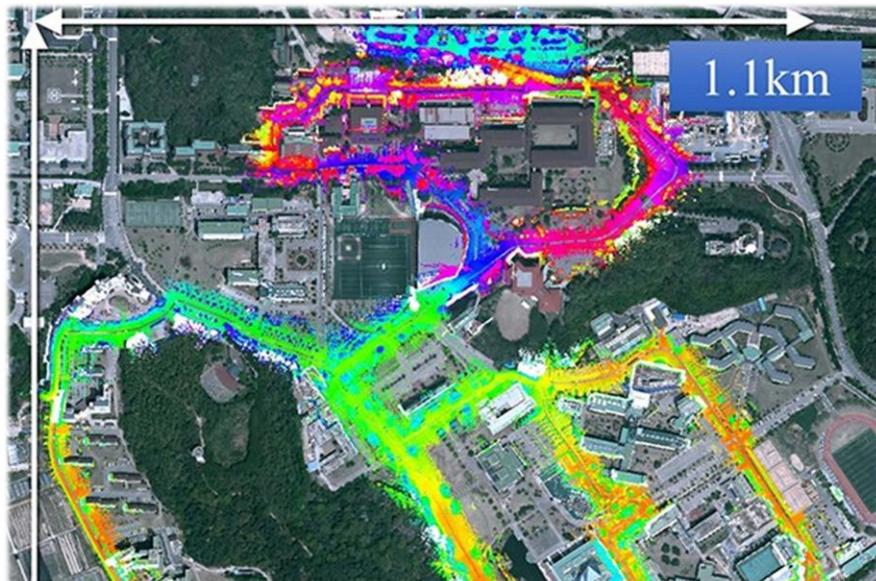
Satellite Navigation



Surround Sensors



# SLAM (Simultaneous Localization & Mapping)



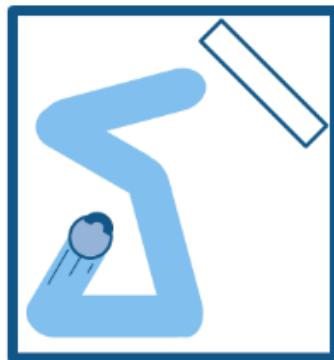
- Technique that **estimates the map** (the coordinates of the landmarks) in addition to **estimating the coordinates of our vehicle**
- Can **utilize Lidar** to find walls, sidewalks and thus build a map
- **Utilize IMU data** to track robot's movements
- **Very popular for outdoor and indoor navigation where GPS is not very effective**
- SLAM's algorithms need to know how to recognize landmarks, then position them and add elements to the map



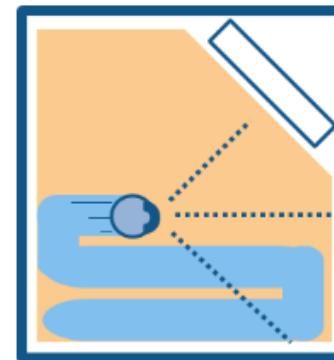
# Why SLAM is important?



- **Without SLAM, the robot has no information on the environment and will just move randomly around** (e.g. a vacuum cleaner robot); not power efficient
- Use cases for SLAM: Parking self-driving car in an empty parking lot, navigating a fleet of mobile robots to arrange shelves in a warehouse, delivering a package by navigating a drone in an unknown environment



Without SLAM:  
Cleaning a room randomly.

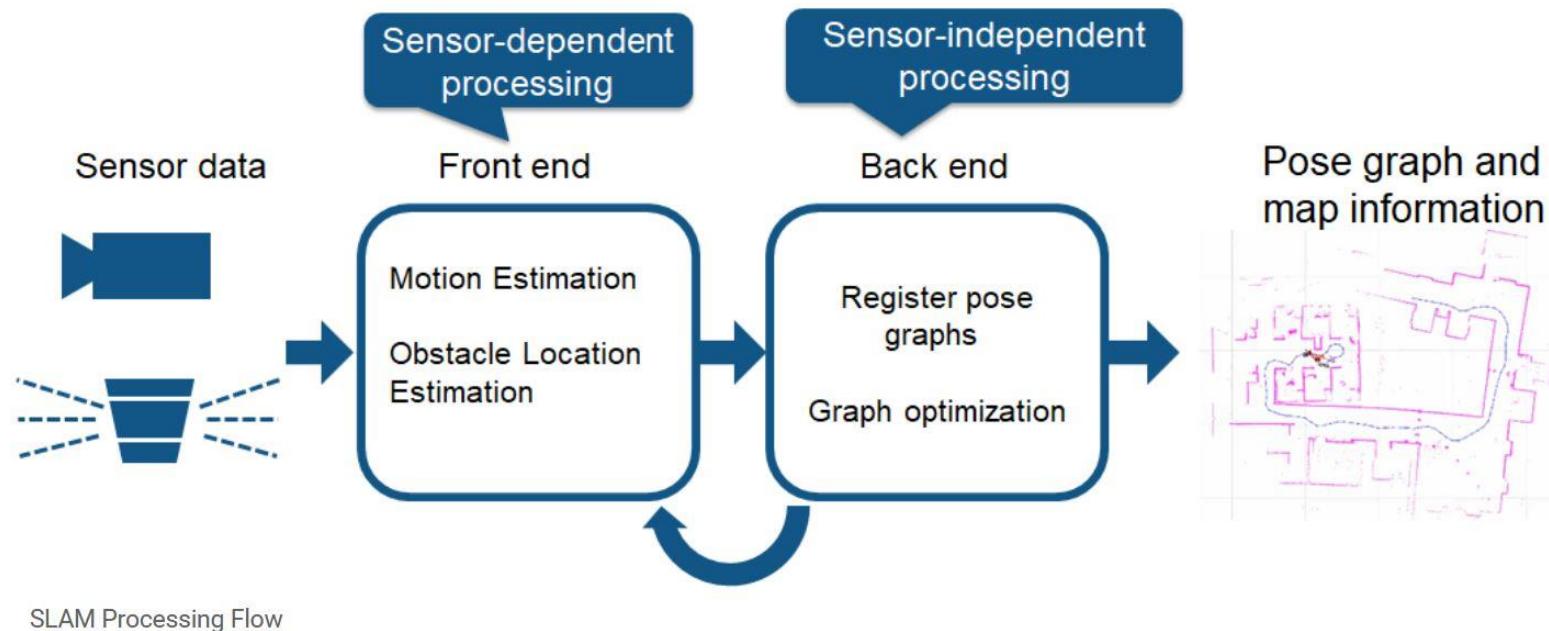


With SLAM:  
Cleaning while understanding the room's layout.

Benefits of SLAM for Cleaning Robots



# SLAM (Simultaneous Localization & Mapping)



Source: <https://www.mathworks.com/discovery/slam.html>

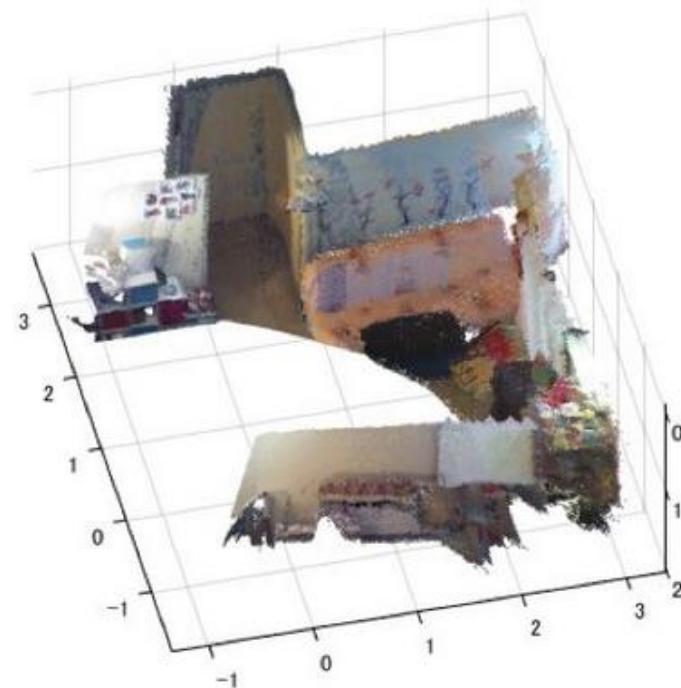


# SLAM (Simultaneous Localization & Mapping)

## Visual SLAM (aka vSLAM)

- Uses images acquired from cameras and other image sensors (wide angle, fish-eye, 360, stereo, multi, depth)
- Can be implemented at low cost with relatively inexpensive cameras
- Monocular SLAM = vSLAM using a single camera as the only sensor;
  - Challenging to define depth using a single camera
  - Hence requiring AR markers, checkerboards, or other known objects in the image for localization or by fusing the camera information with another sensor such as IMU

Source: <https://www.mathworks.com/discovery/slam.html>



Point Cloud Registration for  
RGB-D SLAM



# SLAM (Simultaneous Localization & Mapping)



## LIDAR SLAM

- Compared to cameras and other sensors, lasers are **significantly more precise**, and are used for applications with high-speed moving vehicles such as self-driving cars and drones
- 2D (or 3D) point cloud maps can be represented as a grid map (or voxel map)
- Localization for autonomous vehicles may involve fusing other measurement results such as wheel odometry, global navigation satellite system (GNSS), and IMU data

Source: <https://www.mathworks.com/discovery/slam.html>



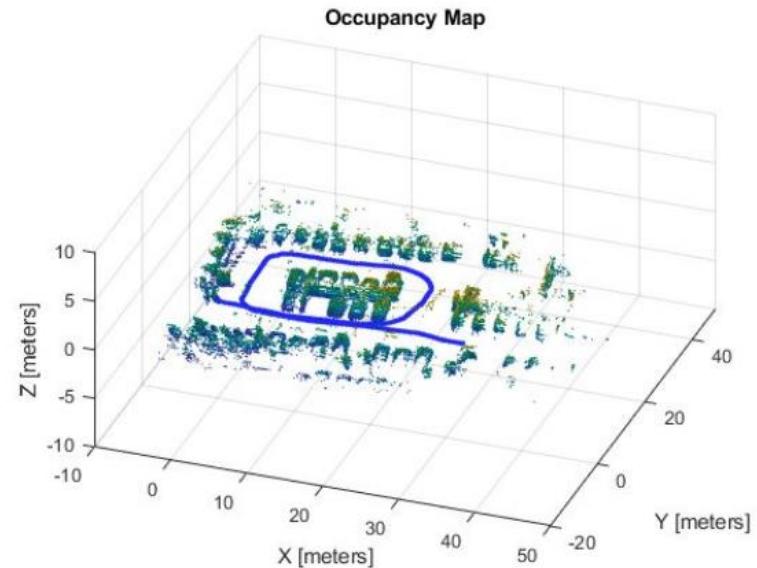
# SLAM (Simultaneous Localization & Mapping)



## LIDAR SLAM



SLAM with 2D LiDAR

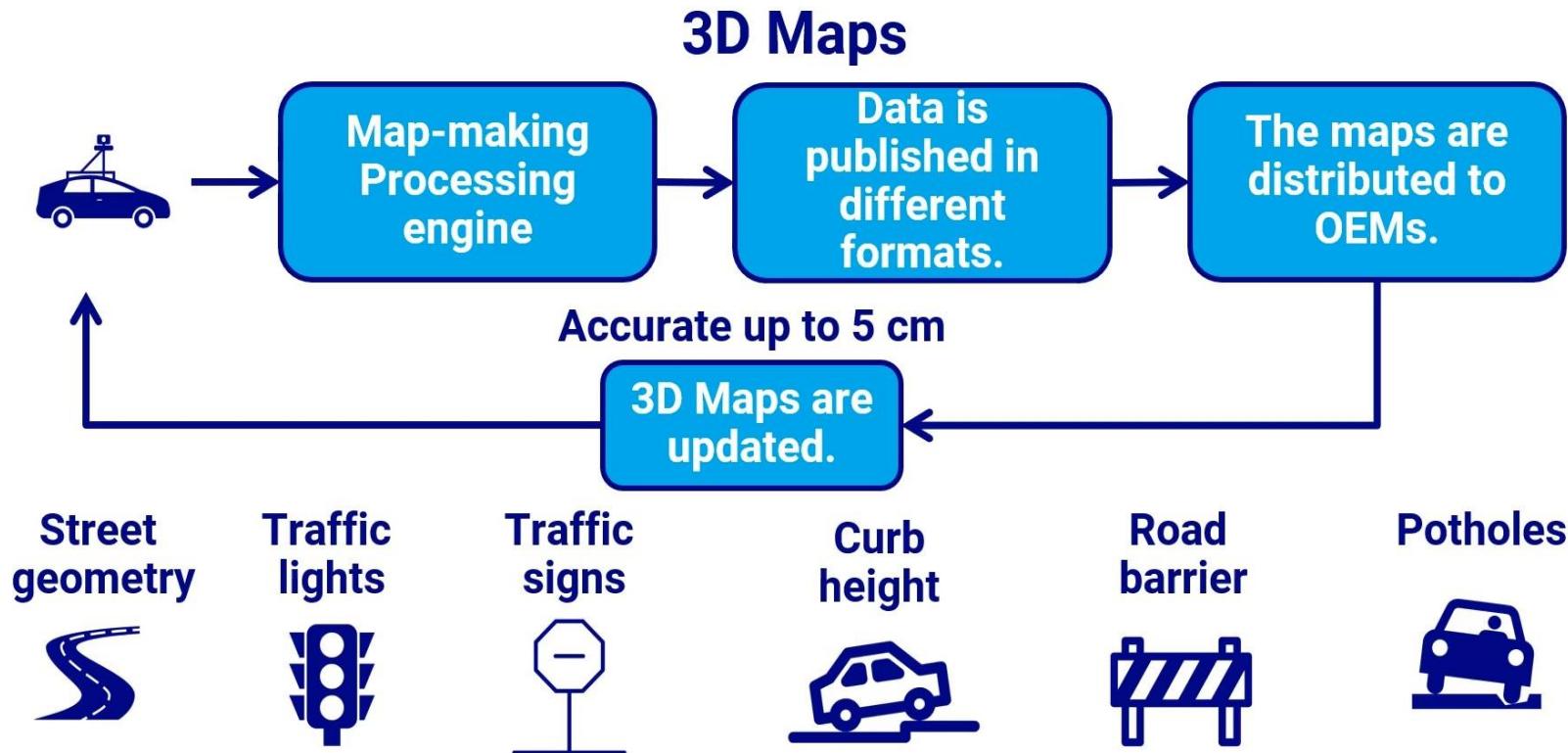


SLAM with 3D LiDAR

Source: <https://www.mathworks.com/discovery/slam.html>

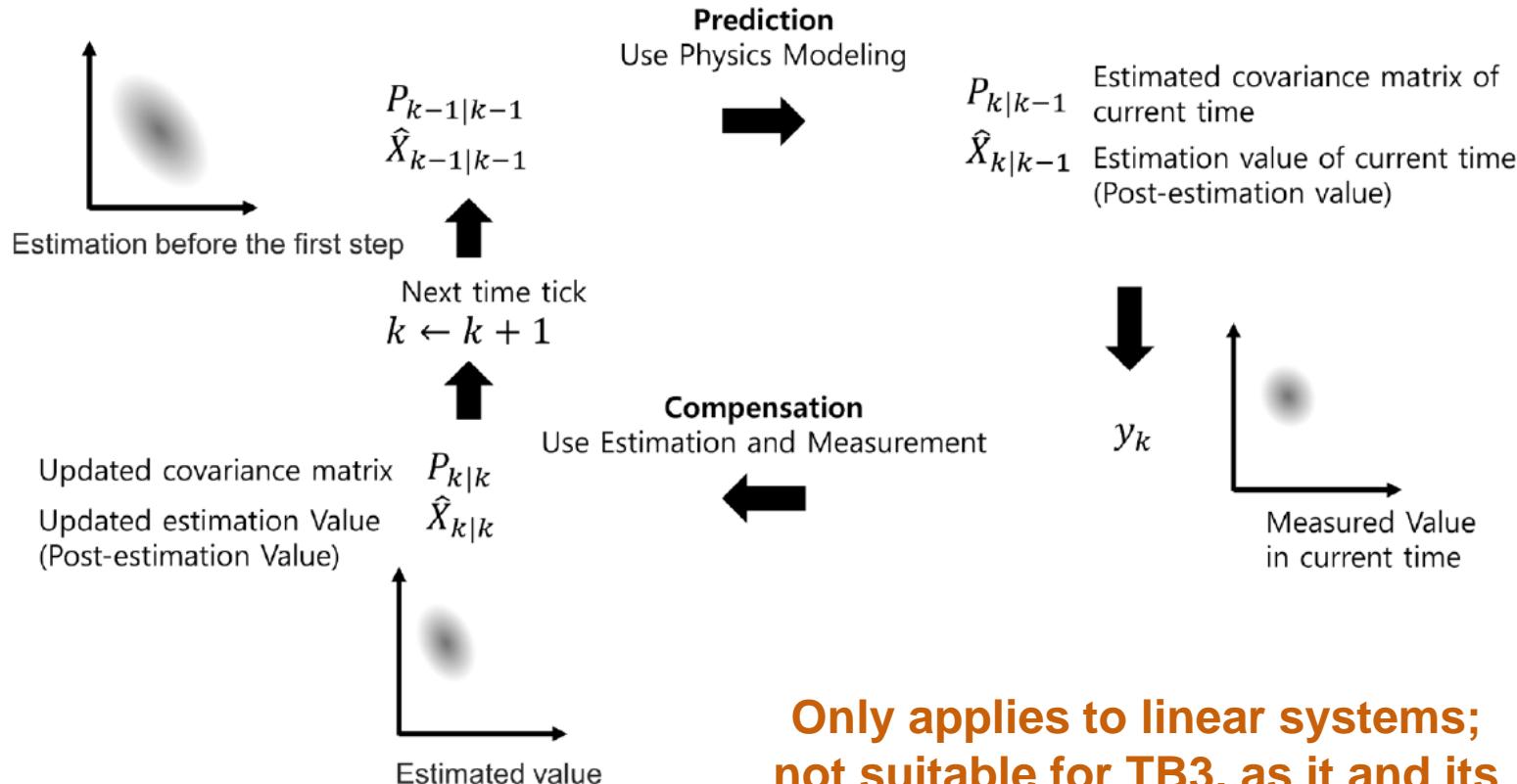


# SLAM (Simultaneous Localization & Mapping)





# Localization Method 1: Kalman Filter



**Only applies to linear systems;  
not suitable for TB3, as it and its  
sensors are non-linear systems**



# Localization Method 2: Particle Filter



- Also a **Bayes Filter Implementation**; Used in TB3 (specifically AMCL; Adaptive Monte Carlo Localization)
- A technique to predict through simulation based on **try-and-error** method
- Estimated value generated by the probability distribution in the system is represented as **particles**
- Estimates the pose of the object **assuming that the error is included** in the incoming information
- The particles are first moved to a new estimated position and orientation, based on the robot's motion model and probabilities
- The weight of each particle is then measured according to the actual measurement value, and the **noise is gradually reduced to estimate a precise pose**



# Localization Method 2: Particle Filter

- Particle filter are initialized by a very high number of particles spanning the entire state space
- As you get additional measurements, you predict and update your measurements which makes your robot have a multi-modal posterior distribution
- This is a big difference from a Kalman Filter which approximates your posterior distribution to be a Gaussian
- Over multiple iterations, the particles converge to a unique value in state space



# Localization Method 2: Particle Filter



## 5 procedures (steps 2~5 repeated):

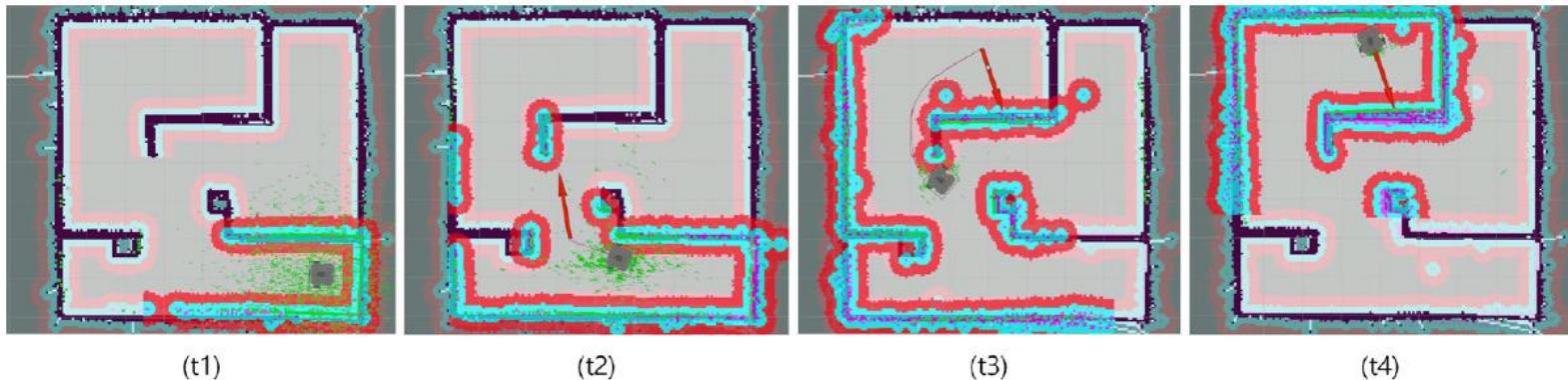
1. **Initialization** – Particles are randomly arranged within the range where the pose can be obtained with N particles
2. **Prediction** – Based on the system model describing the motion of the robot, it moves each particle as the amount of observed movement with odometry information and noise
3. **Update** – Based on the measured sensor information, the probability of each particle is calculated and the weight value of each particle is updated based on the calculated probability
4. **Pose Estimation** – The position, orientation, and weight of all particles are used to calculate the average weight, median value, and the maximum weight value for estimating pose of the robot
5. **Resampling** – The less weighed particles are removed, and new particles that inherit the pose information of the weighted particles will replace the removed particles



# Localization Method 2: Particle Filter



## AMCL Process for TB3 Pose Estimation:



AMCL is an **improved version of Monte Carlo pose estimation**, which **improves real-time performance by reducing the execution time with less number of samples** in the Monte Carlo pose estimation algorithm



## Adaptive particle filter:

- Better to use an adaptive particle filter which **converges much faster and is computationally much more efficient** than a basic particle filter
- The **key idea is to bound the error** introduced by the sample-based representation of the particle filter
- To use adaptive particle filter for localization, we **start with a map of our environment** and we can either set robot to some position, in which case we are manually localizing it or we could very well make the robot start from no initial estimate of its position
- Now **as the robot moves forward, we generate new samples that predict the robot's position after the motion command**
- **Sensor readings are incorporated by re-weighting these samples and normalizing the weights**
- The reason why it takes the filter multiple sensor readings to converge is that within a map, we **might have dis-ambiguities due to symmetry in the map**, which is what gives us **a multi-modal posterior belief**

- AMCL = An adaptive particle filter method
- A probabilistic localization system for a robot moving in 2D
- Currently AMCL works only with laser scans; however, it can be extended to work with other sensors
- AMCL takes in a laser-based map (generated from SLAM), laser scans, and transform messages, and outputs pose estimates

- **Subscribed topics:**

- scan – Laser scans
- tf – Transforms
- initialpose – Mean and covariance with which to (re-) initialize the particle filter
- map – the map used for laser-based localization

- **Published topics:**

- amcl\_pose – Robot's estimated pose in the map, with covariance.
- particlecloud – The set of pose estimates being maintained by the filter
- tf – Publishes the transform from odom (which can be remapped via the ~odom\_frame\_id parameter) to map.



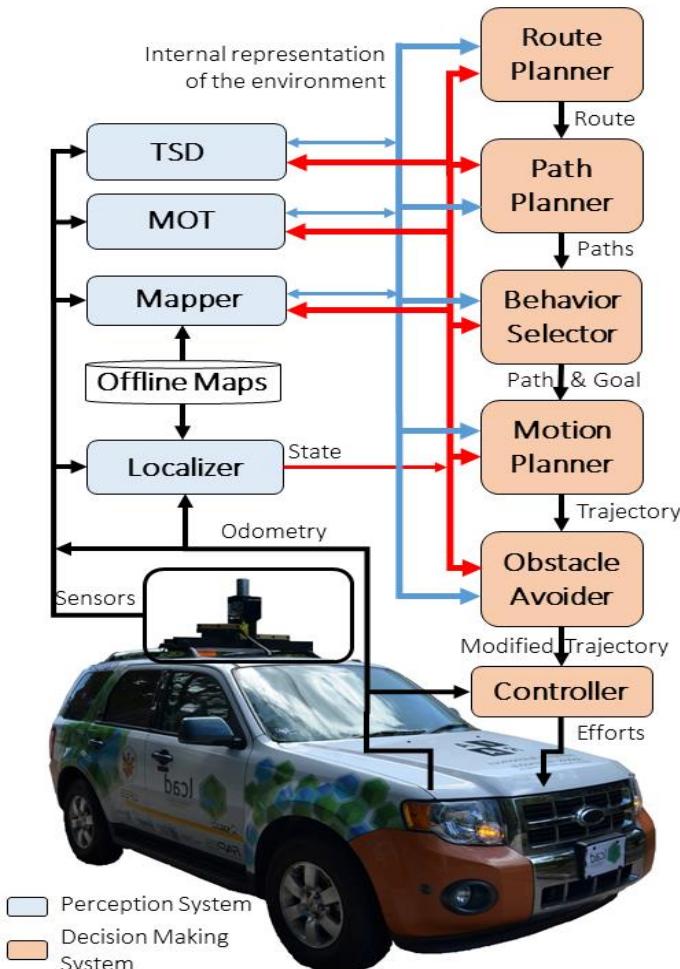
Parameter	Description	Default
min_particles	Minimum allowed number of particles	100
max_particles	Maximum allowed number of particles	5000
laser_model_type	Which model to use, either beam or likelihood_field	likelihood_field
laser_likelihood_max_dist	Maximum distance to do obstacle inflation on map, for use in likelihood_field model	2.0
initial_pose_x	Initial pose mean (x), used to initialize filter with Gaussian distribution	0.0
initial_pose_y	Initial pose mean (y), used to initialize filter with Gaussian distribution	0.0
initial_pose_a	Initial pose mean (yaw), used to initialize filter with Gaussian distribution	0.0



## 2. AV DECISION-MAKING (DM)



# Typical Architecture of Self-Driving Cars

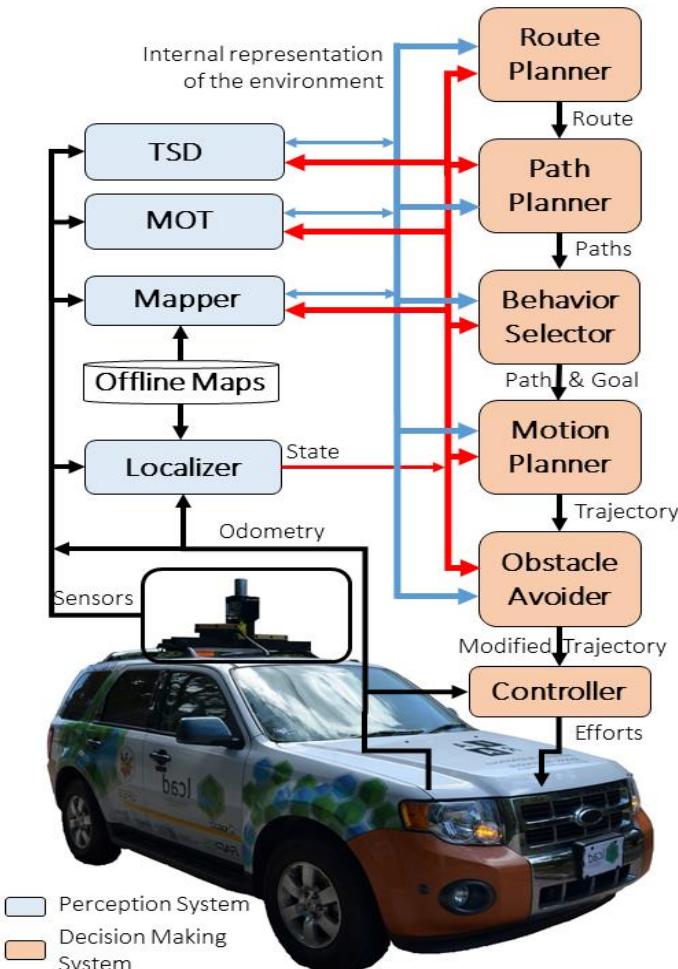


## The DM Subsystems:

- The **Route Planner subsystem** is responsible for **computing a Route** (i.e. a sequence of way points) **in the Online Maps**, from the current self-driving car's State to the Final Goal
- Given the computed Route, the **Path Planner subsystem** **computes a set of Paths** (a Path is a sequence of poses) after **considering the current self-driving car's State** and the **internal representation of the environment** as well as **traffic rules**



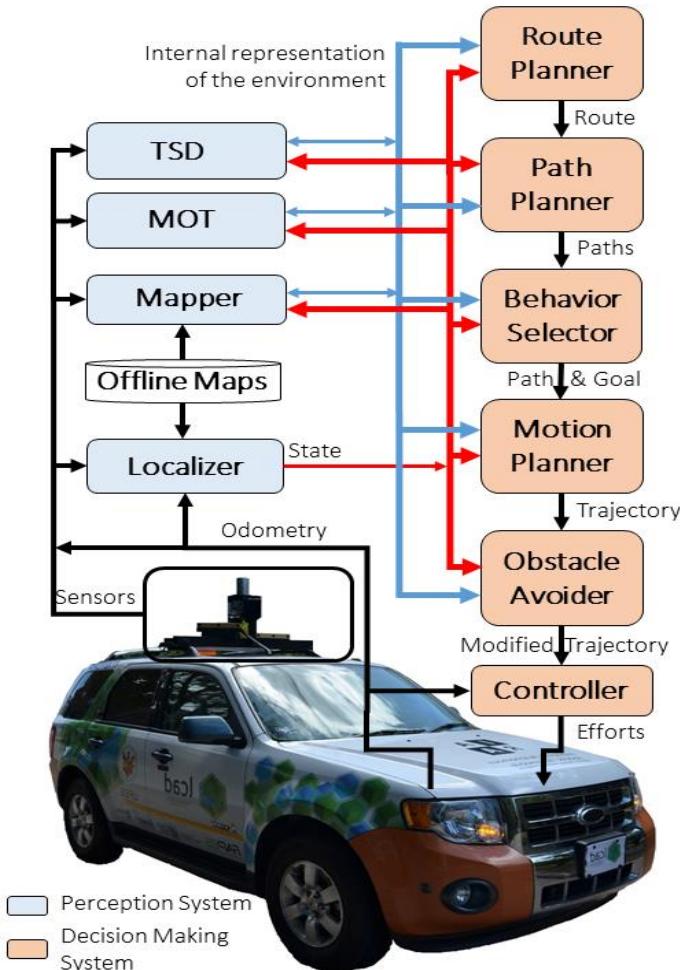
# Typical Architecture of Self-Driving Cars



## The DM Subsystems:

- **The Behavior Selector subsystem** is responsible for **choosing the current driving behavior** (e.g. lane keeping, intersection handling, traffic light handling)
  - ❖ does so by **first selecting the most suitable Path**
  - ❖ **From this Path, the anticipated Goal is constantly selected in real-time;** consists of two components: **(a) the anticipated pose, and (b) the anticipated desired velocity**

# Typical Architecture of Self-Driving Cars

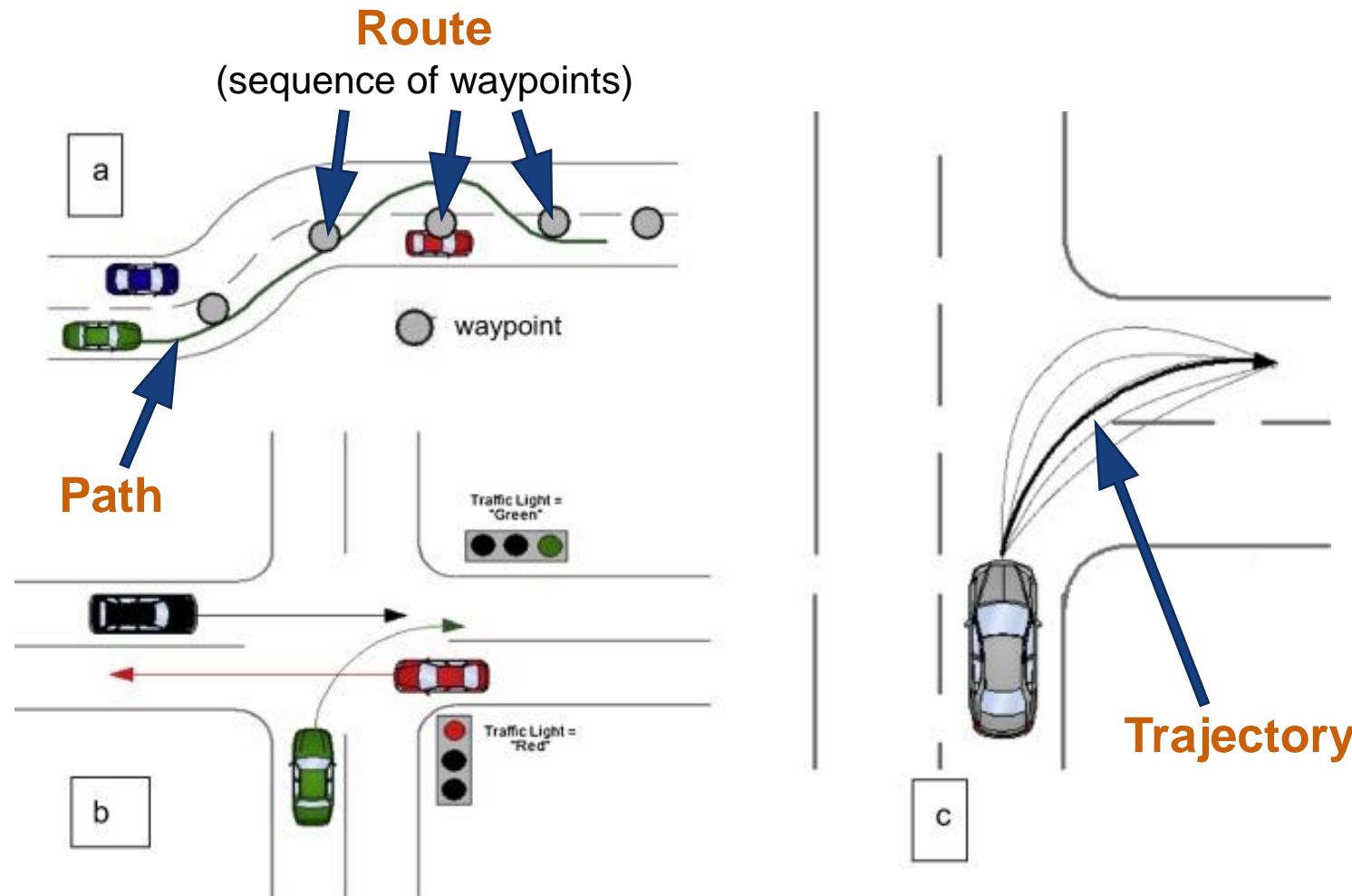


## The DM Subsystems:

- **The Motion Planner subsystem** is responsible for **computing a Trajectory** (i.e. a sequence of commands);
- The Trajectory
  - ❖ takes the car from its current **State** to the current **Goal** smoothly and safely
  - ❖ follows the **Path** defined by the **Behavior Selector**
  - ❖ must **satisfy the car's kinematic and dynamic constraints**, and **provides comfort** to the passengers



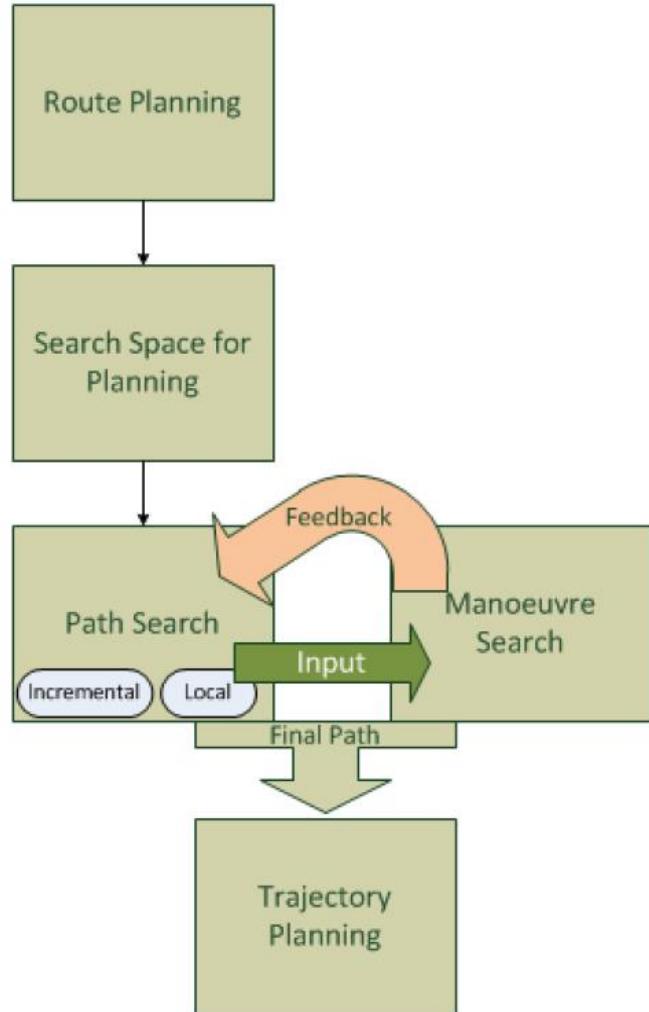
# Routes vs Paths vs Trajectories



(a) Path planning, (b) Manoeuvre planning and (c) Trajectory planning



# Flow Chart of Planning Modules



1. A route is chosen from the route planner
2. Path search is initiated
3. Path search acts as input to the search for the best manoeuvre (i.e. the manoeuvre which places the car with the most correct and safe behaviour)
4. The final path may change, based on the best manoeuvre, as shown with a feedback loop between these two search modules
5. Once the path is finalised, the final trajectory planning is generated



# Path Calculation and Driving

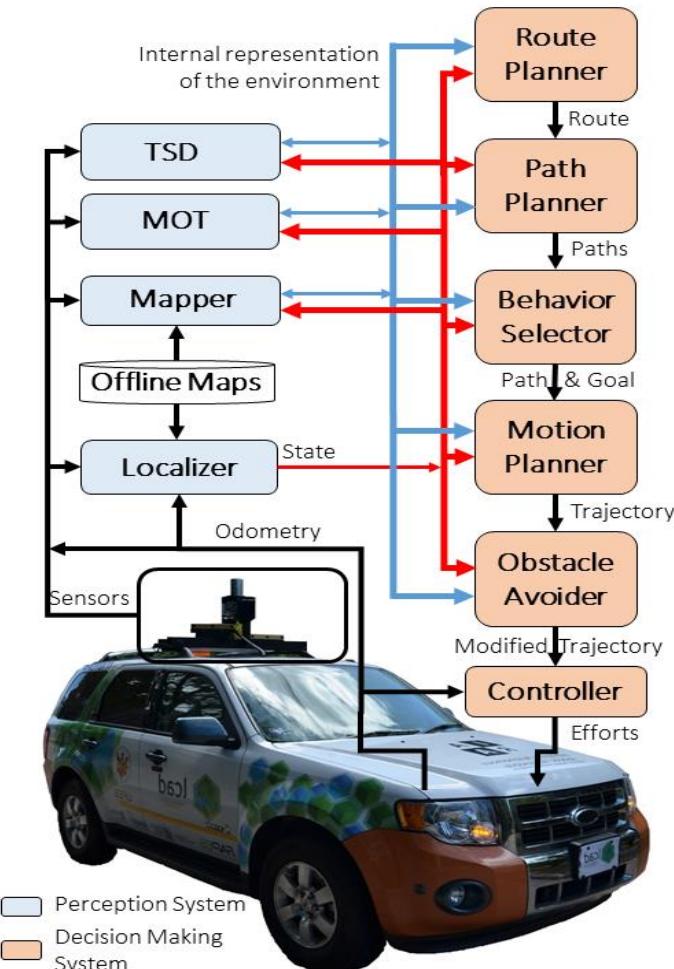


**Many Algorithms that perform path search  
and planning (i.e. calculating optimal routes):**

1. Dijkstra's algorithm
2. A\* algorithm
3. Potential field
4. Particle filter
5. RRT (Rapidly-exploring Random Tree)

**Some of which are covered in Robotic Systems Course  
(i.e. Module 5 Robotic Pathway Planning)**

# Typical Architecture of Self-Driving Cars



## The DM Subsystems:

- **The Obstacle Avoider subsystem** is responsible for **modifying the computed Trajectory** (e.g. reducing the velocity, changing directions), **if necessary, to avoid collisions**
- **The Controller subsystem** is responsible for **computing and sending Effort commands to the actuators of the steering wheel, throttle and brakes** based on the Modified Trajectory



# Uncertainty Handling

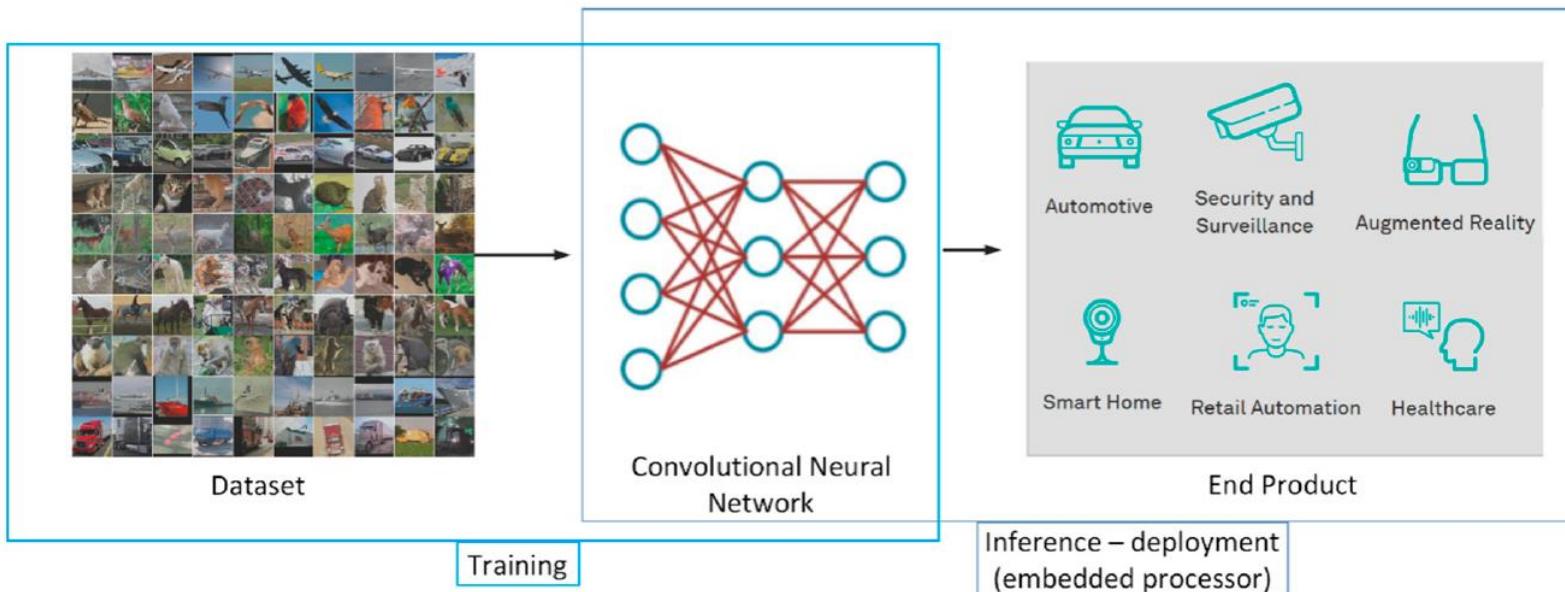


	State uncertainty	Existance uncertainty	Class uncertainty
Characteristic	Uncertainty in the state variables (position, speed...)	Uncertainty whether an object captured really exists	Uncertainty of class membership (car or truck)
Cause	Stochastic measuring error of sensors	Detection uncertainty of cameras, lidar, radar...	Classification uncertainties of algorithms / sensor limitations
Modeling	Probabilistics; Expected value with variances / covariances	Probabilistic by means of detection probabilities	No persistent method; at present mainly heuristic
Methods	Closed theory via Bayes filter (includes Kalman filter variants)	Closed theory coupled with estimate state uncertainty (JPDA filter)	Feature based: Bayes, Dempster-Shafer Learning based: Neural networks, cascaded procedures (Viola Jones...)
Prediction of the future	Generally no; limited possibility using trend indications	Generally no	Generally no

Source: Fraunhofer IAO (2015) Hochautomatisiertes Fahren auf Autobahnen - Industriepolitische Schlussfolgerungen



# General Deep Learning Development Flow



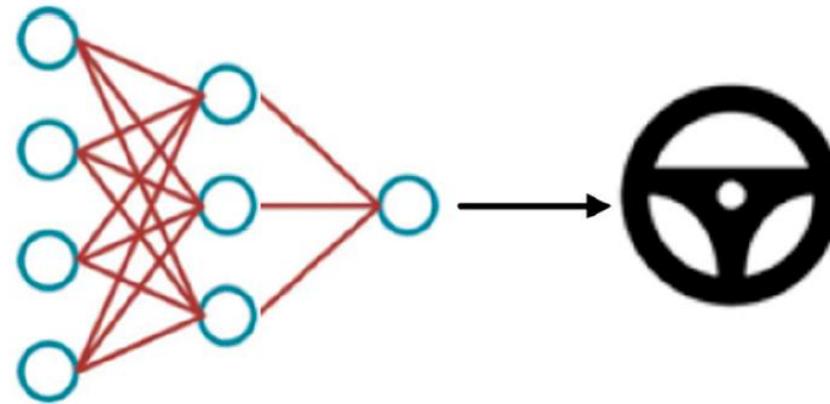
- **Training** — once the CNN model is developed, it is **trained with the appropriate dataset**
- **Inference** — the **trained model is deployed** at the end product and **used for inference with real-time input data**



# Application of Deep Learning to AVs (E.g.)



image acquired in real-time



trained DNN

steering wheel angle

## Real-time Autonomous Driving

- **Image acquired** from the central camera is **fed to the trained deep neural network (DNN) model**
- **Output of this model is the steering angle prediction** that controls the vehicle



# Application of Fuzzy Logic to AVs (E.g.)



## Automatic Braking System

- Using **fuzzy logic** to determine the distance of the obstacle in front of our vehicle and **apply the appropriate amount of brake required to stop the car**;
- Will slowly apply the brakes considering the distance of the vehicle around it and finally stop; will not apply complete brake immediately
- **Avoid unnecessary accident risk**

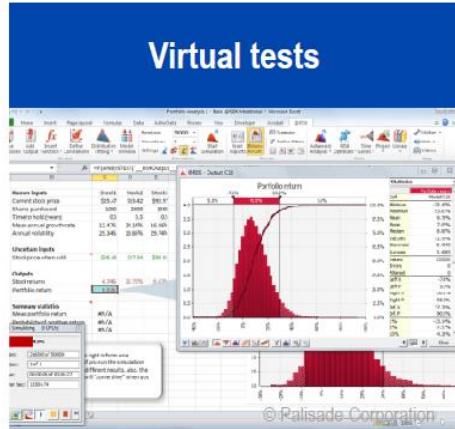


# CHAPTER 2: **BASICS OF SIMULATION & ANALYSIS**

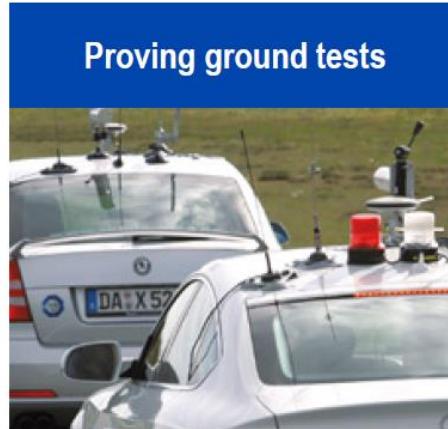




# Various Testing Avenues for AVs



- Analysis of a huge number of scenarios, environments, system configurations and driver characteristics



- Reproducibility by use of driving robots, self driving cars and targets; critical manoeuvres are possible



- Investigation of real driving situations and comparison with system specifications

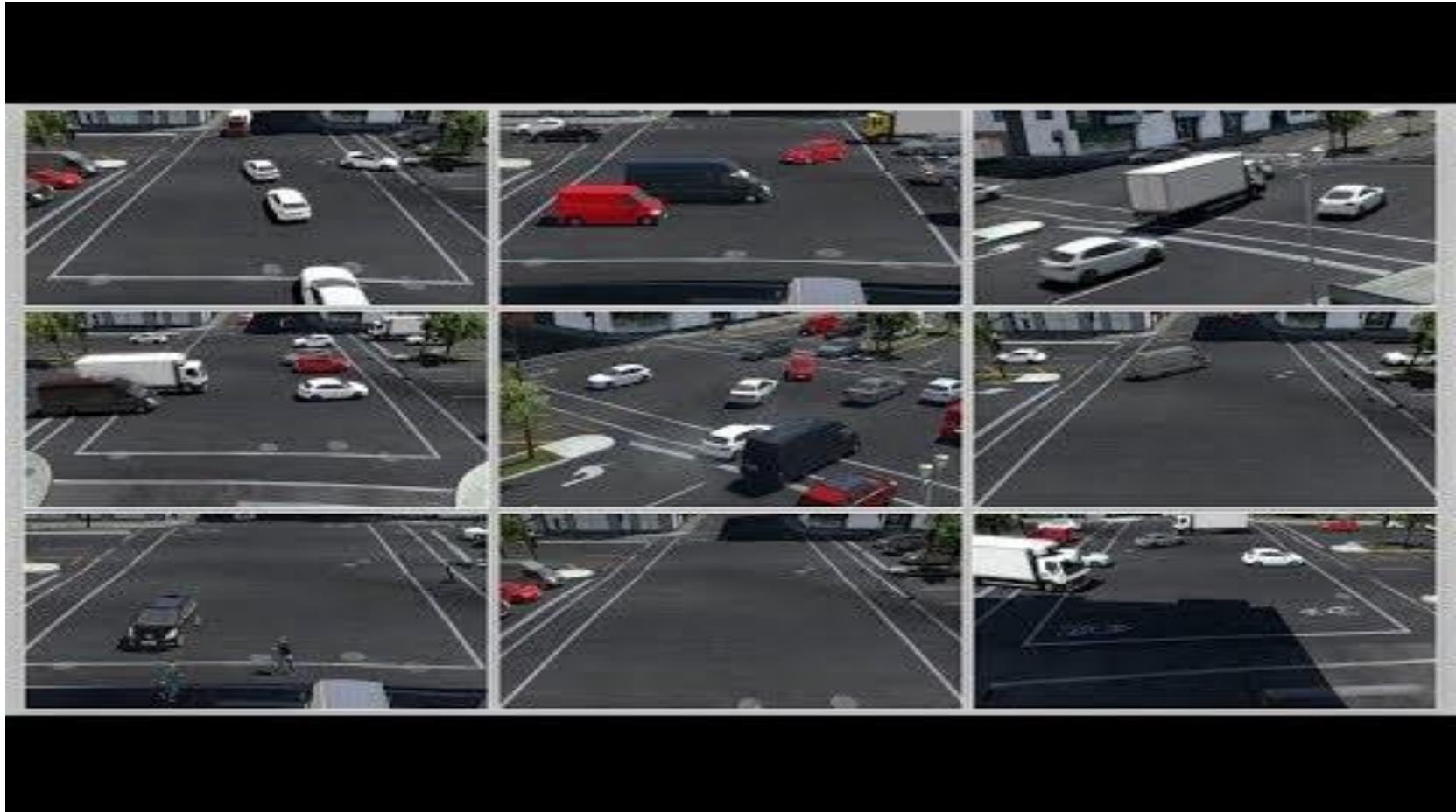
**Effort for coverage of all relevant scenarios & environments**

## Uncertainties & simplifications

Source: U. Steininger, H.P. Schöner, M. Schiemetz: Requirements on tools for assessment and validation of assisted and automated driving systems, 7. Tagung Fahrerassistenz, München, Nov. 2015



# Importance of Simulation & Analysis



Source: <https://www.youtube.com/watch?v=vj-YJ4IDS3I>



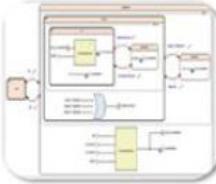
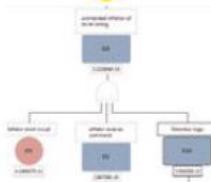
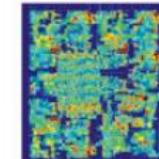
# Importance of Simulation & Analysis



- **Validate safety**
- **Shorten analysis times**; efficiently verify functional requirements
- **No real damages/injuries** inflicted in simulations
- **Test and re-test variations** of specific scenarios, environments, system configurations
- **Able to scale testing massively**
- **Channel to train machine learning agents**; quote from Microsoft's AirSim team:
  - *"Training models on AirSim first and then fine tuning them with real-world data greatly reduces the amount of real-world data you will need for a fully trained model."*



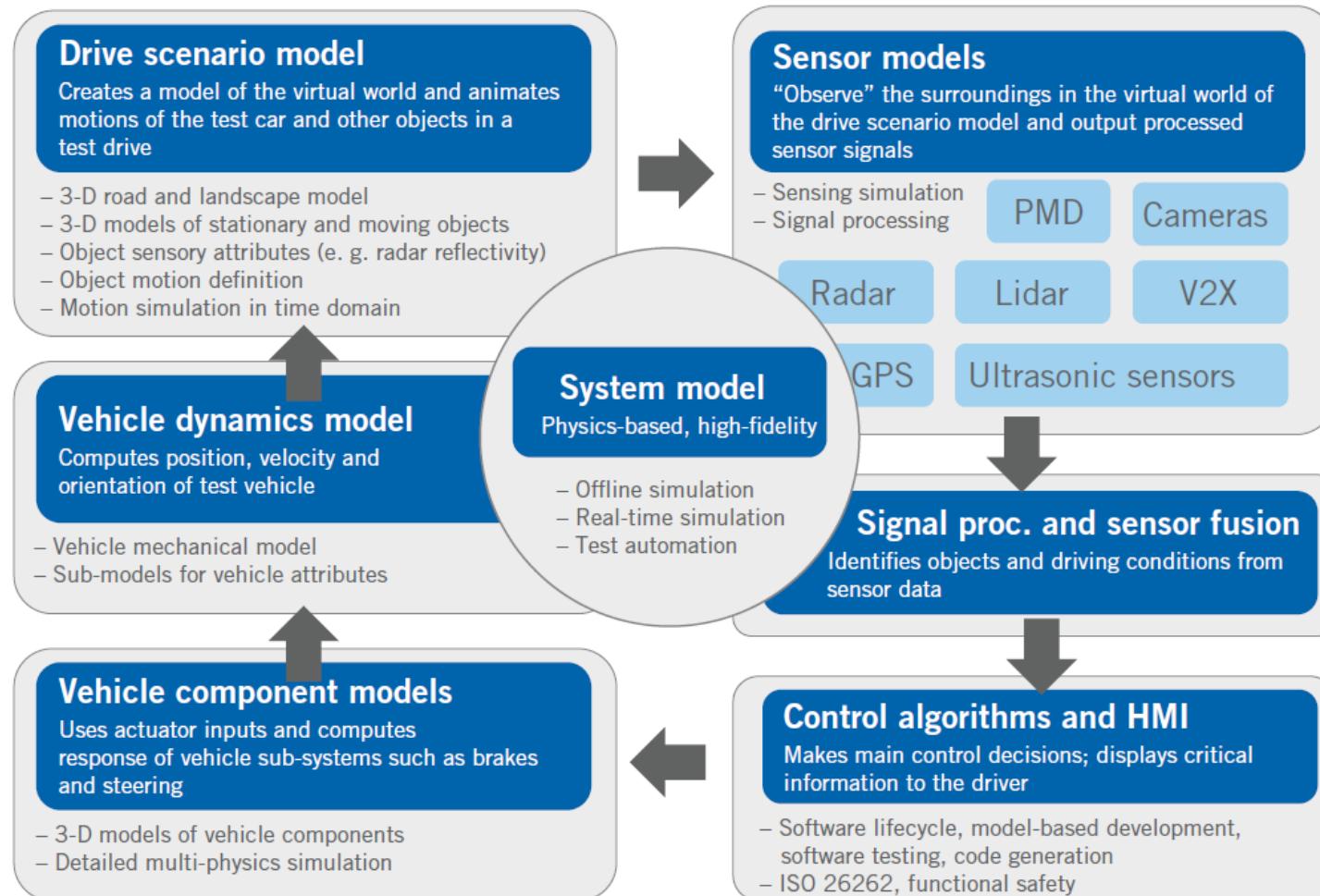
# Various Types of Simulation & Analysis Methods for AVs

Driving scenario system simulation	Software and algorithm modelling and development	Functional safety analysis	Sensor performance simulation	Electronics hardware simulation	Semi-conductor simulation
 	 	 	 	 	 
Simulate driving scenarios with detailed physics; virtually test control algorithms, sensor accuracy and vehicle dynamics	Develop ISO 26262 qualified, Autosar compliant control and HMI software with model based development tools	Ensure safety of automated systems with reliability analysis methods, using simulation for verification	Accurately model radars, V2X communication, GPS antennas, ultrasonic and other sensors with high-fidelity physics	Optimise signal integrity and thermal, structural, electro-magnetic reliability of electronics and mechanical hardware	Optimise power efficiency, power noise integrity and thermal-mechanical reliability of ICs

Integrated development with a common platform – faster development – cost economy – better product performance and quality



# Simulation of the Control Loop for AVs





# Virtual Driving with Model Based Simulation (Simplified)





# Use Case Example: Function Development for Complex Traffic Scenarios





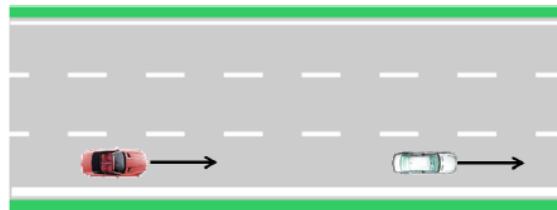
# Use Case Example: Function Development for Complex Traffic Scenarios



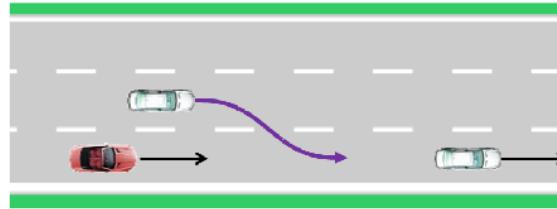
Challenging Traffic Situations !

Base Scenario

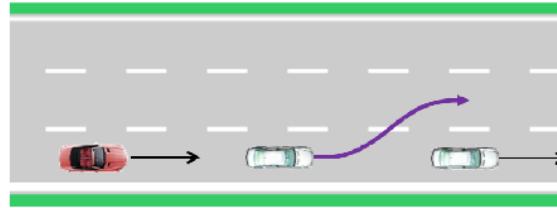
Following



Cut-in

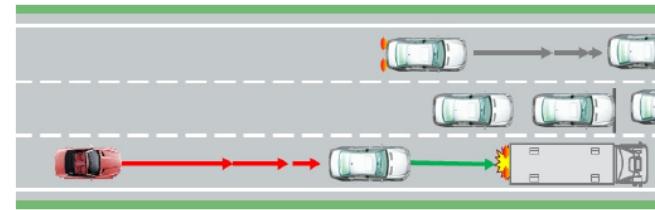


Cut-out

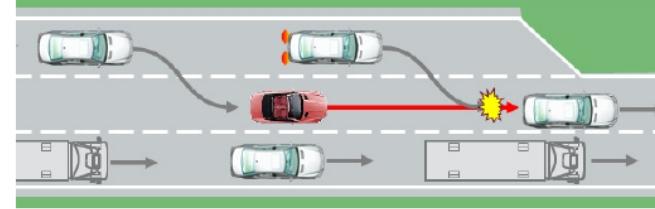


Critical scenario

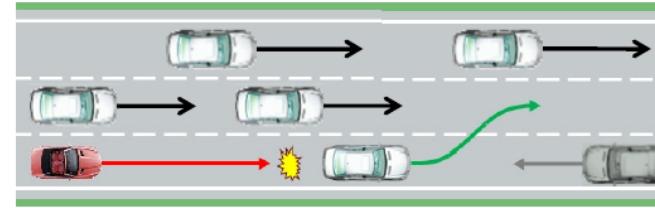
Preceding car drives into traffic jam without braking



Cut-in vehicle brakes hard, no evasion space



Car cuts out just before obstacle or oncoming car

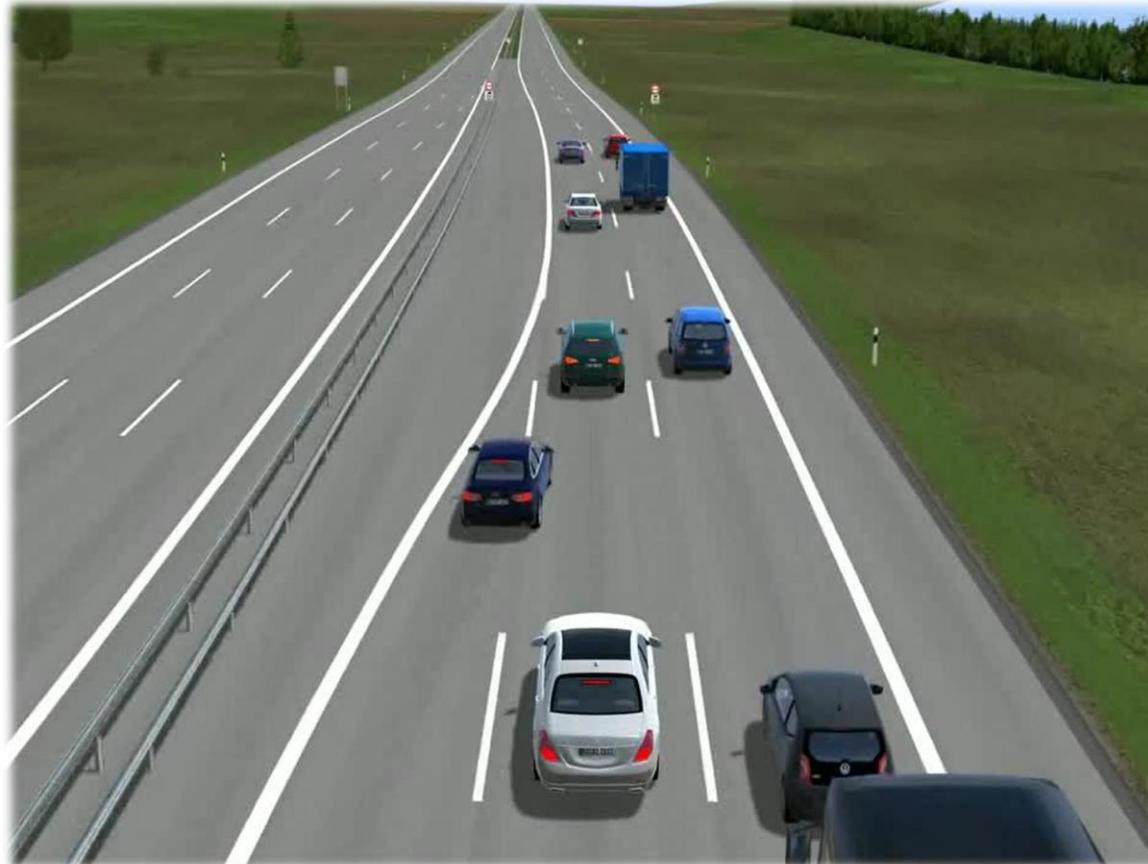




# Use Case Example: Function Development for Complex Traffic Scenarios



## Simulation Example: Cut-in Scenario





# WORKSHOP: INTRODUCTION TO SOFTWARE PERTAINING TO TOPICS ON SIMULATION & ANALYSIS FOR AUTONOMOUS VEHICLES





# Various Software



- 1. ROS Gazebo (Open Source)**
2. BlenSor (Open Source)
3. CARLA (Open Source)
4. Webots (Open Source)
5. Windows AirSim (Open Source)



# Introducing Gazebo



GAZEBO

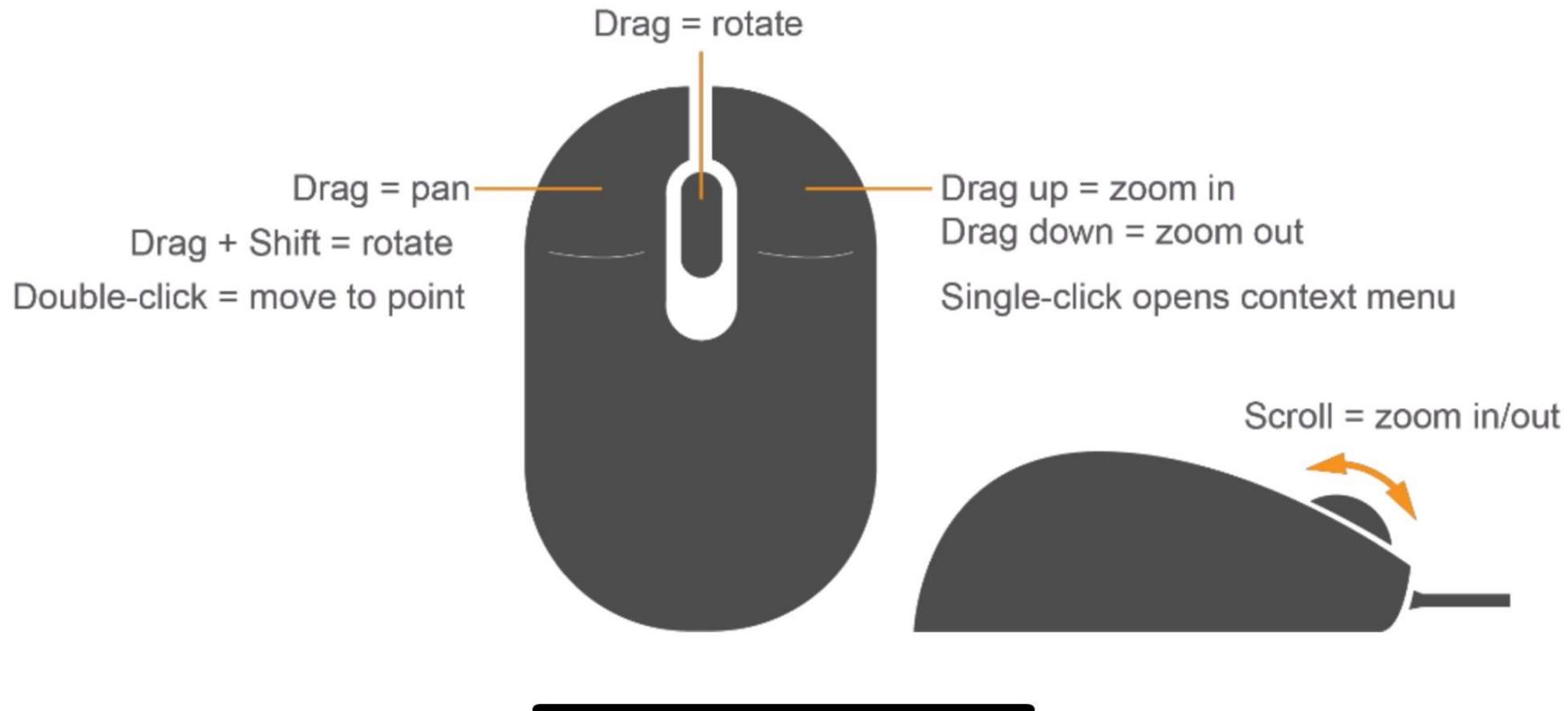
- **3D robot simulator** that provides robots, sensors, environment models for 3D simulation required for robot development
- Offers **realistic simulation** with its physics engine
- **High performance** even though open source
- **Very compatible with ROS**



# Introducing Gazebo

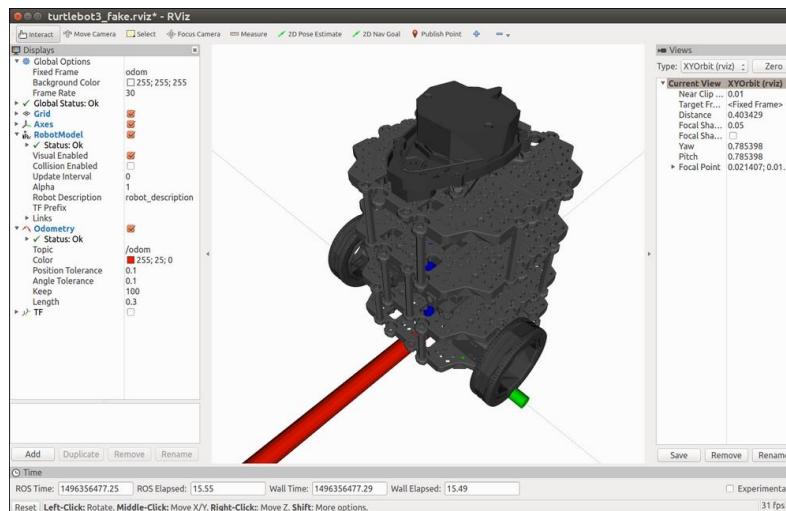
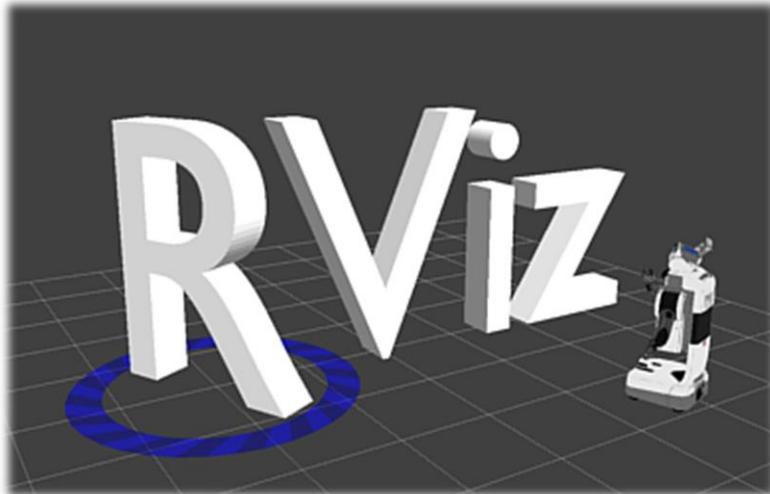


## Gazebo mouse controls





# Introducing RViz



- **3D visualization tool**
- **Display sensor data and state information from ROS**
- **A very useful tool to control TurtleBot3 and test SLAM and Navigation**



# Creating a 3D ROS Model using URDF (will NOT be covered in this course)



- URDF = Unified Robot Description Format; an XML file that represents the robot model; has XML tags to represent the joints/links
- It has all the information on the robot 3D models, joints, links, sensors, actuators, controllers, etc
- Examples:
  - ❖ TB3 – Navigate to catkin\_ws → src → turtlebot3 → turtlebot3\_description → urdf
  - ❖ OM – Navigate to catkin\_ws → src → open\_manipulator → open\_manipulator\_description → urdf
- To learn how to build a robot model with URDF, go to <http://wiki.ros.org/urdf/Tutorials/>



# Creating a 3D ROS Model using URDF (will NOT be covered in this course)



To view the TB3/OM model in Rviz, type the following command in terminal:

```
$ rosrun  
turtlebot3_manipulation_description  
turtlebot3_manipulation_view.launch
```

OR

```
$ rosrun  
open_manipulator_description  
open_manipulator_rviz.launch
```



# Workshop Stages

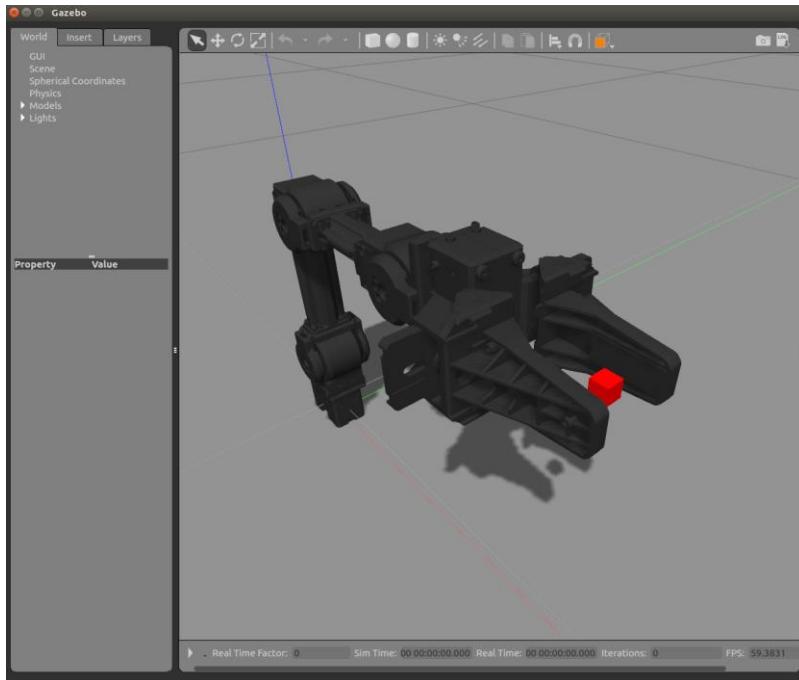


## Simulation of:

- 1. OpenManipulator-X**
- 2. TurtleBot3 Waffle Pi**
  - a) Manual Movements
  - b) Random Autonomous Navigation and Obstacle Avoidance
  - c) SLAM and Controlled Navigation
- 3. TurtleBot3 Waffle Pi with OpenManipulator-X (to be covered in M6)**



# 1. SIMULATION OF OPENMANIPULATOR-X



Basically, the control process is the same as the previous workshop session, except that the physical robot is replaced by the virtual one

## Type in Terminal:

- `$ roslaunch open_manipulator_gazebo open_manipulator_gazebo.launch`
- This will load OpenManipulator-X on Gazebo simulator
- Click “Play” when Gazebo is launched



# OpenManipulator-X

```
/clock  
/gazebo/link_states  
/gazebo/model_states  
/gazebo/set_link_state  
/gazebo/set_model_state  
/open_manipulator/gripper/kinematics_pose  
/open_manipulator/gripper_position/command  
/open_manipulator/gripper_sub_position/command  
/open_manipulator/joint1_position/command  
/open_manipulator/joint2_position/command  
/open_manipulator/joint3_position/command  
/open_manipulator/joint4_position/command  
/open_manipulator/joint_states  
/open_manipulator/option  
/open_manipulator/states  
/rosout  
/rosout_agg
```



## Type (in New Terminal):

- \$ rostopic list
- This will list up the activated topics (examples on left)

## Type (in New Terminal):

- \$ rosservice list
- This will list up the active services



# OpenManipulator-X

## Activate the Controller

```
SUMMARY
=====
PARAMETERS
  * /open_manipulator/control_period: 0.01
  * /open_manipulator/moveit_sample_duration: 0.05
  * /open_manipulator/planning_group_name: arm
  * /open_manipulator/using_moveit: False
  * /open_manipulator/using_platform: False
  * /rosdistro: kinetic
  * /rosversion: 1.12.14

NODES
/
  open_manipulator (open_manipulator_controller/open_manipulator_controller)

ROS_MASTER_URI=http://localhost:11311

process[open_manipulator-1]: started with pid [9820]
[ INFO] [1544506914.862653563]: Ready to simulate /open_manipulator on Gazebo
```

**\*\*\*You have to activate the controller using this code before you can control the virtual robot via the following various methods**



**Next, type (in New Terminal):**

- \$ roslaunch open\_manipulator\_controller open\_manipulator\_controller.launch **use\_platform:=false**
- If launched successfully, the terminal will appear as follows (left)
- You are ready to control your virtual robotic arm



# OpenManipulator-X



## (a) Manual Control

```
Control Your OpenMANIPULATOR-X!
-----
w : increase x axis in task space
s : decrease x axis in task space
a : increase y axis in task space
d : decrease y axis in task space
z : increase z axis in task space
x : decrease z axis in task space

y : increase joint 1 angle
h : decrease joint 1 angle
u : increase joint 2 angle
j : decrease joint 2 angle
i : increase joint 3 angle
k : decrease joint 3 angle
o : increase joint 4 angle
l : decrease joint 4 angle

g : gripper open
f : gripper close

1 : init pose
2 : home pose

q to quit
-----
```

## Type (in New Terminal):

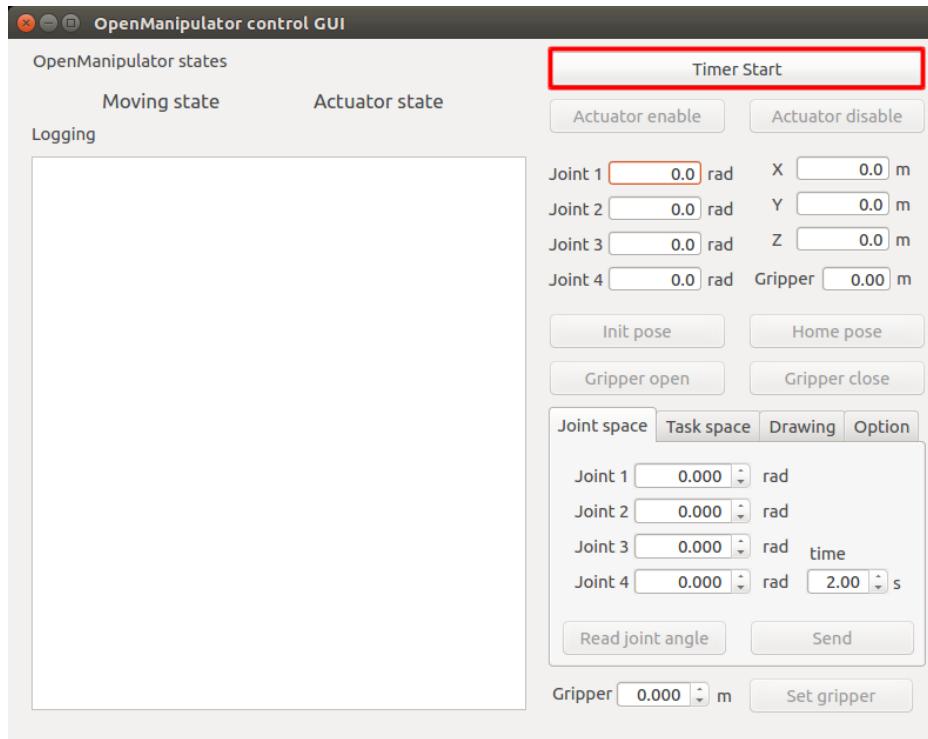
- \$ roslaunch open\_manipulator\_teleop open\_manipulator\_teleop\_keyboard.launch
- If the node is successfully launched, the following instruction will appear in the terminal window (left)
- Use your keyboard keys to control the arm; response will reflect in the Gazebo
- Close terminal when done



# OpenManipulator-X



## (b) Control via GUI



**\*\*\*Ensure Gazebo and the Controller are activated first**

**Type (in New Terminal):**

- \$ roslaunch open\_manipulator\_control\_gui open\_manipulator\_control\_gui.launch
- This will open the GUI for the arm control
- Click “Timer Start” & then “Actuator enable” and you can start controlling the arm; see Gazebo window for response

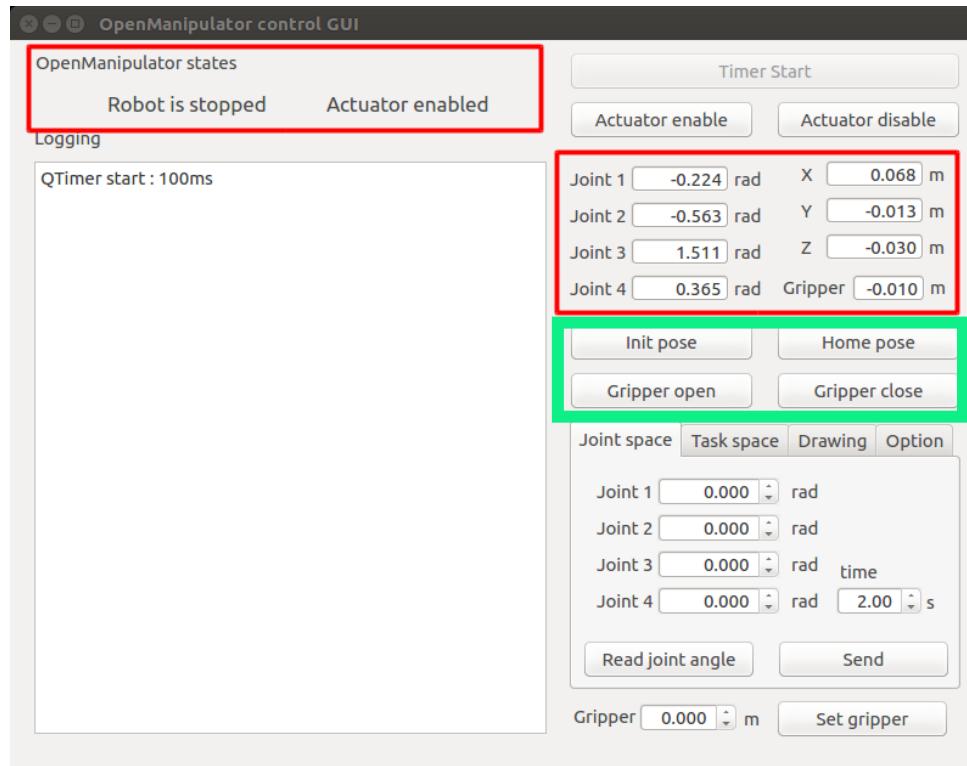


# OpenManipulator-X



## (b) Control via GUI

- You can **check the status of the arm** (i.e. joint states, kinematics pose, end effector position on X-Y-Z)
- To manipulate the arm to get it into **simple poses** (i.e. Init pose, Home pose, gripper open/close), click on the various buttons (in green box) one-by-one



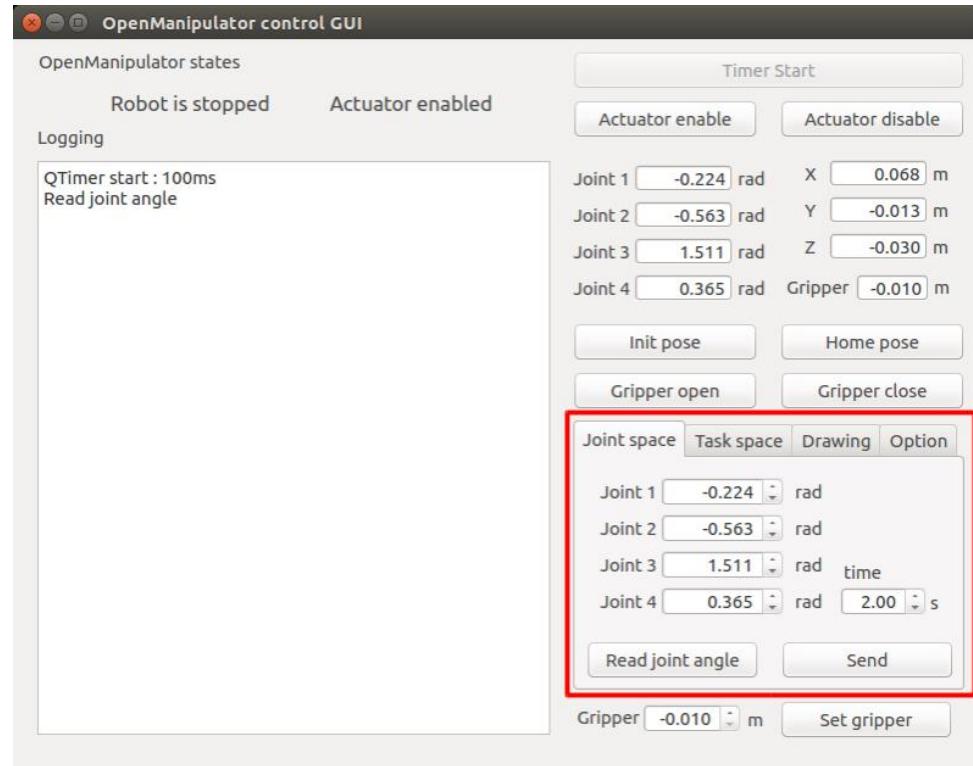


# OpenManipulator-X



## (b) Control via GUI

To manipulate the arm in the joint space (i.e. **Forward Kinematics**), enter the joint angles and trajectory time; click “Send” when done:



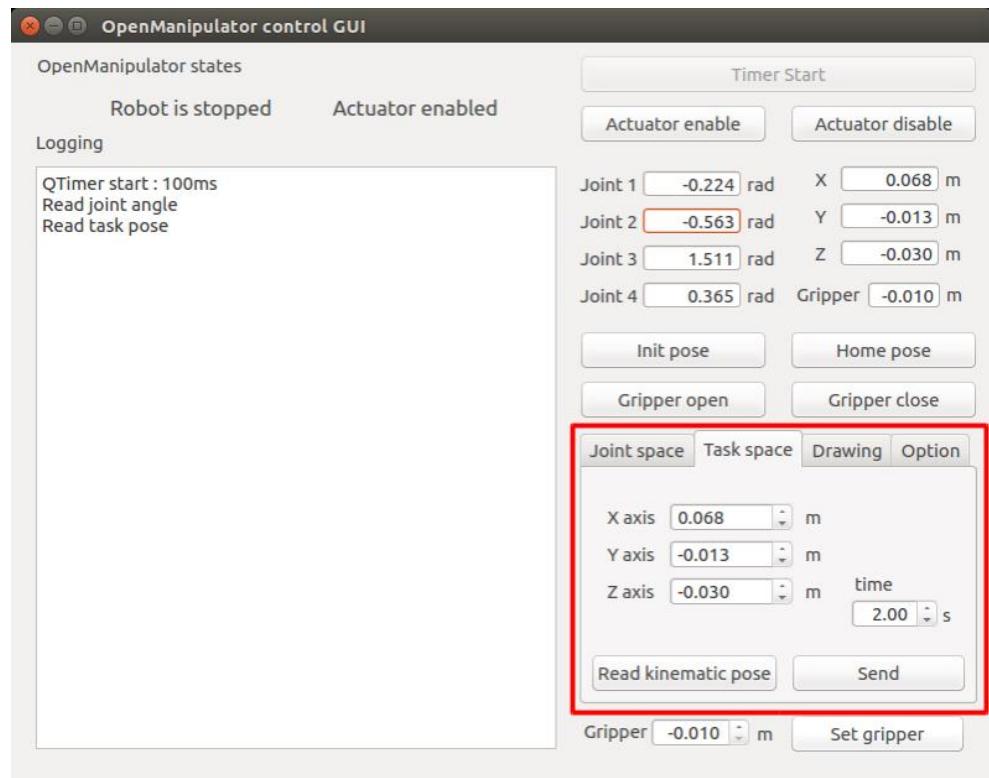


# OpenManipulator-X



## (b) Control via GUI

To manipulate the arm in the task space (i.e. **Inverse Kinematics**), enter the X-Y-Z values for your end effector's desired position; click "Send" when done:





## (c) Control via Python (rospy)

**\*\*\*Ensure Gazebo and the Controller are activated first**

From terminal, type: \$ rosservice list

```
/goal_joint_space_path
/goal_joint_space_path_from_present
/goal_joint_space_path_to_kinematics_orientation
/goal_joint_space_path_to_kinematics_pose
/goal_joint_space_path_to_kinematics_position
/goal_task_space_path
/goal_task_space_path_from_present
/goal_task_space_path_from_present_orientation_only
/goal_task_space_path_from_present_position_only
/goal_task_space_path_orientation_only
/goal_task_space_path_position_only
/goal_tool_control

/gripper_position/pid/set_parameters
/gripper_sub_position/pid/set_parameters
/gripper_sub_publisher/get_loggers
/gripper_sub_publisher/set_logger_level
/open_manipulator_controller/get_loggers
/open_manipulator_controller/set_logger_level
/rosout/get_loggers
/rosout/set_logger_level
/set_actuator_state
```

To move OM in the Gazebo is the same as in actual situation

For actual/Virtual OM, you have to service messages to move the arm (covered in M3 and in RBS Course)



## (c) Control via Python (rospy)

- Open terminal and type:

```
$ rosrun autonomous control_om.py
```

- The OM will move to a point determined by the joint angles. To alter these joint angles, open the python file, find the following line and change the angles in it; these angles are in radians:

```
joint_position.position = [-0.5, 0, 0.5, -0.5]
```

- To alter the gripper angles, alter the following line (-0.01 for fully close and 0.01 for fully open):

```
gripper_position.position = [0.01]
```



## (c) Control via Python (rospy)

control\_real\_om.py

```
#!/usr/bin/env python
# works for actual OM ONLY!
# does not work for actual OM_with_TB3

import rospy
from open_manipulator_msgs.msg import JointPosition
from open_manipulator_msgs.srv import SetJointPosition
from sensor_msgs.msg import JointState
import math
import time

def callback(msg):
    print msg.name
    print msg.position

def talker():
    rospy.init_node('OM_publisher') #Initiate a Node
    set_joint_position = rospy.ServiceProxy('/open_manipulator/goal_joint_space_path', SetJointPosition)
    set_gripper_position = rospy.ServiceProxy('/open_manipulator/goal_tool_control', SetJointPosition)

    while not rospy.is_shutdown():
        joint_position = JointPosition()
        joint_position.joint_name = ['joint1', 'joint2', 'joint3', 'joint4']
        joint_position.position = [-0.5, 0, 0.5, -0.5] # in radians
        resp1 = set_joint_position('planning_group', joint_position, 3)
        gripper_position = JointPosition()
        gripper_position.joint_name = ['gripper']
        gripper_position.position = [0.01] # -0.01 for fully close and 0.01 for fully open
        respg2 = set_gripper_position('planning_group', gripper_position, 3)

        sub_joint_state = rospy.Subscriber('/open_manipulator/joint_states', JointState, callback)

if __name__ == '__main__':
    try:
        talker()
    except rospy.ROSInterruptException:
        pass
```

Note if you cant execute the python file, you have to give execution permissions to it by typing:

```
$ chmod +x name_of_the_file.py
```

### Service Server

### Subscriber



## (d) Hand Guiding via Python

Instead of using the “*Processing*” app as done in M3, we will use *rospy* to execute the Hand Guiding process for the simulated OM

### Using Given Package,

- Change to the source space directory of the catkin workspace:

```
$ cd ~/catkin_ws/src
```

- Git Clone the Robotics package:

```
$ git clone  
https://github.com/nicholashojunhui/open_manipulator_save_and_load.git
```

- Build the packages in the catkin workspace:

```
$ cd ~/catkin_ws && catkin_make
```

- Go to *catkin\_ws/src/open\_manipulator\_save\_and\_load/nodes* and make python file executable

- **Run Gazebo and the OM controller (refer to README file for commands)**

- **Run *roslaunch* on a new terminal to begin Hand Guiding (refer to README file for commands)**



## (d) Hand Guiding via Python (Cont)

- Since you can't use your hand to guide the OM in Gazebo, use teleop manual control instead. In new terminal, type command:

```
$ rosrun open_manipulator_teleop  
open_manipulator_teleop_keyboard.launch
```

- Go back to terminal that you ran your save\_and\_load launch command (make sure you click on it first). When ready, type “1” and the programme starts recording the movements of the OM
- Go back to the “teleop” terminal, and move the OM in Gazebo using your keyboard. When done .....



## (d) Hand Guiding via Python (Cont)

- Go back to the “save\_and\_load” terminal, and type “2” to stop the recording and to save the records into a file in the cfg folder
- To command the OM to perform the recorded tasks, at the “save\_and\_load” terminal, type “3”. Observe that the OM will move by itself by loading the recorded file (i.e. the trajectories/actions that you teach the OM)



## 2. SIMULATION OF TURTLEBOT3 WAFFLE PI



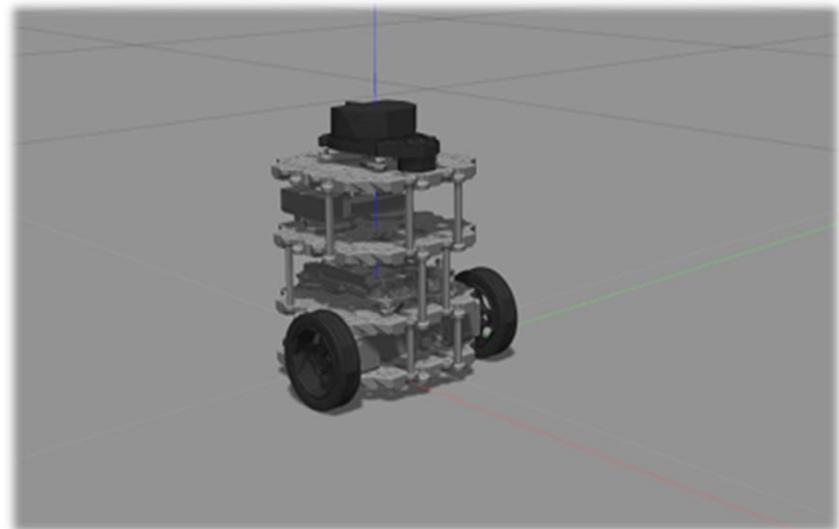
# Introduction of Various Worlds



## Using Gazebo:

### Empty World

- \$ roslaunch  
turtlebot3\_gazebo  
turtlebot3\_empty\_  
world.launch





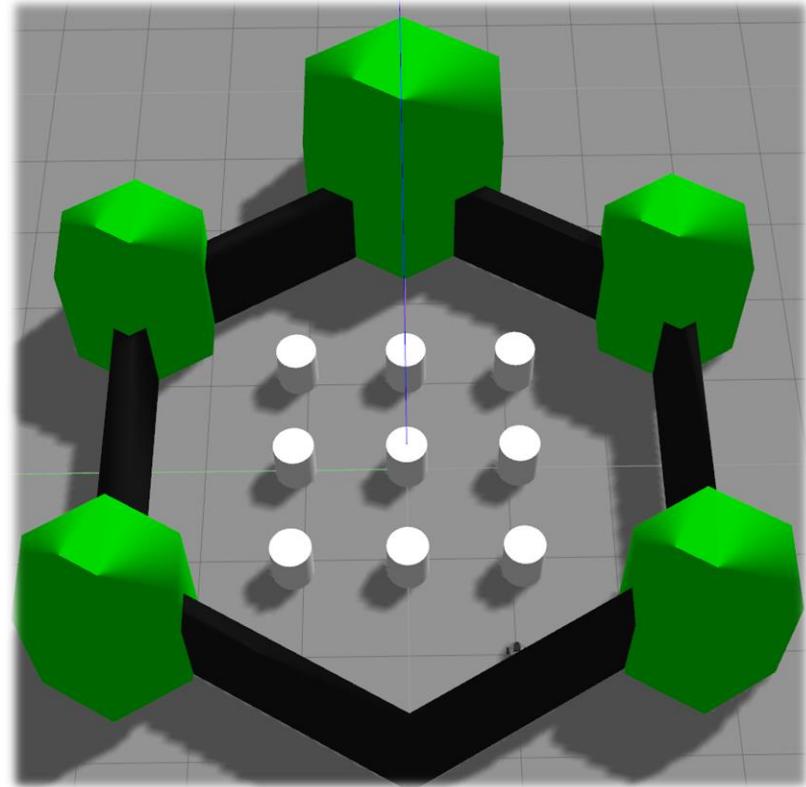
# Introduction of Various Worlds



## Using Gazebo:

TurtleBot3 World (Map to be mostly used for today)

- \$ roslaunch turtlebot3\_gazebo turtlebot3\_world.launch





# ROS Basics (RECAP)



**After launching the following command:**

```
$ roslaunch turtlebot3_gazebo turtlebot3_world.launch
```

**We will open new terminal and try the following (one by one):**

1. \$ rostopic list
2. \$ rosservice list
3. \$ rostopic echo /odom -n1
4. \$ rostopic echo /imu -n1
5. \$ rqt
6. \$ rqt\_image\_view



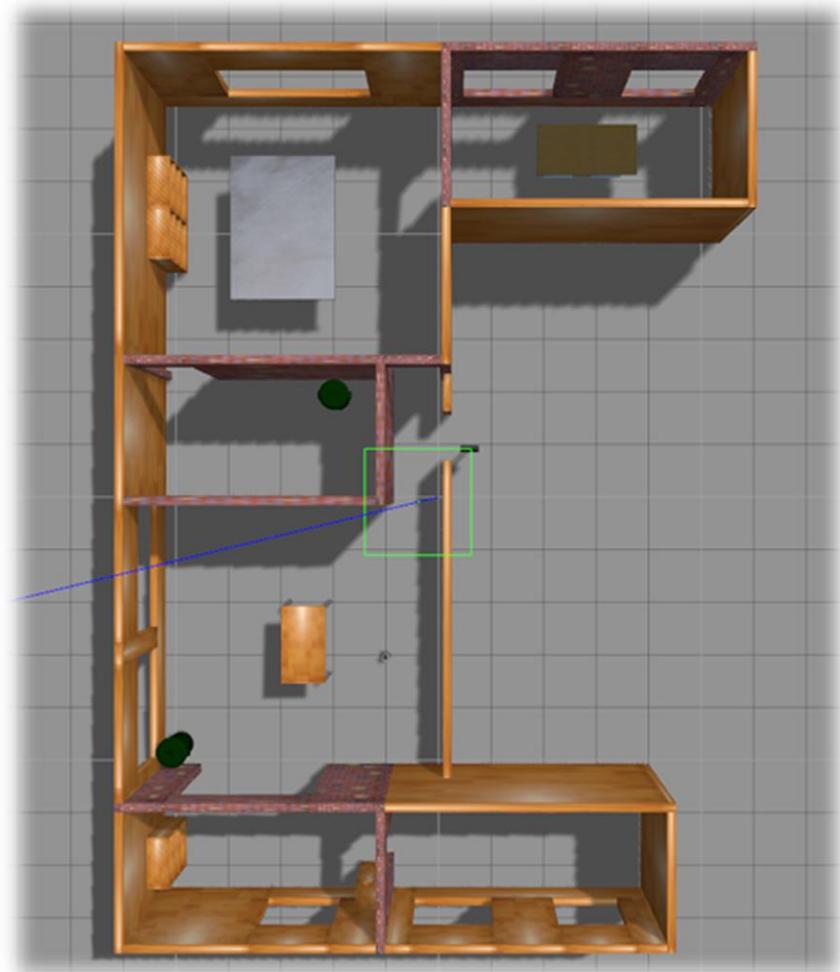
# Introduction of Various Worlds



## Using Gazebo:

### TurtleBot3 House

- \$ roslaunch turtlebot3\_gazebo turtlebot3\_house.launch





## (a) Manual Movements (Gazebo)

**Using Gazebo; while any of the worlds above is launched, type in new terminal:**

- \$ roslaunch turtlebot3\_teleop turtlebot3\_teleop\_key.launch
- **You are now able to move the TB3 around using the keyboard (i.e. w, s, x, a, d)**



## **(b) Random Autonomous Navigation and Obstacle Avoidance**

**Using Gazebo, type in new terminal to launch the TurtleBot3 World:**

- `$ roslaunch turtlebot3_gazebo turtlebot3_world.launch`

**In new terminal, enter below command to activate autonomous navigation and obstacle avoidance:**

- `$ roslaunch turtlebot3_gazebo turtlebot3_simulation.launch`
- Do not end the programme yet; see next slide



## (b) Random Autonomous Navigation and Obstacle Avoidance (cont)

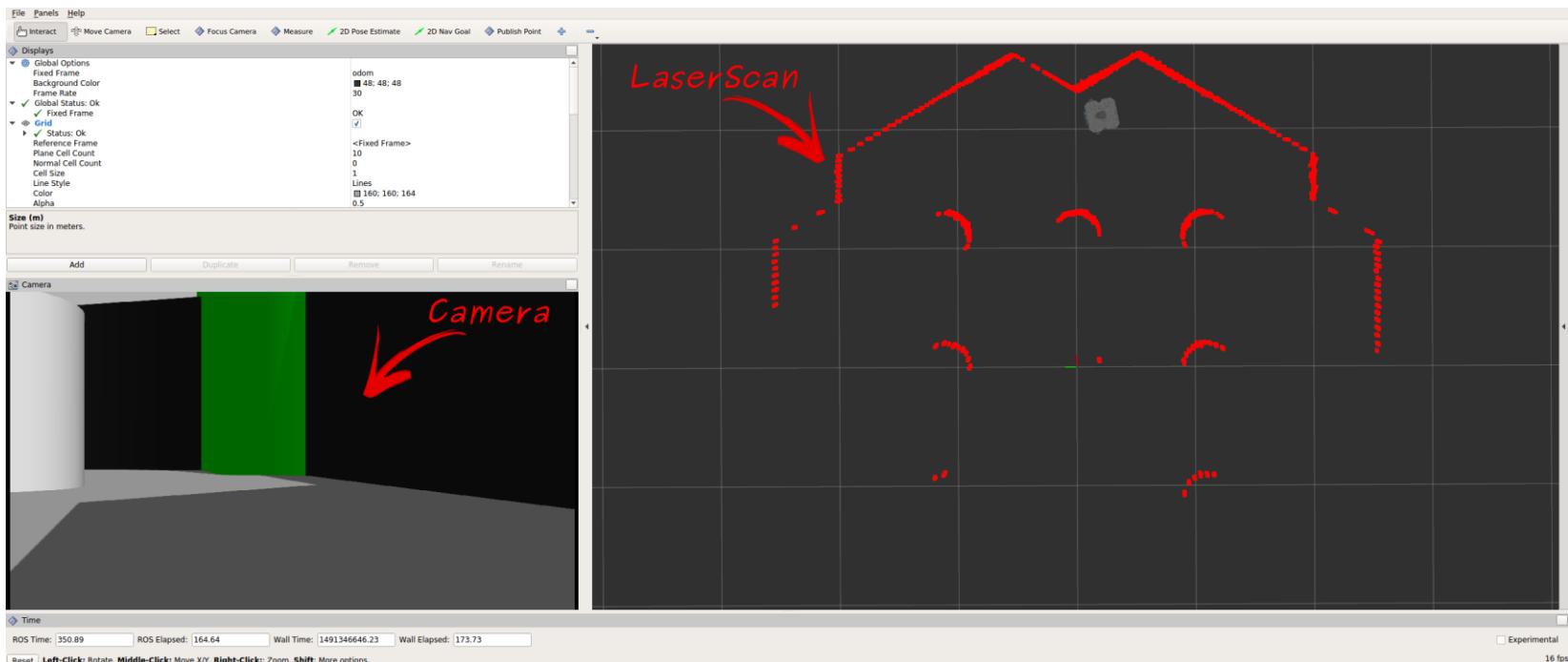
**While the TB3 is moving autonomously around the virtual world, we can open RViz to visualize the LaserScan topic; in a new terminal, type:**

- \$ rosrun turtlebot3\_gazebo turtlebot3\_gazebo\_rviz.launch



## (b) Random Autonomous Navigation and Obstacle Avoidance (cont)

Your output in RViz will be as follows:





## (c) SLAM and Controlled Navigation



**For Virtual SLAM (one TB3), 4 Steps:**

**Step 1 - Launch Gazebo in TurtleBot3 World**

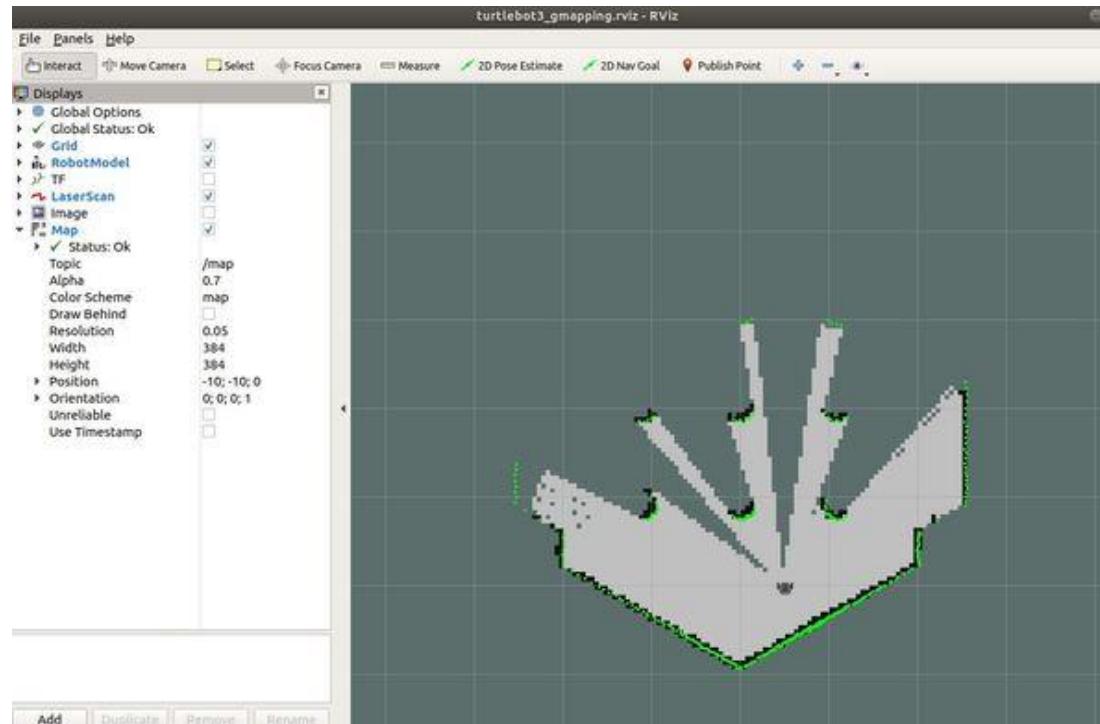
- `$ roslaunch turtlebot3_gazebo turtlebot3_world.launch`

**Step 2a - Launch SLAM in a new terminal**

- `$ roslaunch turtlebot3_slam turtlebot3_slam.launch slam_methods:=gmapping`
- Note that if your SLAM module don't work, close all terminals, install it in a new terminal:
  - `$ sudo apt install ros-noetic-slam-gmapping`
  - Restart from Step 1

# (c) SLAM and Controlled Navigation

Step 2a - Launch SLAM in a new terminal (cont);  
the initial state will be like below:





## (c) SLAM and Controlled Navigation



Step 3a - Activate Autonomous Navigation in a new terminal (only works for simulation!):

- `$ roslaunch turtlebot3_gazebo turtlebot3_simulation.launch`

Note that you can choose to do this manually (i.e. Teleop key node as covered earlier)

Step 4 - Save the Map once Completed in a new terminal:

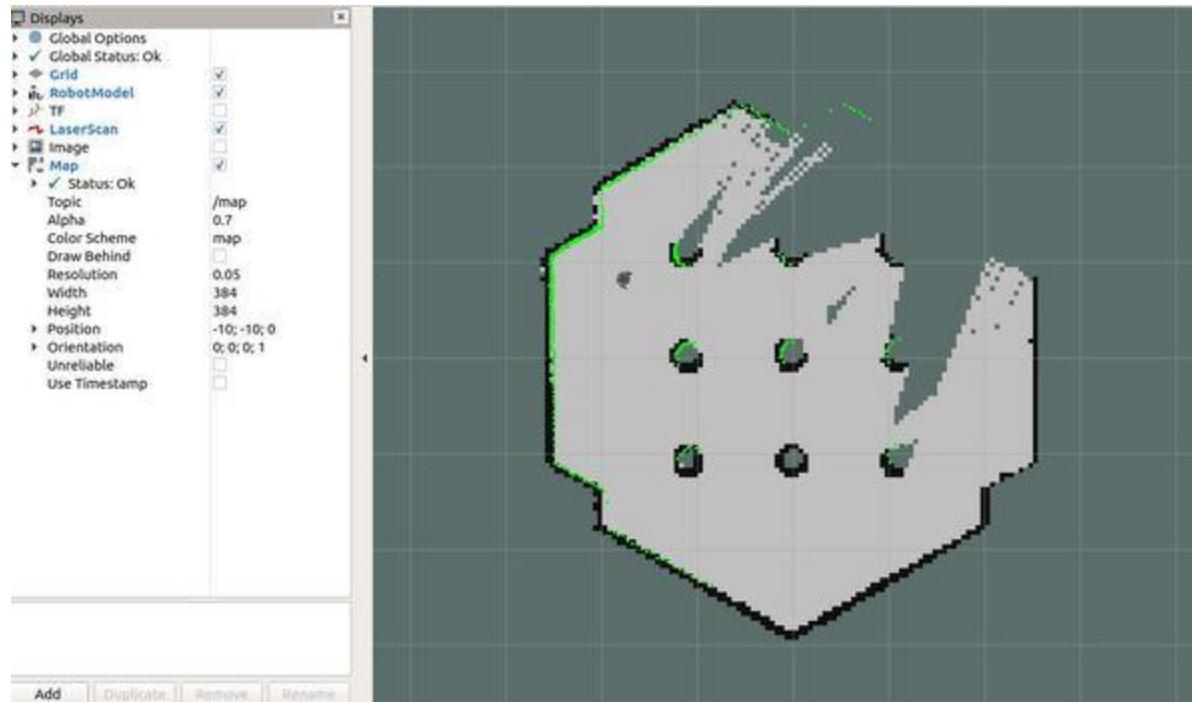
- `$ rosrun map_server map_saver -f ~/TB3_WORLD`
- **You can name your map (in red)**



## (c) SLAM and Controlled Navigation

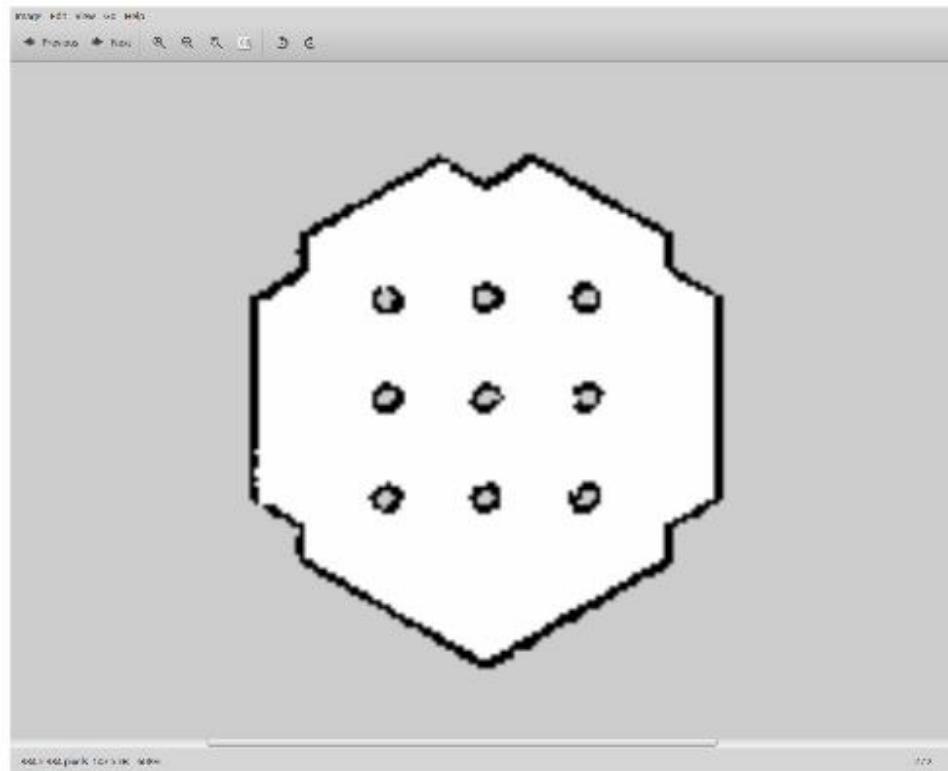


Step 3a - Activate Autonomous Navigation OR Teleop Node in a new terminal (cont); the map will be created as the TB3 moves around:



## (c) SLAM and Controlled Navigation

Step 4 - Save the Map once Completed in a new terminal (cont):

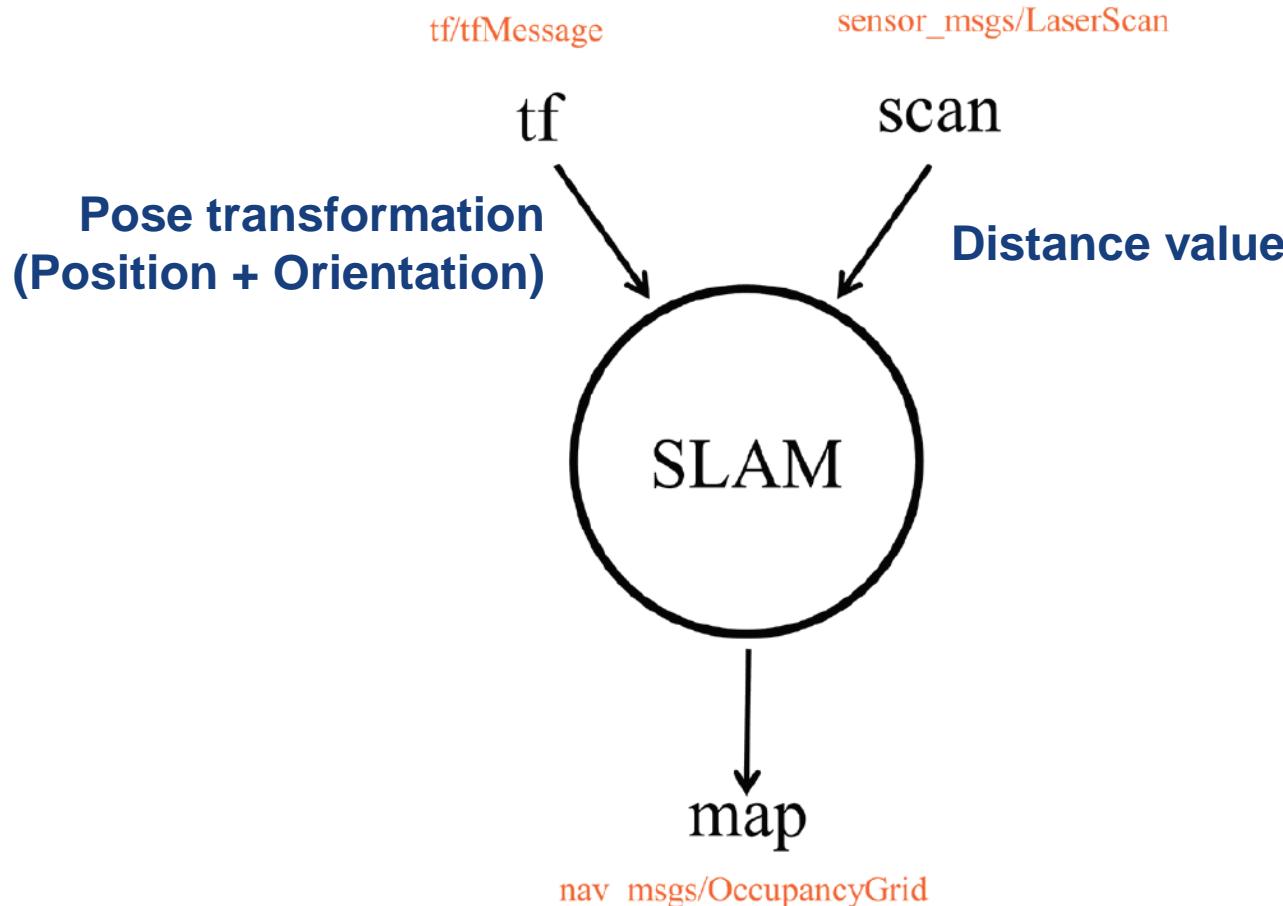




# SLAM Application



## Information Required in SLAM:

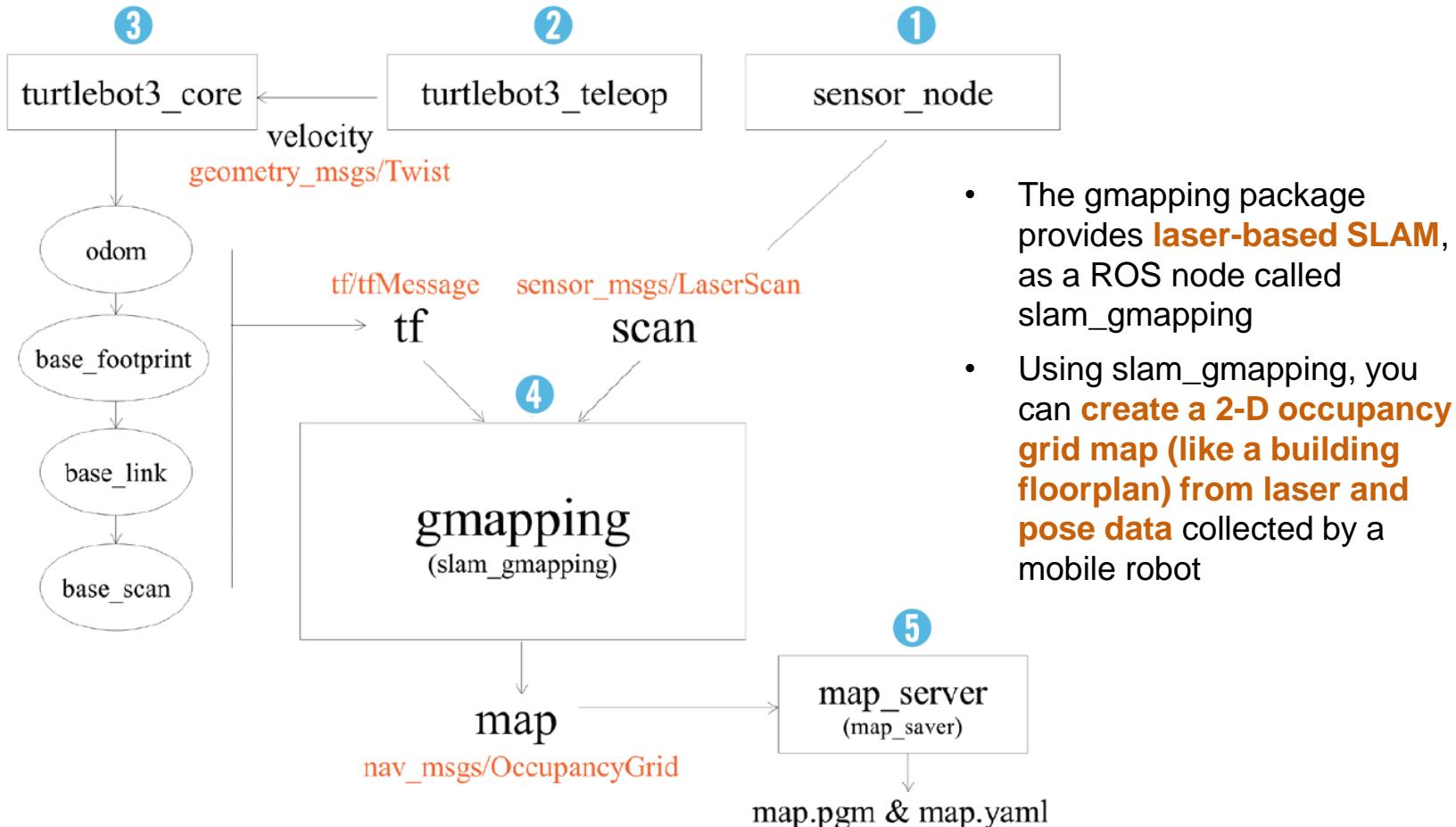




# SLAM Application

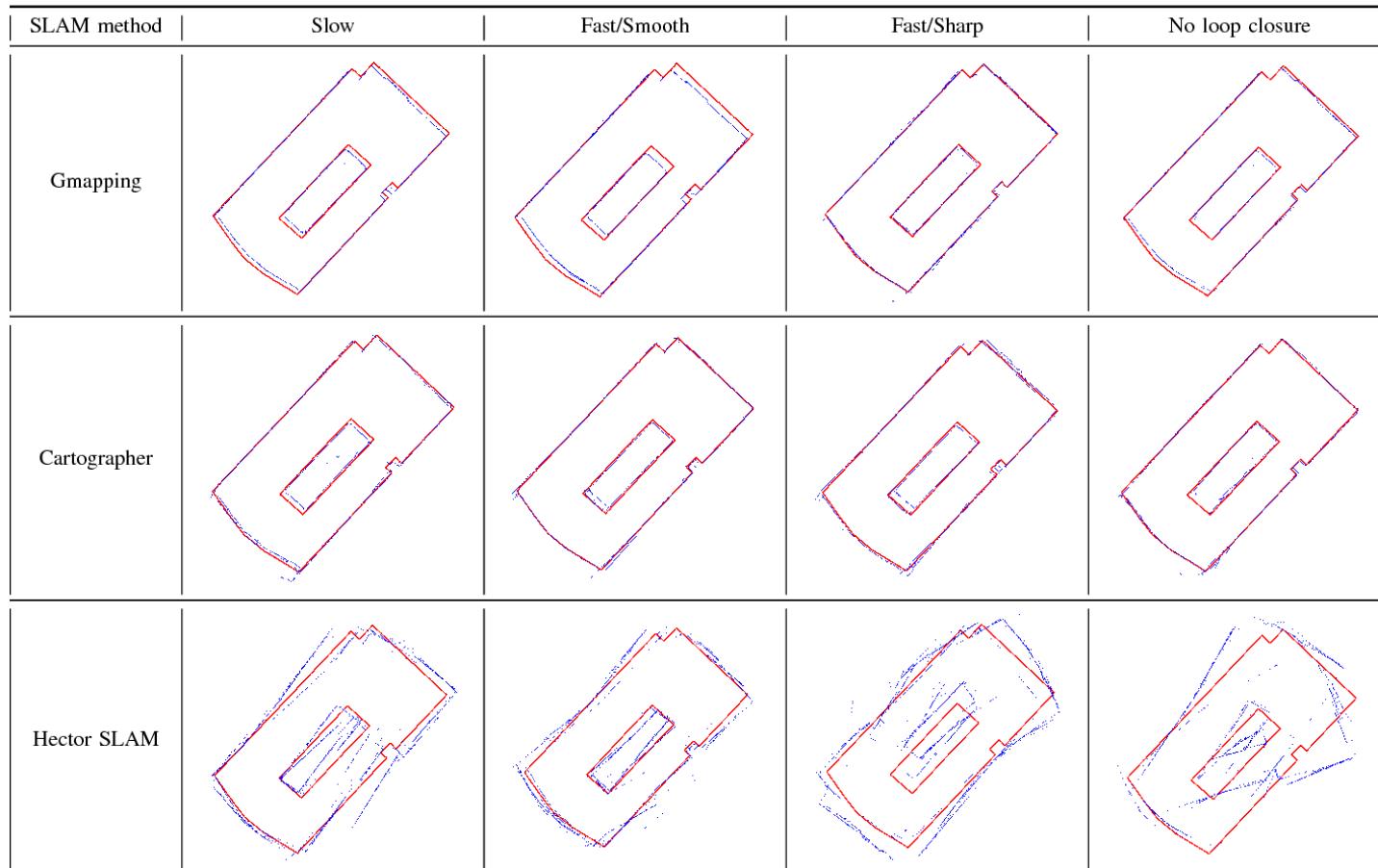


## SLAM Process for TB3:





# Extra: Comparisons among SLAM Methods



**Map comparison constructed from  
SLAM Algorithms (blue colour) and Ground Truth (red colour)**



# Extra: Comparisons among SLAM Methods



Condition	SLAM algorithm		
	Gmapping	Cartographer	Hector SLAM
Slow ride, smooth rotations, loop closure	8.05	7.41	27.95
Fast ride with smooth rotations, loop closure	11.92	5.35	19.36
Fast ride with sharp rotations, loop closure	3.21	7.37	44.03
Without loop closure	6.11	4.97	51.67

**Map Comparison (Cont): Error Calculated with ADNN  
(Average Distance to the Nearest Neighbor) Metrics  
for SLAM Methods Relative to the ground truth, in cm**

ADNN = Sum of all distances from each point of the SLAM map to the nearest neighbor point on the ground truth map divided by number of occupied cells

$$\text{ADNN} = \frac{\sum_{i=1}^N \text{Nearest\_Neighbour}(\text{occupied\_grid\_cell}(i))}{N}$$



# Extra: Comparisons among SLAM Methods



- **Gmapping** based on particle filter pairing algorithm
- **Hector-SLAM** is based on scan matching algorithm
- **Cartographer** is a scan matching algorithm with loop detection
- **RGB-D** algorithm is an algorithm for mapping using depth images



# Extra: Comparisons among SLAM Methods



- **Gmapping (Particle Filter-based) = A laser-based SLAM algorithm for grid mapping**
- The most used SLAM algorithm; Dubbed GMapping (G for grid) due to the use of grid maps
- **Needs odometry and laser scan data**
- **When the amount of data to process becomes too large** (e.g. in a huge 3D space setting), **particle-based algorithms like Gmapping are not applicable due to their higher computing requirements on the processor**



# Extra: Comparisons among SLAM Methods



- **Hector-SLAM (Scan Matching-based) = a scan matching algorithm**
- Differs from other grid-based mapping algorithms, as it **does not require odometer or IMU sensor data, but it needs laser data and a priori map**
- Based on the Gauss–Newton iteration formula that optimally estimates the pose of the robot as represented by the rigid body transformation from the robot to the prior map
- **The optimal estimation is done by optimally matching the laser data and the prior map**
- **Like Gmapping, Hector-SLAM is not suitable for applications requiring 3D and/or dense point cloud settings**



# Extra: Comparisons among SLAM Methods



- **Cartographer (Graph-based) = a scan matching algorithm with loop detection**
- **Graph optimization algorithms** like Cartographer are more suitable for applications requiring large amount of data to process (e.g. self-driving cars)
- Created by Google, the function of Cartographer is to **process the data from Lidar, IMU, and odometers to build a map**
- Impressive real-time results for solving SLAM in 2D



# Extra: Comparisons among SLAM Methods



**TABLE 1** Popular ROS-compatible lidar and visual SLAM approaches with their supported inputs and online outputs

	Inputs				Online outputs					
	Camera				Lidar			Occupancy		Point
	Stereo	RGB-D	Multi	IMU	2D	3D	Odom	Pose	2D	3D
GMapping					✓		✓	✓	✓	
TinySLAM					✓		✓	✓	✓	
Hector SLAM					✓			✓	✓	
ETHZASL-ICP					✓	✓	✓	✓	✓	Dense
Karto SLAM					✓		✓	✓	✓	
Lago SLAM					✓		✓	✓	✓	
Cartographer					✓	✓	✓	✓	✓	Dense
BLAM						✓		✓		Dense
SegMatch						✓				Dense
VINS-Mono					✓			✓		
ORB-SLAM2	✓	✓								
S-PTAM	✓							✓		Sparse
DVO-SLAM		✓						✓		
RGBBiD-SLAM		✓								
MCPTAM	✓			✓				✓		Sparse
RGBDSLAMv2		✓					✓	✓	✓	Dense
RTAB-Map	✓	✓	✓		✓	✓	✓	✓	✓	Dense

Note. ICP: iterative closest point; IMU: inertial measurement unit; RTAB-Map: real-time appearance-based mapping.



# (c) SLAM and Controlled Navigation



For Virtual Controlled Navigation, 2 Steps:

Step 1 - Launch Gazebo in TurtleBot3 World

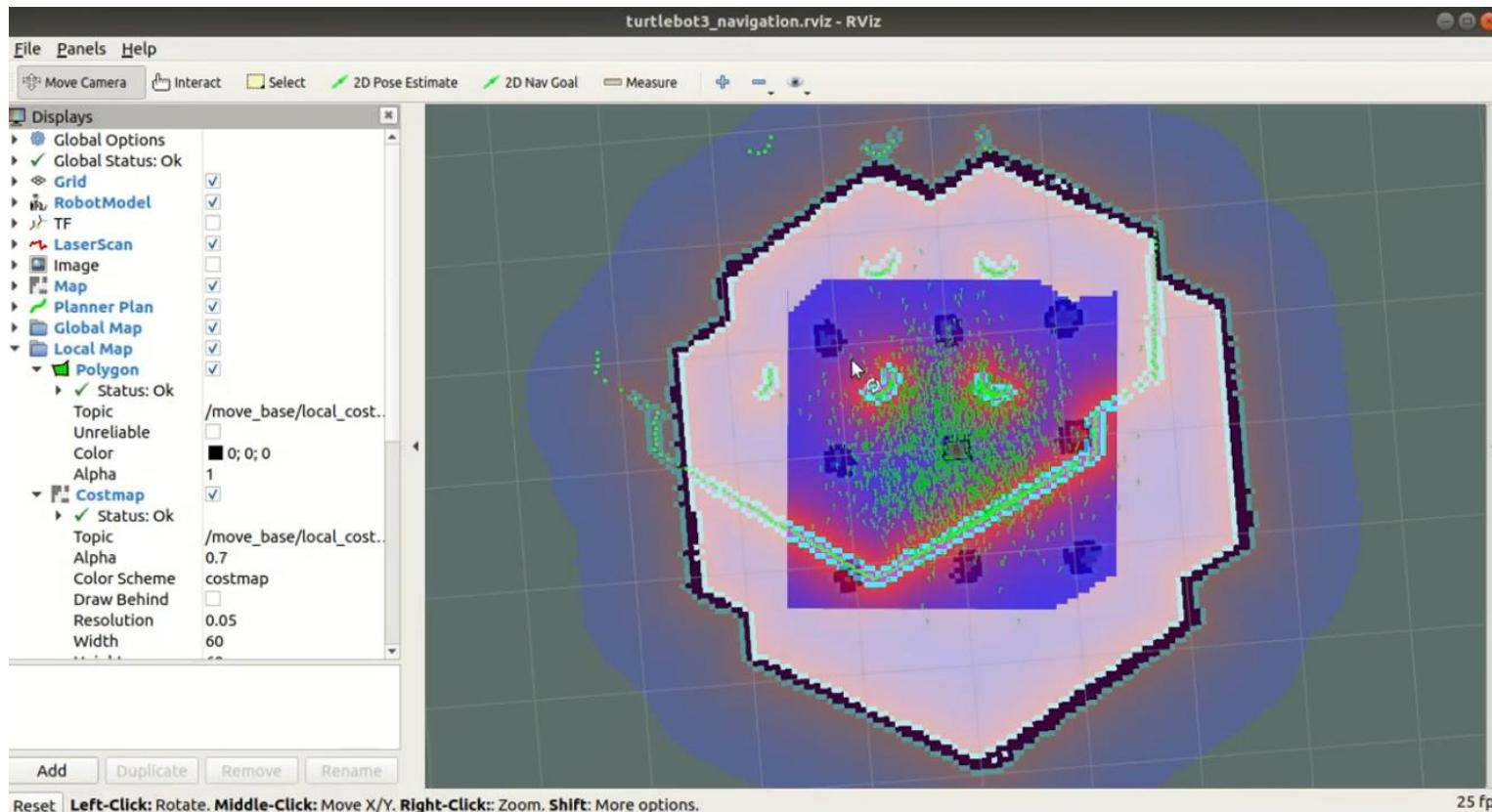
- `$ roslaunch turtlebot3_gazebo turtlebot3_world.launch`

Step 2 - Execute Controlled Navigation in a new terminal

- `$ roslaunch turtlebot3_navigation turtlebot3_navigation.launch map_file:=$HOME/TB3_WORLD.yaml`
- Remember to change the name of your map to the correct one

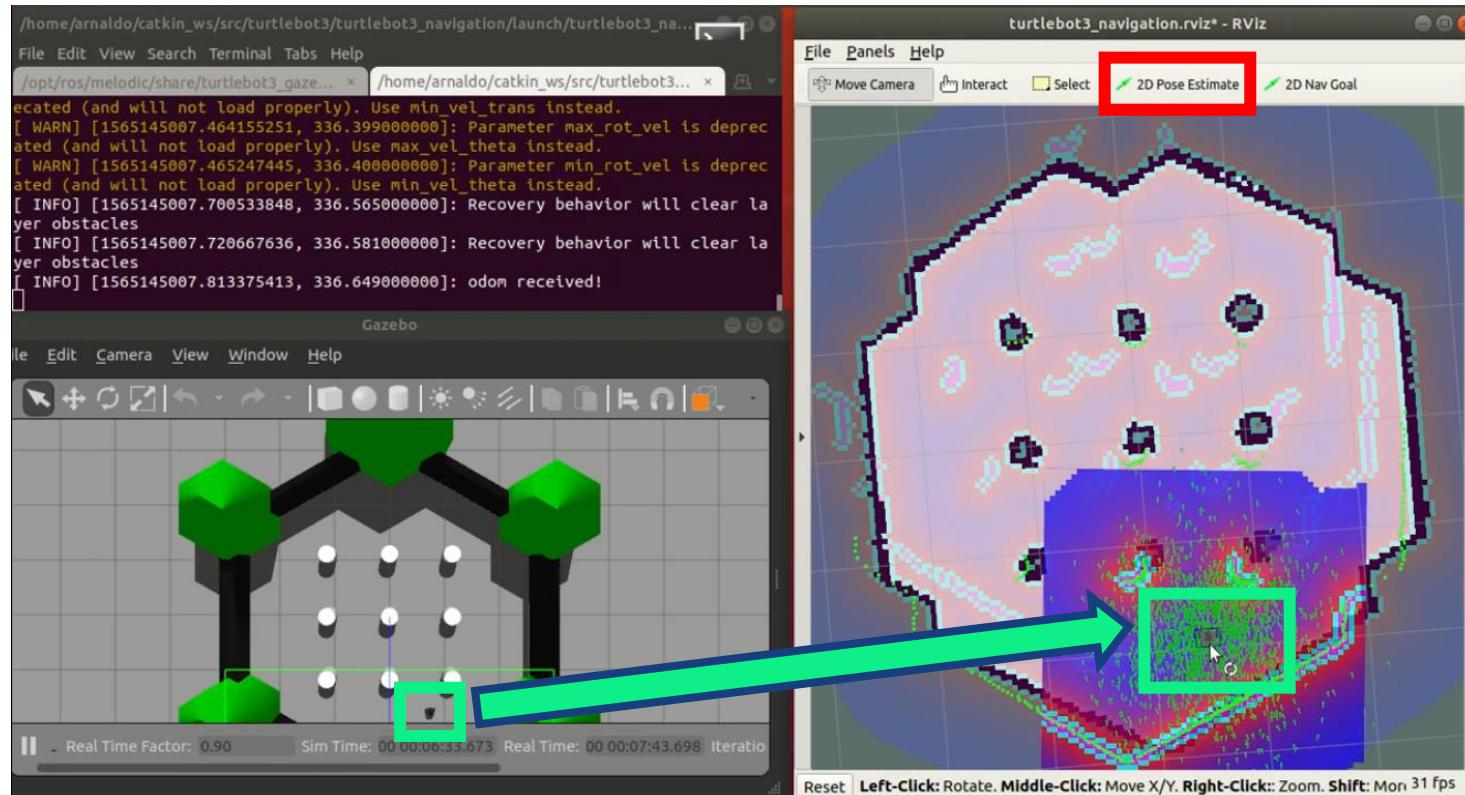
# (c) SLAM and Controlled Navigation

Step 2 - Execute Controlled Navigation in a new terminal  
**(cont); the RViz programme will open as follows:**



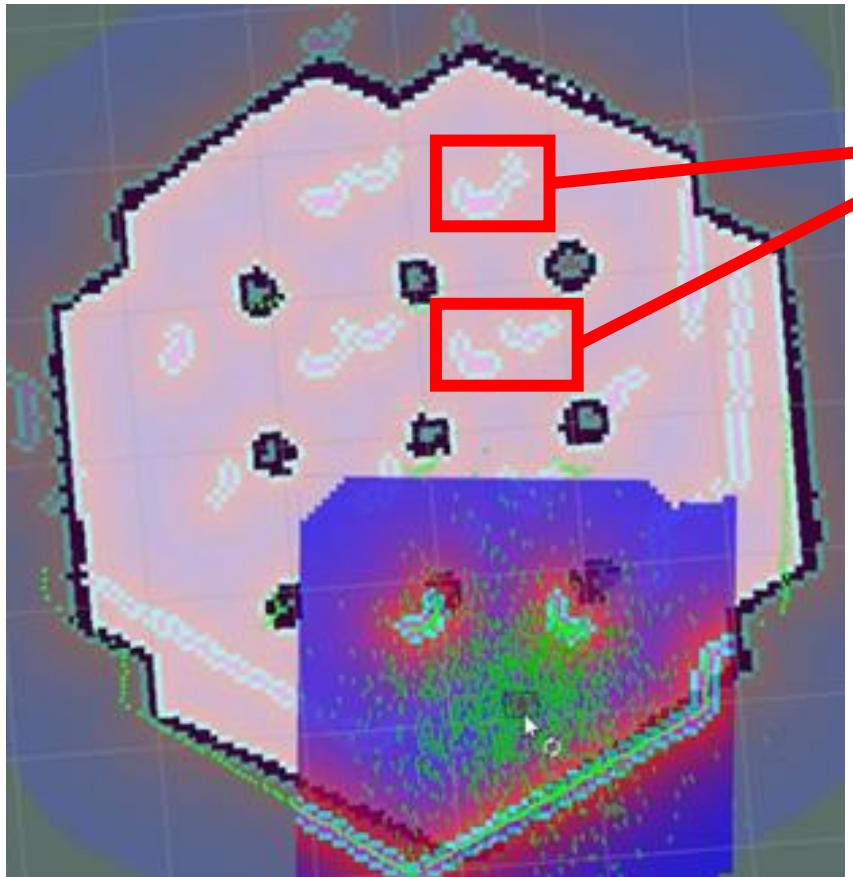
# (c) SLAM and Controlled Navigation

Step 2 (cont) - Click on “**2D Pose Estimate**” (red box) and set the correct initial position for the TB3 (right green box); refer to the left green box in Gazebo:





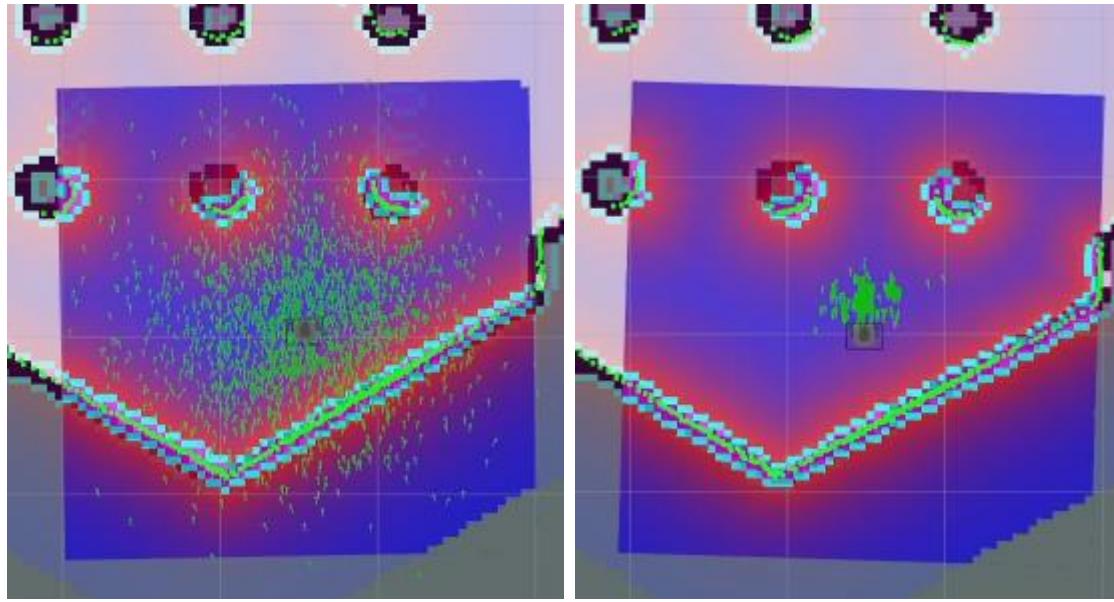
# Removing Unwanted Cost Maps



- Sometimes after you have performed the initial pose, there will be **unwanted cost maps that wrongly represent obstacles in the navigation system**
- The cause of this is usually **due to symmetrical effect** within the environment
- We **have to get rid of these unwanted cost maps** as much as possible before performing the navigation



# Removing Unwanted Cost Maps



**Before Action**

**After Action**

- To remove the unwanted cost maps, **simply rotate the TB3 and/or move it back and forth a bit** to collect the surrounding environment information; to do this, **launch the teleop node to precisely locate it on the map**:  
`$ roslaunch turtlebot3_teleop turtlebot3_teleop_key.launch`
- This will narrow down the estimated location of the TurtleBot3 on the map which is displayed with tiny green arrows



# Displaying Camera in RViz



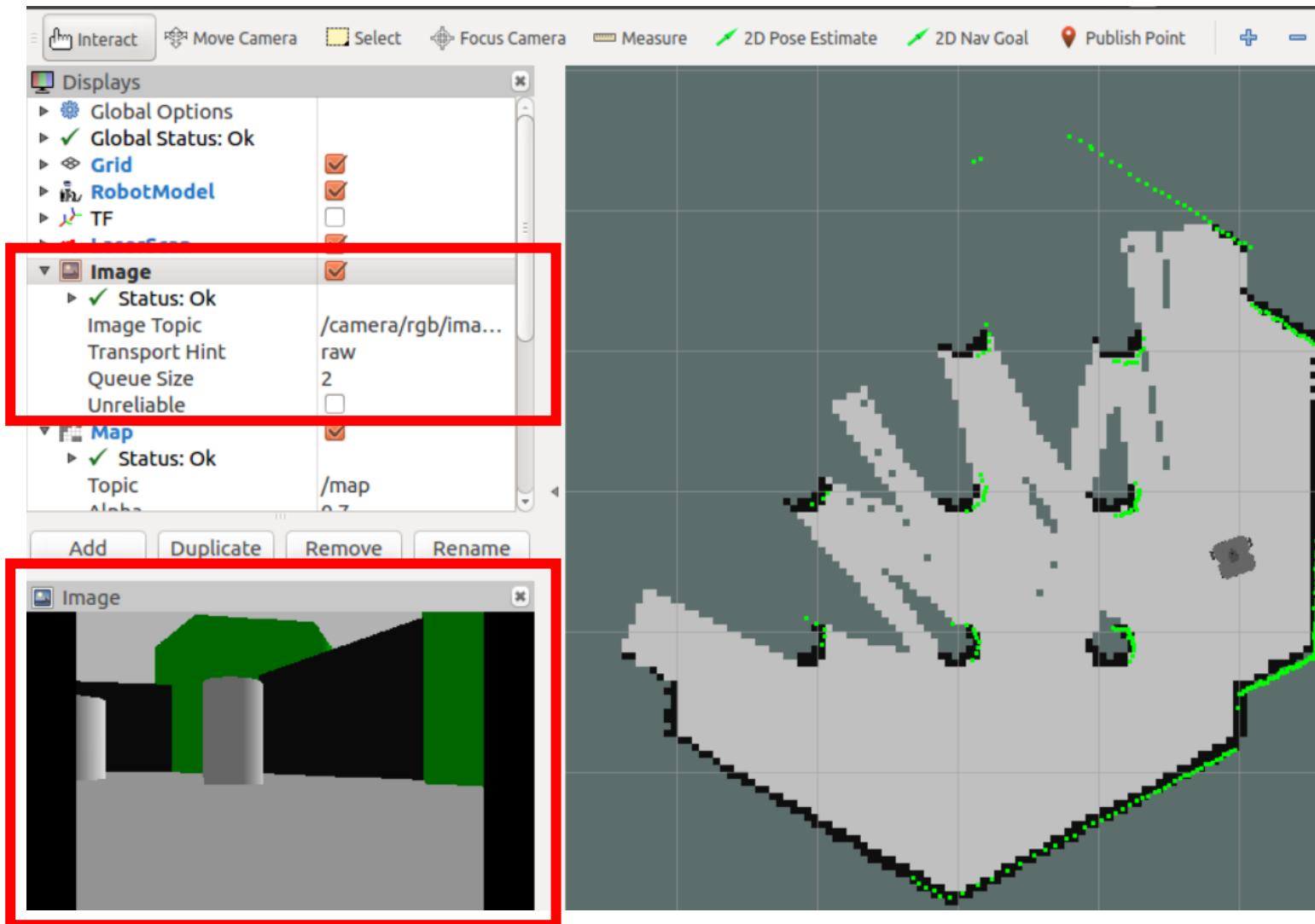
Note that **you can display the TB3's camera while RViz is launched during SLAM or NAVIGATION:**

1. While RViz is launched, go to “Displays” (left panel)
2. Expand “Image” topic at the left panel
3. Under “Image Topic”, change topic to “/camera/rgb/image\_raw”; you can just click on it and scroll down to find this topic and click on this option
4. Under “Transport Hint”, change type to “raw”

\*\*\*If you had explored enough, you will realize that your topic monitor will be able to do the same thing as well



# Displaying Camera in RViz

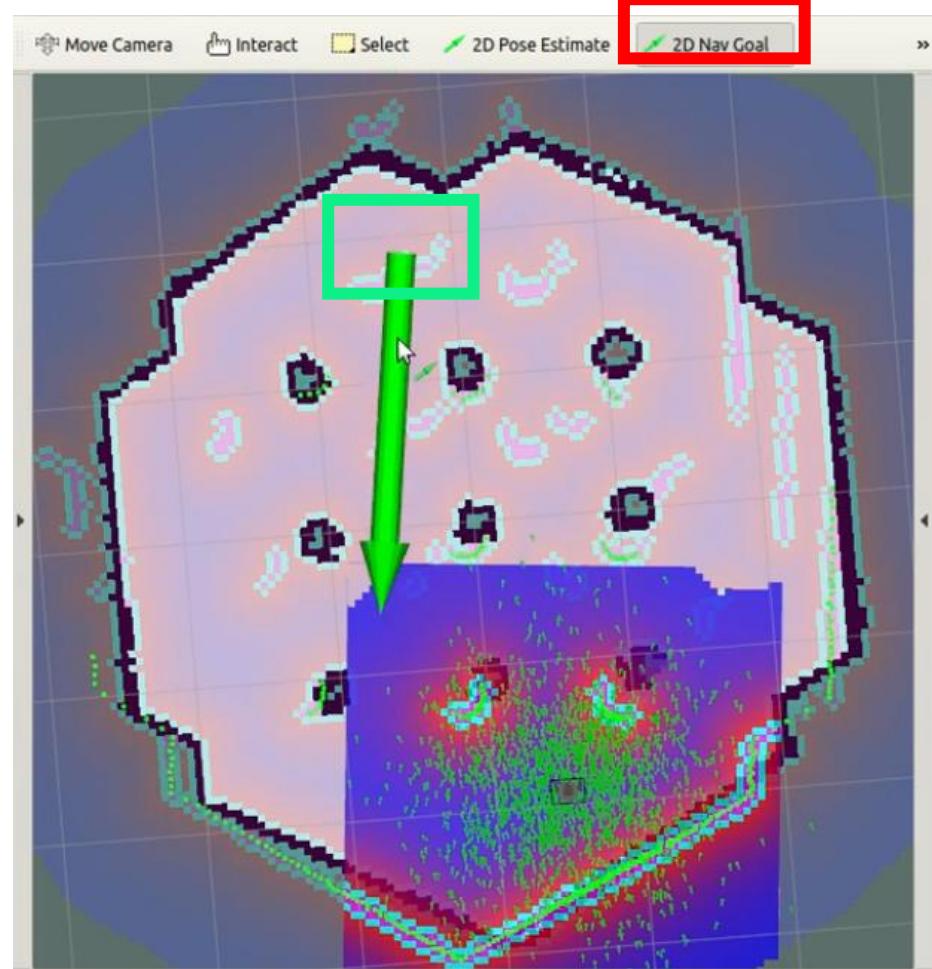


# (c) SLAM and Controlled Navigation

## Step 2 (cont)

- Click on “**2D NAV Goal**” (red box) and set the target destination for the TB3 (green box)
- The green arrow represent the direction of TB3 at its end state

Rmb to terminate any teleop node first!



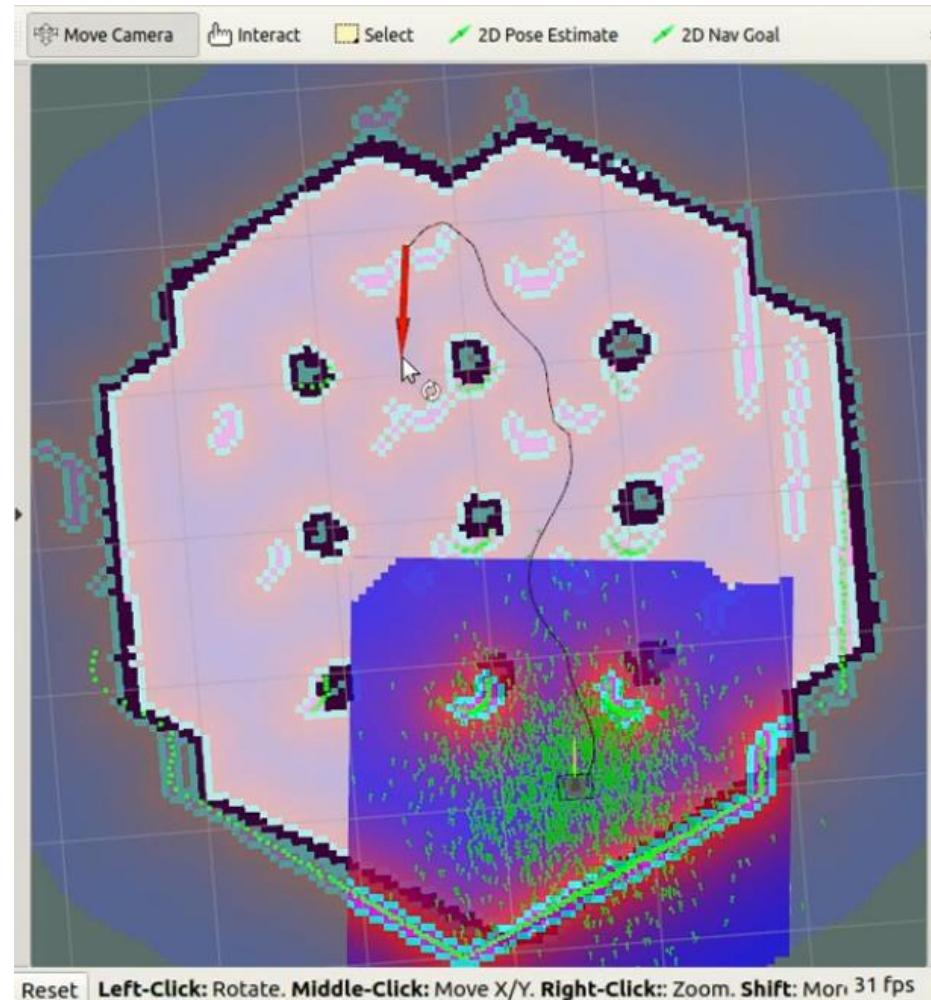


# (c) SLAM and Controlled Navigation



## Step 2 (cont)

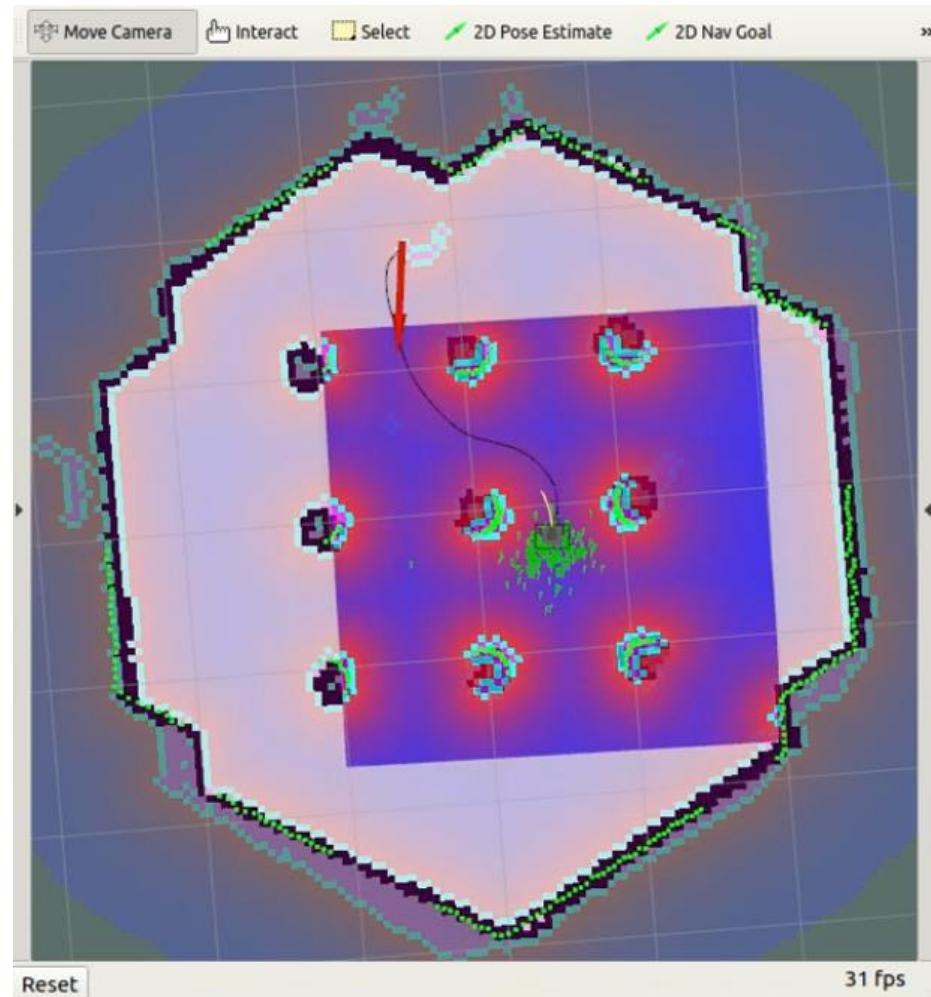
- **The tool will create a path for the TB3 to follow to reach to the end goal**
- **The bot will follow the created path to its destination**



# (c) SLAM and Controlled Navigation

## Step 2 (cont)

- The path may be adjusted automatically to its optimum during the TB3's journey



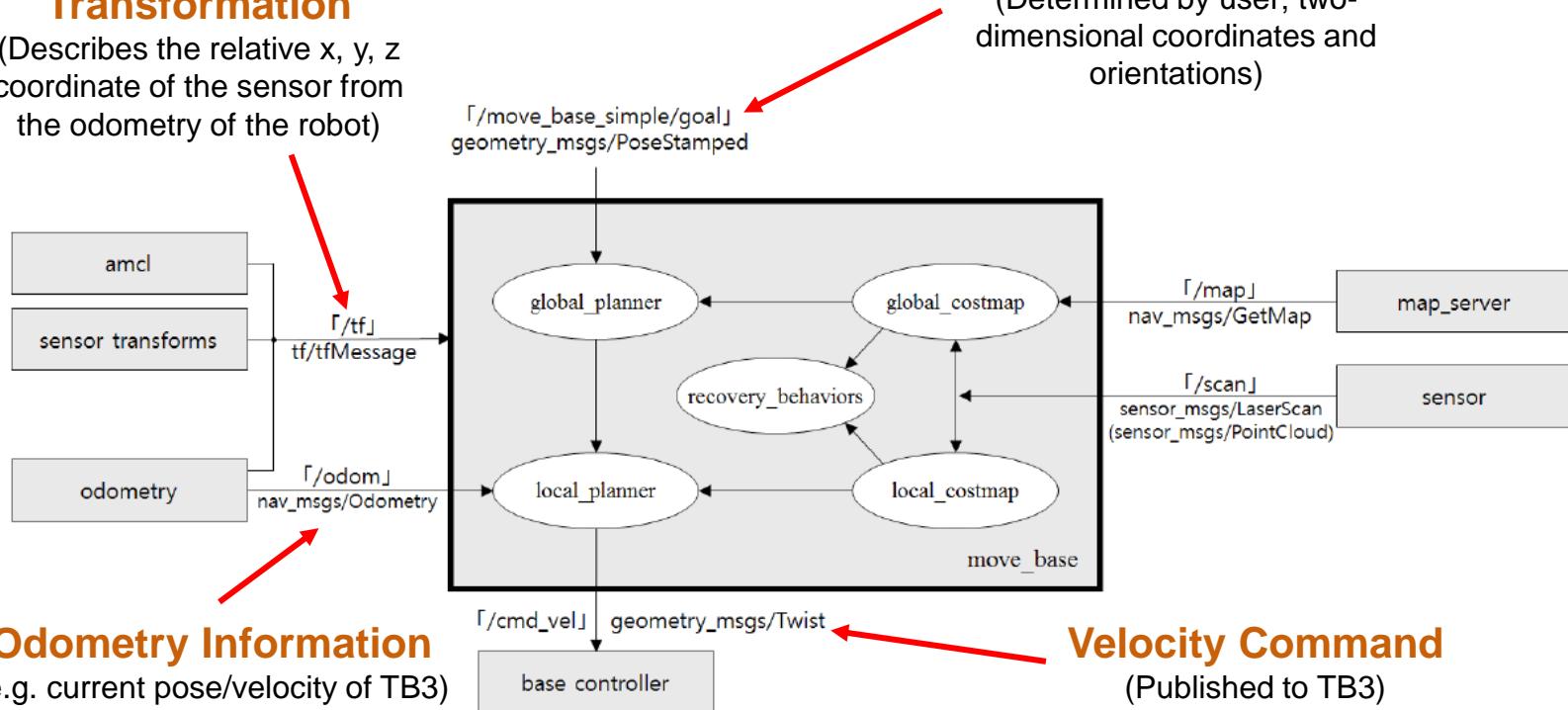


# Navigation Application



## Relative Coordinate Transformation

(Describes the relative x, y, z coordinate of the sensor from the odometry of the robot)





# Using Python to Control TB3



1. Moving TB3 in circles
2. Moving TB3 according to a fixed distance using position feedback
3. Getting laser data
4. Avoiding obstacle in front of TB3
5. Initial pose estimate for navigation
6. Path planning for navigation



# Moving TB3 in circles



- Open terminal and type:

```
$ roslaunch turtlebot3_gazebo  
turtlebot3_empty_world.launch
```

- Open new terminal and type:

```
$ rosrun autonomous trajectory.py
```

- Observe in Gazebo that the TB3 will continuously move in circles
- To change the destination point along the x-axis, change the value for the following variable:

move.linear.x

- To change the direction of movement, change the value for the following variable (in radians):

move.angular.z



# Moving TB3 in circles



trajectory.py

```
#!/usr/bin/env python

import rospy
from geometry_msgs.msg import Twist

def talker():
    rospy.init_node('vel_publisher')
    pub = rospy.Publisher('cmd_vel', Twist, queue_size=10)
    move = Twist()
    rate = rospy.Rate(1)
    while not rospy.is_shutdown():
        move.linear.x = 1
        move.angular.z = 1
        pub.publish(move)
        rate.sleep()

if __name__ == '__main__':
    try:
        talker()
    except rospy.ROSInterruptException:
        pass
```



# Moving TB3 according to a fixed distance using position feedback



- Open terminal and type:

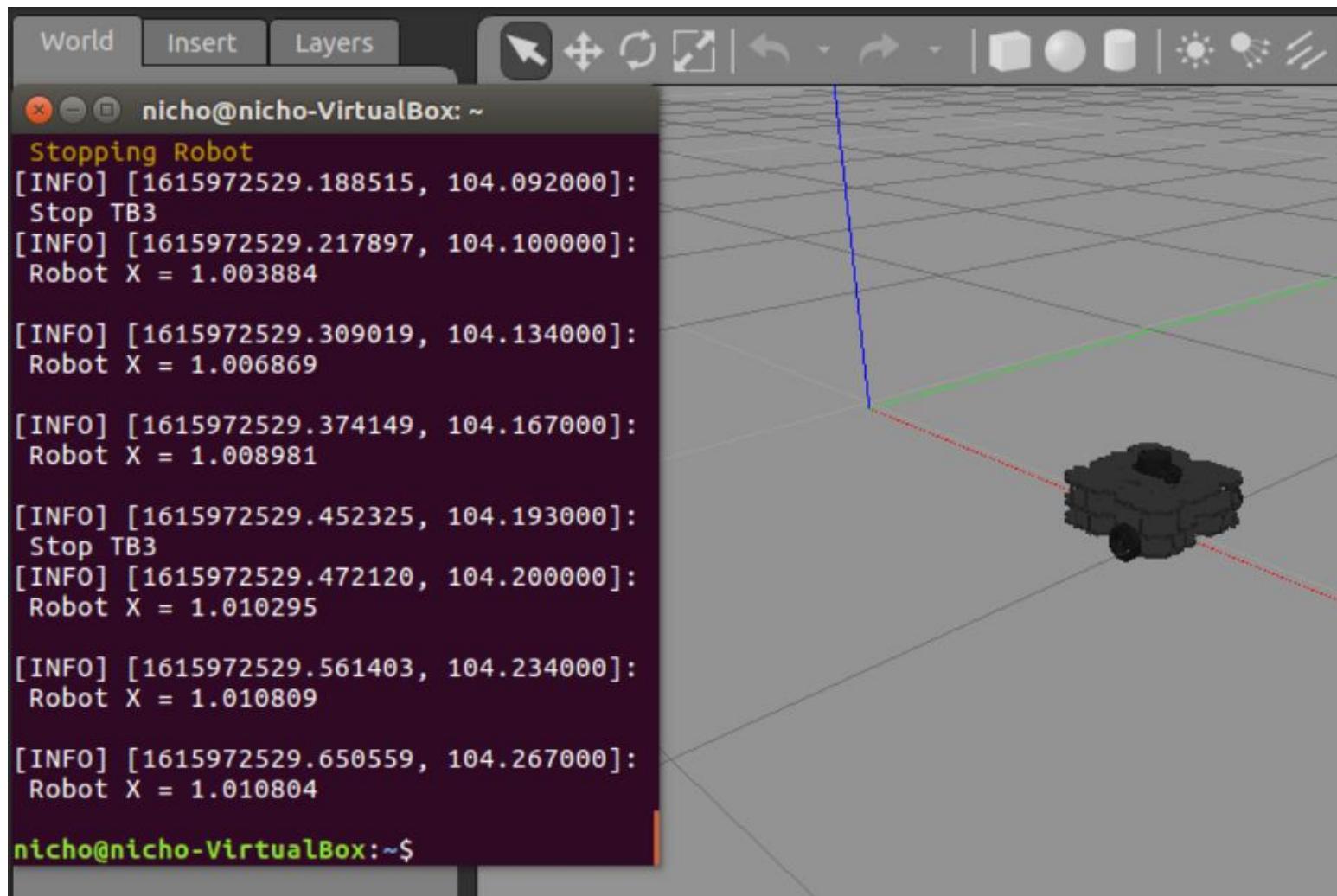
```
$ roslaunch turtlebot3_gazebo  
turtlebot3_empty_world.launch
```

- Open new terminal and type:

```
$ rosrun autonomous  
move_turtlebot_distance.py 0.1 0.0 1.0
```

- Inputs in the following order: [linear.x, angular.z, distance]; you can choose the inputs in your command line
- Observe in Gazebo that the TB3 will move along the x-axis at linear velocity 0.1m/s (i.e. lin\_vel = 0.1) to the position when x = 1m (i.e. distance = 1.0)

# Moving TB3 according to a fixed distance using position feedback





# Moving TB3 according to a fixed distance using position feedback



move\_turtlebot\_distance.py

```
# Function to move turtle: Linear and angular velocities, and distance are arguments
def move_turtle(lin_vel, ang_vel, distance):
    global pub
    global rate
    global robot_x
    rospy.init_node('move_turtlebot_distance')           #Initiate a Node

    # The /turtle1/cmd_vel is the topic in which we have to send Twist messages
    pub = rospy.Publisher('/cmd_vel', Twist, queue_size=10) #Create a Publisher object
    rospy.Subscriber('/odom', Odometry, pose_callback) #Creating new subscriber

    vel = Twist()                                     #Create a var named "vel" of type Twist
    rate = rospy.Rate(10)                            #Set a publish rate of 10 Hz

    rospy.on_shutdown(shutdown)

    while not rospy.is_shutdown():

        # Adding linear and angular velocity to the message
        vel.linear.x = lin_vel
        vel.linear.y = 0
        vel.linear.z = 0

        vel.angular.x = 0
        vel.angular.y = 0
        vel.angular.z = ang_vel

        #rospy.loginfo("Linear Vel = %f: Angular Vel = %f", lin_vel, ang_vel)

        # Checking the robot distance is greater than the desired distance
        # If it is greater, stop the node
        if(robot_x >= distance):
            rospy.loginfo("Robot Reached Destination")
            rospy.logwarn("Stopping Robot")
            shutdown()
            break
```



# Getting laser data



- Open terminal and type:

```
$ roslaunch turtlebot3_gazebo  
turtlebot3_world.launch
```

- Open new terminal and type:

```
$ rosrun autonomous laser_data.py
```

- Observe in the terminal of the received laser data in 5 directions

- You may activate the teleop node to move the TB3 around and observe the change in collected laser data:

```
$ roslaunch turtlebot3_teleop  
turtlebot3_teleop_key.launch
```

- To change the direction of collection for the laser data, change the value for the following variable:

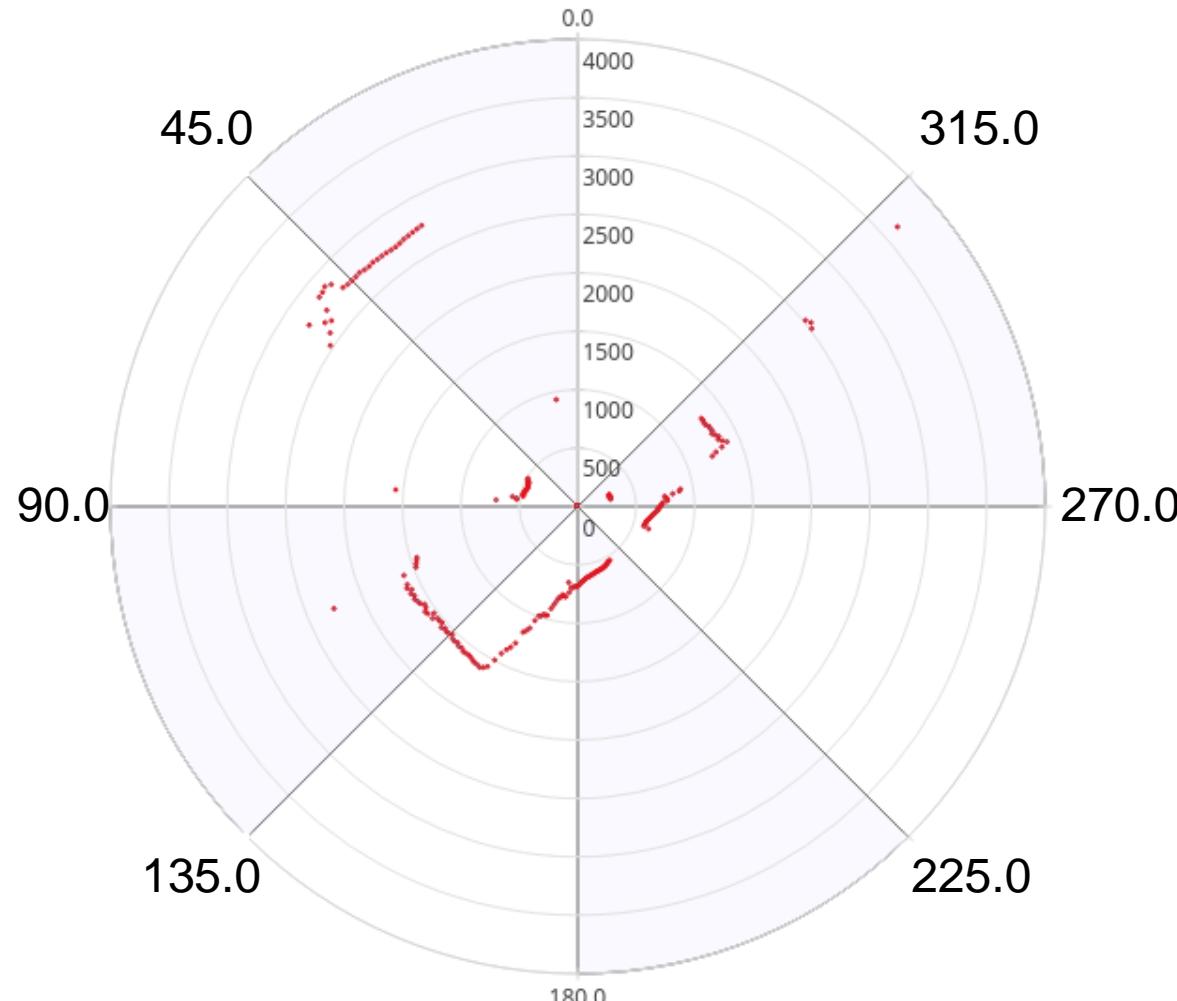
```
msg.ranges[X]
```



# Getting laser data



## Directions Map of LDS:





# Getting laser data



`laser_data.py`

```
#!/usr/bin/env python

import rospy
from sensor_msgs.msg import LaserScan           #import the python library for ROS
                                                #import the laserscan message from the std_msgs package

def callback(msg):                                #define a function called 'callback' that receives a parameter named 'msg'
    print('=====')                               #value for front-direction laser beam
    print('s1 [0]')                             #print the distance to any obstacle in front of the robot. The sensor
    print msg.ranges[0]                          #returns a vector of 359 values, with 0 being in front of the TB3

    print('s2 [90]')
    print msg.ranges[90]

    print('s3 [180]')
    print msg.ranges[180]

    print('s4 [270]')
    print msg.ranges[270]

    print('s5 [359]')
    print msg.ranges[359]

rospy.init_node('laser_data')                      # Initiate a Node called 'laser_data'
sub = rospy.Subscriber('scan', LaserScan, callback) #Create a Subscriber to the laser/scan topic

rospy.spin()
```



# Avoiding obstacle



- Open terminal and type:

```
$ roslaunch turtlebot3_gazebo  
turtlebot3_world.launch
```

- Open new terminal and type:

```
$ rosrun autonomous avoid_obstacle.py
```

- Observe in Gazebo that the TB3 will move in a straight line until it reaches an obstacle that is less than 0.5m in front of it

- To change the destination point along the x-axis, change the value for the following variable:

move.linear.x

- To change the direction of movement, change the value for the following variable (in radians):

move.angular.z



# Avoiding obstacle



avoid\_obstacle.py

```
#!/usr/bin/env python

import rospy
from sensor_msgs.msg import LaserScan
from geometry_msgs.msg import Twist

def callback(msg):
    print('=====')  

    print('s1 [0]')  

    print msg.ranges[0]  

    print('s2 [90]')  

    print msg.ranges[90]  

    print('s3 [180]')  

    print msg.ranges[180]  

    print('s4 [270]')  

    print msg.ranges[270]  

    print('s5 [359]')  

    print msg.ranges[359]  

#If obstacle is at least 0.5m in front of the TB3, the TB3 will move forward
if msg.ranges[0] > 0.5:  

    move.linear.x = 0.5  

    move.angular.z = 0.0
else:  

    move.linear.x = 0.0  

    move.angular.z = 0.0  

    pub.publish(move)  

rospy.init_node('obstacle_avoidance')
sub = rospy.Subscriber('/scan', LaserScan, callback) # Initiate a Node called 'obstacle_avoidance'
pub = rospy.Publisher('/cmd_vel', Twist)
move = Twist()  

rospy.spin()
```



# Initial pose estimate (using only rosrun)



- Open terminal and type:

```
$ roslaunch turtlebot3_gazebo  
turtlebot3_world.launch
```

- Open new terminal and type:

```
$ roslaunch turtlebot3_navigation  
turtlebot3_navigation.launch  
map_file:=$HOME/TB3_WORLD.yaml
```

**Ensure you still have the map that you have saved previously in the HOME directory**

- After RViz is launched, open new terminal and type:

```
$ rosrun autonomous initial_pose.py
```

- Observe in the RViz application that the TB3's pose estimate will be automatically executed



# Initial pose estimate



initial\_pose.py

```
#!/usr/bin/env python

import rospy
from geometry_msgs.msg import PoseWithCovarianceStamped
from tf.transformations import quaternion_from_euler

rospy.init_node('init_pos')
pub = rospy.Publisher('/initialpose', PoseWithCovarianceStamped, queue_size = 10)
rospy.sleep(3)
checkpoint = PoseWithCovarianceStamped()

# Use $ rostopic echo /odom -n1 to obtain poses (both position and orientation)

checkpoint.pose.pose.position.x = -1.99968900545
checkpoint.pose.pose.position.y = -0.499122759107
checkpoint.pose.pose.position.z = -0.0010073990697

[x,y,z,w]=quaternion_from_euler(0.0,0.0,0.0)
checkpoint.pose.pose.orientation.x = -6.03836998093e-06
checkpoint.pose.pose.orientation.y = 0.00158963960308
checkpoint.pose.pose.orientation.z = 0.00275331003065
checkpoint.pose.pose.orientation.w = 0.999994946134

print checkpoint
pub.publish(checkpoint)
```



# Initial pose estimate (using roslaunch No. 1)



## Using roslaunch to reduce steps:

- Open terminal and type:

```
$ rosrun turtlebot3_gazebo  
turtlebot3_world.launch
```

- **Copy and paste given launch files in your “autonomous” package (i.e. `initial_pose.launch`, `initial_pose2.launch`)**; you may create a launch folder to place all your launch files
- Open new terminal and type:  

```
$ rosrun autonomous initial_pose.launch  
map_file:=$HOME/TB3_WORLD.yaml
```
- Observe in the RViz application that the TB3’s pose estimate will be automatically executed



# Initial pose estimate



initial\_pose.launch

```
initial_pose.launch (~/Desktop/autonomous/launch) - gedit
Open ▾ Save
<launch>
  <!-- Arguments -->
  <arg name="model" default="$(env TURTLEBOT3_MODEL)" doc="model type [burger, waffle, waffle_pi]"/>
  <arg name="map_file" default="$(find turtlebot3_navigation)/maps/map.yaml"/>
  <arg name="open_rviz" default="true"/>
  <arg name="move_forward_only" default="false"/>

  <!-- Turtlebot3 -->
  <include file="$(find turtlebot3_bringup)/launch/turtlebot3_remote.launch">
    <arg name="model" value="$(arg model)" />
  </include>

  <!-- Map server -->
  <node pkg="map_server" name="map_server" type="map_server" args="$(arg map_file)"/>

  <!-- AMCL -->
  <include file="$(find turtlebot3_navigation)/launch/amcl.launch"/>

  <!-- move_base -->
  <include file="$(find turtlebot3_navigation)/launch/move_base.launch">
    <arg name="model" value="$(arg model)" />
    <arg name="move_forward_only" value="$(arg move_forward_only)"/>
  </include>

  <!-- rviz -->
  <group if="$(arg open_rviz)">
    <node pkg="rviz" type="rviz" name="rviz" required="true"
          args="-d $(find turtlebot3_navigation)/rviz/turtlebot3_navigation.rviz"/>
  </group>

  <!-- Initial Pose Node -->
  <node pkg="autonomous" name="init_pos" type="initial_pose.py" args="$(arg map_file)"/>
</launch>
```



# Initial pose estimate (using roslaunch No. 2)

## Subscribing /odom data for initial pose positions

- Open terminal and type:

```
$ roslaunch turtlebot3_gazebo  
turtlebot3_world.launch
```

- Open new terminal and type:

```
$ roslaunch autonomous initial_pose2.launch  
map_file:=$HOME/TB3_WORLD.yaml
```

- This launch file involves the following node:

initial\_pose2.py

- Observe in the RViz application that the TB3's pose estimate will be automatically executed



# Initial pose estimate



initial\_pose2.launch

```
initial_pose2.launch (~/Desktop/autonomous/launch) - gedit
Open ▾ Save
<launch>
  <!-- Arguments -->
  <arg name="model" default="$(env TURTLEBOT3_MODEL)" doc="model type [burger, waffle, waffle_pi]" />
  <arg name="map_file" default="$(find turtlebot3_navigation)/maps/map.yaml"/>
  <arg name="open_rviz" default="true"/>
  <arg name="move_forward_only" default="false"/>

  <!-- Turtlebot3 -->
  <include file="$(find turtlebot3_bringup)/launch/turtlebot3_remote.launch">
    <arg name="model" value="$(arg model)" />
  </include>

  <!-- Map server -->
  <node pkg="map_server" name="map_server" type="map_server" args="$(arg map_file)" />

  <!-- AMCL -->
  <include file="$(find turtlebot3_navigation)/launch/amcl.launch" />

  <!-- move_base -->
  <include file="$(find turtlebot3_navigation)/launch/move_base.launch">
    <arg name="model" value="$(arg model)" />
    <arg name="move_forward_only" value="$(arg move_forward_only)" />
  </include>

  <!-- rviz -->
  <group if="$(arg open_rviz)">
    <node pkg="rviz" type="rviz" name="rviz" required="true"
      args="-d $(find turtlebot3_navigation)/rviz/turtlebot3_navigation.rviz"/>
  </group>

  <!-- Initial Pose Node with Automatic Odom Data Collection -->
  <node pkg="autonomous" name="init_pos" type="initial_pose2.py" args="$(arg map_file)" />
</launch>
```



# Initial pose estimate



initial\_pose2.py

```
#!/usr/bin/env python

import rospy
from geometry_msgs.msg import PoseWithCovarianceStamped
from tf.transformations import quaternion_from_euler
from nav_msgs.msg import Odometry

def callback(msg):                                     #define a function called 'callback'
    parameter named 'msg'
    print msg.pose.pose

    global px, py, pz, ox, oy, oz, ow
    px = msg.pose.pose.position.x
    py = msg.pose.pose.position.y
    pz = msg.pose.pose.position.z

    ox = msg.pose.pose.orientation.x
    oy = msg.pose.pose.orientation.y
    oz = msg.pose.pose.orientation.z
    ow = msg.pose.pose.orientation.w

rospy.init_node('init_pos')
odom_sub = rospy.Subscriber("/odom", Odometry, callback)
pub = rospy.Publisher('/initialpose', PoseWithCovarianceStamped, queue_size = 10)

rospy.sleep(3)
checkpoint = PoseWithCovarianceStamped()

checkpoint.pose.pose.position.x = px
checkpoint.pose.pose.position.y = py
checkpoint.pose.pose.position.z = pz

[x,y,z,w]=quaternion_from_euler(0.0,0.0,0.0)
checkpoint.pose.pose.orientation.x = ox
checkpoint.pose.pose.orientation.y = oy
checkpoint.pose.pose.orientation.z = oz
checkpoint.pose.pose.orientation.w = ow

print checkpoint
pub.publish(checkpoint)
```



# Path planning



- Open terminal and type:

```
$ roslaunch turtlebot3_gazebo turtlebot3_world.launch
```

- Open new terminal and type:

```
$ roslaunch turtlebot3_navigation  
turtlebot3_navigation.launch  
map_file:=$HOME/TB3_WORLD.yaml
```

**Ensure you still have the map that you have saved previously in the HOME directory**

- After RViz is launched, initiate the pose estimate manually or via python file execution
- Open new terminal and type:  

```
$ rosrun autonomous path_planning.py
```
- Observe in the RViz application and/or Gazebo that the TB3 will first move to the 1<sup>st</sup> waypoint, later move to the 2<sup>nd</sup> waypoint, and back to the 1<sup>st</sup>; this behaviour will be looped until the file stops running (clt c)



# Path planning



path\_planning.py

```
#!/usr/bin/env python

import rospy
import os,sys
import actionlib

# move_base is the package that takes goals for navigation
# there are different implemenetations with a common interface
from move_base_msgs.msg import MoveBaseAction, MoveBaseGoal

# You need to know the coordinates that the map you are working
# in is. I estimated these numbers using the turtlebot3_world
# map from Turtlebot3. The center of the map is (0.0, 0.0, 0.0); each grid is 1m.

#The first waypoint array is x,y,z location.
#The second one is a "quaternion" defining an orientation.
# Quaternions are a different mathematical represenrtation
#for "euler angles", yaw, pitch and roll.

#path planning sequences (loop phase)
waypoints = [
    [ (-0.5, 0.0, 0.0),
      (0.0, 0.0, 0.0, 1.0)],
    [ (0.0, 2.0, 0.0),
      (0.0, 0.0, 0.0, 1.0)]
]

def goal_pose(pose):
    goal_pose = MoveBaseGoal()
    goal_pose.target_pose.header.frame_id = 'map'
    goal_pose.target_pose.pose.position.x = pose[0][0]
    goal_pose.target_pose.pose.position.y = pose[0][1]
    goal_pose.target_pose.pose.position.z = pose[0][2]
    goal_pose.target_pose.pose.orientation.x = pose[1][0]
    goal_pose.target_pose.pose.orientation.y = pose[1][1]
    goal_pose.target_pose.pose.orientation.z = pose[1][2]
    goal_pose.target_pose.pose.orientation.w = pose[1][3]
    return goal_pose

# Main program starts here
if __name__ == '__main__':
    rospy.init_node('Navigation_Node')
    client = actionlib.SimpleActionClient('move_base', MoveBaseAction)

    # wait for action server to be ready
    client.wait_for_server()

    # Loop until ^c; delete this line if you want the TB3 to stop at the last waypoint
    while not rospy.is_shutdown():

        # repeat the waypoints over and over again
        for pose in waypoints:
            goal = goal_pose(pose)
            print("Going for goal: ", goal)
            client.send_goal(goal)
            client.wait_for_result()
```



# GROUP PROJECT 3

## APPLICATION OF ROSRUN, ROSLAUNCH, PATH PLANNING, LIDAR WITHIN THE TB3 WORLD



# Project 3



For this project, you are **required to write 2 Python files and 1 launch file** with the following details; **use turtlebot3\_world map** for both:

a) autonomous\_exploring.py

- This file when executed will allow the TB3 to autonomously explore the map while avoiding collisions  
  
(i.e. similar to turtlebot3\_simulation.launch)
  - Come out with a simple algorithm first that will allow you to achieve this

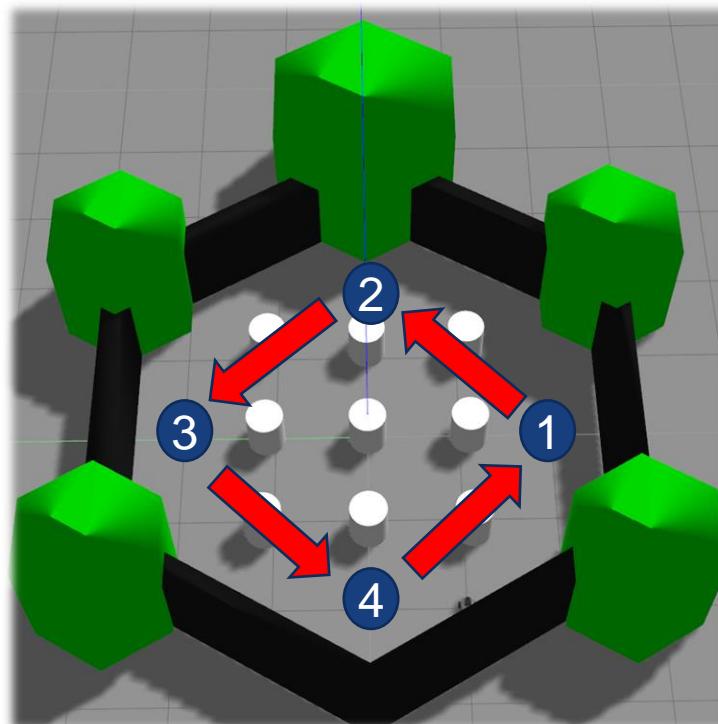


# Project 3



b) Project3.launch & P3\_path\_planning.py

The launch file when executed will open the RViz, then run the initial pose node (i.e. initial\_pose.py), which enables the TB3 to first initiate the pose estimate for you. And lastly, run the path planning node (i.e. P3\_path\_planning.py), which enables the TB3 to follow the desired path; the desired path is illustrated below in the map:



**FAQ:**  
**How do I obtain  
the coordinates  
of the respective  
locations???**



/odom → related to current pose of the TB3

As part of the setup, you can first manually adjust the TB3's positions/orientations that you desire and type the command below in a new terminal to obtain the position/orientation values at each location

```
$ rostopic echo /odom -n1
```

Topic Monitor				
Topic	Type	Bandwidth	Hz	Value
▶ /magnetic_field/ intra	rcl_interfaces/msg/IntraProcessMessage			not monitored
▼ ✓ /odom	nav_msgs/msg/Odometry	unknown	20.06	
child_frame_id	string			'base_footprint'
header	std_msgs/Header			
pose	geometry_msgs/PoseWithCovariance			
covariance	double[36]			array([ 0., 0.])
pose	geometry_msgs/Pose			
orientation	geometry_msgs/Quaternion			
w	double			0.9905796933241854
x	double			0.0
y	double			0.0
z	double			-0.136937471766361
position	geometry_msgs/Point			
x	double			0.6957032165876164
y	double			-0.09637047943958986
z	double			0.0



# Project 3



## **REMINDER:**

You have to launch your Gazebo first (to load TB3 in the TB3 World) first before you launch the launch file, Project3.launch

## **Example:**

1. Launch Gazebo (to load TB3 in the TB3 World) :

```
$ roslaunch turtlebot3_gazebo turtlebot3_world.launch
```

2. Execute launch file to execute required tasks:

```
$ roslaunch autonomous Project3.launch  
map_file:=$HOME/TB3_WORLD.yaml
```

Meaning you are only required to type 2 command lines on 2 separate terminals to perform the given tasks



# Group Project 3



**3 Items to Submit  
(can zip all in one file):**

- 1. autonomous\_exploring.py**
- 2. Project3.launch**
- 3. P3\_path\_planning.py**



**Please upload all your codes in  
Luminus with your names as  
part of the title:**

**(e.g. DANIEL\_KEN\_TAN\_Group\_Project\_3)**

**OR**

**(e.g. AXX\_AXA\_AXA\_Group\_Project\_3)**



# BONUS PROJECT

**OPTIONAL; IF YOU HAVE EXTRA TIME**



# Bonus Project

For this project, you are **required to modify the Python file** autonomous\_exploring.py which enables the TB3 to:

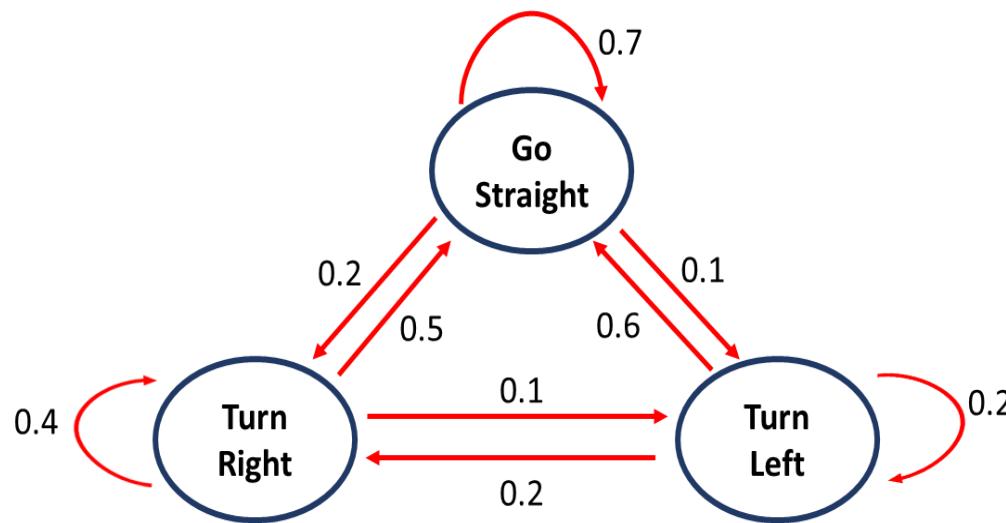
1. **Autonomously explore the space** based on a given Markov Chain algorithm (uncertainty representation)
2. **Avoid obstacles** using a given algorithm that is dependent on the laser data (knowledge representation)

The algorithms for Goal 1 and Goal 2 are depicted in the next few slides. Use TB3 world map for this project. You may use the given template: “bonus\_project\_template.py” as a reference



## Bonus Project: Markov Chain Algorithm to Decide on the TB3 Exploring Movements

The required Markov Chain for the TB3's exploring movements is summarized below:



**Details on various states:**

- 1. Go Straight**  
(`move.linear.x = 0.4`)
- 2. Turn Right**  
(`move.linear.x = 0.2 & move.angular.z = -1`)
- 3. Turn Left**  
(`move.linear.x = 0.2 & move.angular.z = 1`)



## Bonus Project: Algorithm to Avoid Obstacle based on Laser Data

**The algorithm for the TB3 to avoid obstacles is summarized below:**

- If the TB3 is all clear of obstacles (i.e.  $\geq 0.5m$  at the front of the TB3 in directions 0, 45 and 315 degrees with respect to the TB3), it will perform its Markov-Chain-based exploring movements as mentioned in the previous slides
- Else if an obstacle is detected ( $< 0.5m$ ) in direction 45 degrees with respect to the TB3, the TB3 will stop moving linearly and move 60 degrees to the right until it is cleared of obstacles
- Else if an obstacle is detected ( $< 0.5m$ ) in direction 315 degrees with respect to the TB3, the TB3 will stop moving linearly and move 60 degrees to the left until it is cleared of obstacles
- Considering all else situations whereby obstacles are detected, the TB3 will stop moving linearly and move 90 degrees to the left until it is cleared of obstacles



# Bonus Project: Ideal Output



The image shows a software interface with a terminal window on the left and a 3D simulation environment on the right.

**Terminal Window (Left):**

```
nicholas@nicholas-HO1987:~  
s3 [315]  
2.00518774986  
Transition matrix is ok!!  
Start state: Straight  
End state: Straight  
Moving based on given Markov Chain  
=====  
s1 [0]  
1.82547616959  
s2 [45]  
2.07127428055  
s3 [315]  
1.86832165718  
Transition matrix is ok!!  
Start state: Straight  
End state: Straight  
Moving based on given Markov Chain  
=====  
s1 [0]  
1.82421207428  
s2 [45]  
2.39157271385  
s3 [315]  
1.60532808304  
Transition matrix is ok!!  
Start state: Straight  
End state: Straight  
Moving based on given Markov Chain  
=====  
s1 [0]  
1.91480314732  
s2 [45]  
2.40156769753  
s3 [315]  
0.488394021988  
obstacle at 315 degrees (or left) in front  
=====  
s1 [0]  
1.89355182648  
s2 [45]  
0.667058765888  
s3 [315]  
0.466662126541  
obstacle at 315 degrees (or left) in front  
=====  
s1 [0]  
1.76512694359  
s2 [45]  
0.651874423027  
s3 [315]  
1.58599805832  
Transition matrix is ok!!  
Start state: Straight  
End state: Straight  
Moving based on given Markov Chain
```

**3D Simulation Environment (Right):**

The simulation shows a 3D grid-based environment with several green hexagonal obstacles. A black path or trajectory is plotted on the grid, starting from the bottom center and moving upwards and to the sides. There are also some white circular markers on the grid.



# End of Module 5



**THANK YOU  
for your kind  
attention!**