



eInfochips – An Arrow Company

Internship Documentation

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Table of Content

1. Introduction	3
2. Preface	4
3. State-Space Models?	5
4. Sensor Fusion and Algorithms	6 - 9
4.1. Kalman Filter	
4.1.1. Extended Kalman Filter	
4.1.2. Unscented Kalman Filter	
4.2. Particle Filter	
4.3. Bayesian Networks	
5. Why Extended Kalman Filter?	10
6. Implementing Kalman Filter	12
6.1. Python Implementation	
6.2. MATLAB Implementation	
7. ROS Packages for EKF	13 - 14
7.1. robot_localization	
7.2. robot_pose_ekf	
8. Simulating the turtlebot3	15 - 17
8.1. Launching	
8.2. Moving the turtlebot	
8.3. Checking for topics	
8.4. Incorporating EKF	
9. Introducing Noise	18 - 19
9.1. Odometry Noise	
9.2. IMU Noise	
10. Tuning EKF parameters	20 - 22
10.1. Covariance matrix	
10.2. Sensor Configuration matrix	
10.3. Sensor differential parameter	
10.4 Rejection Threshold	
11. Surface friction of Gazebo	23
12. Conclusion	24
13. Future Scope	25
14. References	26

Introduction

Observing an autonomous vehicle that stops at the sign of red lights shows the rapid response of the vehicle and such a response is generated by the fusion the output from multiple sensors. AV and mobile robots are the latest players in this ecosystem of sensor fusion aiming at basically combining sensors that assists in tracking both stationary and moving objects in order to simulate human intelligence. In the context of sensor fusion, predict equation is the one that predicts the state of the car, and update equation is the one that continuously updates that prediction. The predict equation uses the previous prediction of the state (the range of possible state values calculated from the last round of predict-update equations) along with the motion model to predict the current state. This prediction is then updated (via the update equation) by combining the sensory input with the measurement model. Based on the above explanation, It can be deduced that performing sensor fusion provides us with much more accurate results as opposed to using an individual sensor for simulation. Therefore, the topic of focus will be performing Sensor fusion using ROS based packages on turtlebot3. For the given task, we will be using IMU and odometry sensor and aim to introduce certain type of elements that would present us with a more realistic simulation environment including noise addition to the sensors in any form including weather and environmental noise to surface friction and more.

Preface

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State-Space Models

A state-space model is basically a mathematical equation. Observing an autonomous vehicle that stops at the sign of red lights shows the rapid response of the vehicle and such a response is generated by the fusion of the output from multiple sensors. AV and mobile robots are the latest players in this ecosystem of sensor fusion aiming at basically combining sensors that assist in tracking both stationary and moving objects in order to simulate human intelligence. In the context of sensor fusion, the predict equation is the one that predicts the state of the car, and the update equation is the one that continuously updates that prediction. The predict equation uses the previous prediction of the state (the range of possible state values calculated from the last round of predict-update equations) along with the motion model to predict the current state. This prediction is then updated (via the update equation) by combining the sensory input with the measurement model. Based on the above explanation, it can be deduced that performing sensor fusion provides us with much more accurate results as opposed to using an individual sensor for simulation. Therefore, the topic of focus will be performing sensor fusion using ROS-based packages on turtlebot3. For the given task, we will be using IMU and odometry sensor and aim to introduce certain type of elements that would present us with a more realistic simulation environment including noise addition to the sensors in any form including weather and environmental noise to surface friction and more.

a. GRCNN (Generative Residual CNN)

A lightweight, fully convolutional network which predicts the quality and pose of antipodal grasp at every pixel in an input depth image allowing for fast execution and single-loop control with its single-pass generative nature. The proposed goal is to train the GGCNN expert on the Cornell grasp dataset and further combine it with other experts to achieve diverse results. Here, I will step down points required to perform the training.

- Downloading and extracting the Cornell grasp dataset (<https://www.kaggle.com/oneoneliu/cornell-grasp>)
- Creating a virtual environment and installing the required python libraries mentioned in the .txt file
- `utils.dataset_processing.generate_cornell_depth` to generate depth images of the point cloud files
- Extracting the GGCNN weights pre-trained on the Cornell grasping dataset using the depth images
- `train_ggcnn.py` being the primary training for generative grasping
- Architecture of GGCNN -

b. Resnet50 (Residual Neural Network)

A lightweight, fully convolutional network which predicts the quality and pose of antipodal grasp at every pixel in an input depth image allowing for fast execution and single-loop control with its single-pass generative nature. The proposed goal is to train the GGCNN expert on the Cornell grasp dataset and further combine it with other experts to achieve diverse results. Here, I will step down points required to perform the training.

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IoU Results for Individual experts