1D09

COVARIANCE INFLATION METHOD IN ROS BASED MOBILE ROBOT NAVIGATION

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COVARIANCE INFLATION METHOD IN ROS BASED MOBILE ROBOT NAVIGATION

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ABSTRAK

Penyelidikan robot mudah alih telah meningkat dengan pesat, kerana kebolehan mereka dalam pergerakan, Dengan persekitaran yang sangat dinamik untuk aplikasi robot, terdapat peningkatan permintaan terhadap pergerakan robot mudah alih dan keupayaan gerakan robot. Pada zaman ini, bidang robotik telah menjadi bidang pengajian penting dimana ia menggunakan pengetahuan daripada pelbagai profesion, termasuk mekanik, elektronik dan kejuruteraan untuk membuat robot bergerak mengikut cara yang dikehendaki pengguna dengan penambahan tahap autonomi. Tesis ini membentangkan sesuatu tentang robot mudah alih ‘state covariance ‘ dalam keadaan berbeza di mana ia menggambarkan pentingnya silang hubungan. Tesis ini menggunakan ‘Extended Kalman Filter (EKF)’ sebagai teknik alternatif untuk mengatasi isu-isu dalam robot mudah alih terutamanya dalam menempatkan lokasinya sendiri. Robot mudah alih harus berjaya membuat peta dan mempunyai perancangan laluan mereka sendiri. Selain itu, ‘SLAM algorithm’juga digunakan bersama untuk menjana peta sambil menempatkan dirinya dalam satu persekitaran. Oleh itu, dengan mengambil kira kaedah yang digunakan ialah’ covariance inflation’ ,dimana ia lebih memfokuskan kepada penghiasan subset minggu kepada kovarians negeri terbukti mempunyai prestasi yang lebih baik di samping mengurangkan kos pengiraan. Kemudian, tesis ini juga mempertimbangkan perisian ROS untuk pengesanan dan kebolehan mengelak dari halangan. Dalam robot mudah alih, navigasi adalah masalah yang sukar. Robot mudah alih adalah wajib untuk mengenali kedudukan dan orientasi khususnya sama ada dalam persekitaran yang diketahui atau tidak biasa untuk bergerak dan melakukan aktivitinya. Hasilnya telah direkodkan dan dianalisis untuk cadangan masa hadapan dan menyokong kajian teori kami.

ABSTRACT

Mobile robot research has risen tremendously, because of their ability in movements, With the highly dynamic environment for robot applications, there has been an increasing demand on mobile robot movement and capabilities of robot motions. In any areas, robotics is an important field of study that applies knowledge from a variety of professions, including mechanics, electronics, and engineering in order to make the robot move in a way that the user desired with addition of a degree of an autonomy. This thesis presented the investigation of state covariance mobile robot with different condition where it illustrates the important of cross-correlation in the case of mobile robot localization. This thesis deals with the Extended Kalman Filter (EKF) as an alternative technique to overcome issues in mobile robot especially in term of localization. of robot, the mobile robot should manage to map and has their own path planning. Moreover, the algorithm of SLAM (Simultaneous Localization and Mapping) is also used together in order to generate map while locate itself in one environment. Therefore, by considering the method used is covariance inflation, it focuses more on decorrelating week subsets to the state covariance is proved to have better performance while reducing computational cost. Then, this thesis also considers the ROS software for the detection and avoidance of obstacles. In mobile robots, navigation is a difficult problem. A mobile robot is compulsory to recognize its specific position and orientation in either a known or unfamiliar environment in order to move and perform its activities. The result has been recorded and analyze for future recommendation and support our theoretical study.

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LIST OF ABBREVIATIONS

ROS	Robot Operating System
KF	Kalman Filter
SLAM	Simultaneous Localization and Mapping
EKF	Extended Kalman Filter
UnKF	Unscented Kalman Filter
PF	Particle Filter
CI	Covariance Inflation
OSRF	Open-Source Robot Foundation
LISP	Locator Identifier Separation Protocol (computer networking)
HAL	Hardware Abstraction Layer
HF	H infinity filter
FET	Finite Escape Time

CHAPTER 1

INTRODUCTION

1.1 Project Background

Mobile robot technology nowadays is going well with the adaptation of changes in human lifestyle. It is now becoming the focus of research technology in order to update with the latest robotics technology. It is a great remarkable for human. In the field of robotics, navigation can be a vital challenge because of their common intelligence. They also is a worldwide application which include transportation, industry, and hospitality, warehouse service. In order to operate and perform any tasks, in the first task mobile robot should be able to know its location whether it is in indoor or outdoor environment via variable condition. Path planning is one of the most crucial and important aspects of in autonomous mobile robot especially in navigation. For the past two decades, researchers have been working on a solution of path planning, in a way that they would find better solution while saving cost. Path planning consists of a collision-free path from one point to another while lessening the associated path's total cost. Path planning can be divided into static and dynamic environments based on the nature of the environment. If obstacles change their position in relation to time, this is referred to as static path planning; if obstacles change their position and orientation in relation to time, this is referred to as dynamic path planning. On the other hand, there are many utilizations of mobile robot include the navigation aspect. Countless studies on mobile robot navigation have been conducted by researchers, with the challenges typically focusing on path planning or localization, mapping. These combinations have been analysed through the SLAM approach. Navigation can be accomplished by the use of numerous strategies, including such estimate approaches or the incorporation of optimization techniques into the robot control algorithm. In this manner, we found out that, one of the most important aspects to address in navigation is localization where the mobile robot would lose its way and cannot perform the assigned duties without localization.

Figure 1: example of industry robot

1.2 Problem Statement

In robotics, there are main problem that need to be focus. The robot itself need to be able to know where would they be, meaning that the robot needs to estimate its current position, the robot also needs to know where would they go and how to go from point A to point B. To answer all of these questions, there are three fundamental things that they need to determine which are its localization. Then, its map where the robot needs to know where they should move. Thus, we can conclude that most crucial problem of mobile robot is its decision-making where it utilizes in building a robot that are successfully to navigate itself.

Significantly, to localize its position, the assistance of landmarks is really essential to move accurately. Hence, the EKF estimation and SLAM approach is utilized. However, there are limitation of using EKF-SLAM where it necessary to update the state covariance especially in a new landmark where it may cause map divergence and erroneous result. EKF based SLAM involves a lot of mathematical process. The mathematical process due to the enlarge of multiplication of the covariance matrix due to the others parameter. As many landmarks being observed, the risk of linearization error can increase hence the map can be divergence. Thus, it resulted to high computational cost.

1.3 Objective

The major objective of this thesis is to analyse the most effective method mobile robot performance with variety of condition. Concerning of the aim, there are goals need to be achieved which are:

I. To simulate state covariance behaviour with different condition.

II. To develop performance of mobile robot in various condition-based ROS

1.4 Scope of Project

This research will be carried out by analysing the method to save computational cost. To overcome this problem, we are utilizing decorrelation approach, which can be denominated as covariance inflation method has been used. Cross-correlation is used to eradicate the weak subset. Cross-correlation is the relationship between robot and observed landmark. The purpose of cross-correlation to improve the estimation for good performance of mobile robot. Therefore, there are two conditions are tested on this method which are observing mobile robot-based landmark and without landmark. If the mobile robot able to move with the assist of landmark, the pattern of state covariance behaviour will be observed via MATLAB software.

While for localization, the mobile robot performance with condition is carried out more on the ROS ubuntu operating system. In ROS, the mobile robot is simulated using Gazebo and the map generation is simulated in RViz with obstacle using outdoor environment.

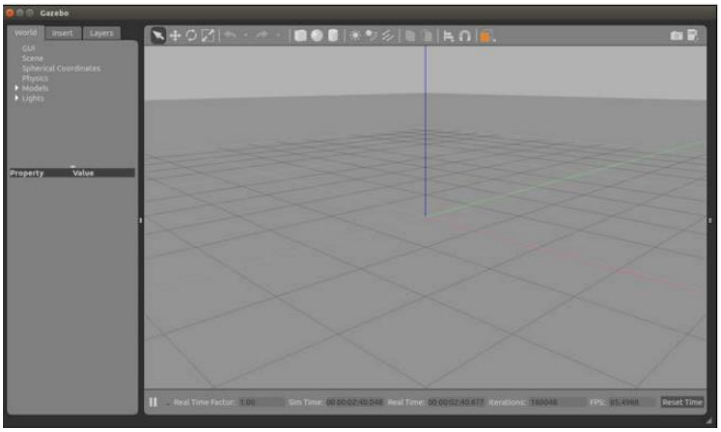

Figure 2:Gazebo main screen

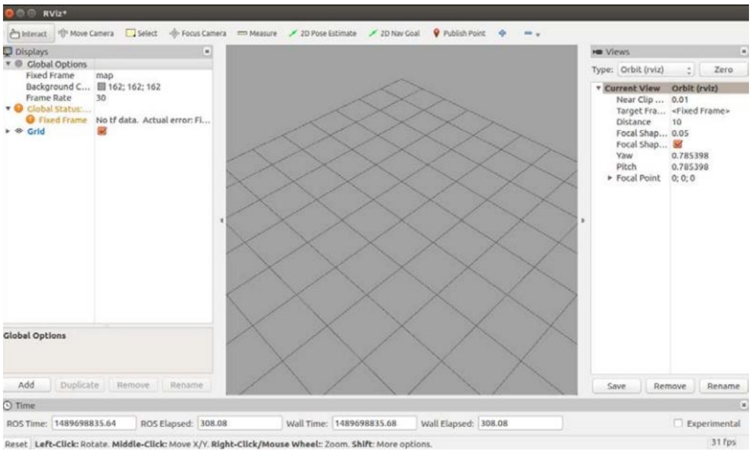

Figure 3:RViz main screen

1.5 Thesis Outline

This thesis is divided into five sections: Introduction, Literature Review, Methodology, Results and Discussion, and Conclusion. The first chapter introduces the research. This chapter discussed the Project Background, Problem Statement, Project Objective, and Project Scope. The second chapter provides a review of the thesis topic's literature. This chapter reviewed the subject of interest by comparing the results to what other researchers had to say in their published papers. The result of this analyzation will be utilised as a basis for our study later on. The methodology for this thesis is discussed in Chapter 3. The elements and tools utilised will be described in detail in this chapter, along with the analysis of state covariance and analysis of performance of mobile robot . All the findings, and outcome was covered in Chapter 4. Chapter 5 is about the project conclusion. The system's weaknesses will be examined in this chapter along with the enhancements will then be suggested for future study on this field

CHAPTER 2

LITERATUREREVIEW

2.1 Introduction

In this chapter, we will be narrow down into ROS in mobile robot navigation performance, obstacle avoidance, its approach algorithm which are Kalman filter using technique covariance inflation. All of these are needed in order to determine the performance of mobile robot.

2.2 Background of ROS and Gazebo

Formerly, ROS(Robot Operating System) is developed in 2007 at the Artificial Intelligence Laboratory, developed in 2007 at the Stanford Artificial Intelligence Laboratory, it has been governed by OSRF since 2013(Fankhauser, 2017). There are five philosophy of ROS which are peer to peer, multi-lingual, tool-based, thin and free, open source. Peer to peer describes that a ROS-based system is made up of a number of processes that operate on many hosts and are linked in a peer-to-peer topology during runtime. Despite frameworks based on a single server, (Montemerlo, 2003)the benefit it is multi-process and multi-host architecture, a central data server is complex when computers are linked in a heterogeneous network. ROS can only work on several different languages which are C++, Python, Octave, and LISP. It is tool based as its rather of developing a monolithic development and runtime environment, a large number of sized tools are employed to build and operate the many ROS components which can perform many tasks. It is thin because it depends on standalone libraries besides free and open-source system.

ROS is something between middleware and a framework built for robot application. ROS consists of hardware abstraction layer(HAL) where it communicates using programming and access to hardware as in Figure 2, stated in (Hax, Duarte Filho, Botelho, & Mendizabal, 2013). ROS provide standard robotics application with a separation of code and communication tools. In view ROS, to design a mobile robot with low cost, but high efficiency as in their research (Yong Li, 2018).

Figure 4: ROS description

ROS has Gazebo which acts as 3D simulator robot. The Gazebo can be defined as one of the interfaces of robot toolbox. Using Gazebo, we can design the robot and develop various condition for robot in order to test its performance. For the environment, the robot itself can be setup to be simulated in indoor or outdoor. Gazebo helps us to identify and give the overview for the robot estimation trajectory. Each robot has variety of elements which can be described in the URDF (Universal Robotic Description), which also as an XML file where we can convert and simulated in Gazebo. We can construct a virtual "world" with Gazebo and put simulated versions of our robots into it. Simulated sensors are used to detect the surroundings and post data to the same ROS topics as actual sensors, as it will be easier in testing the algorithms

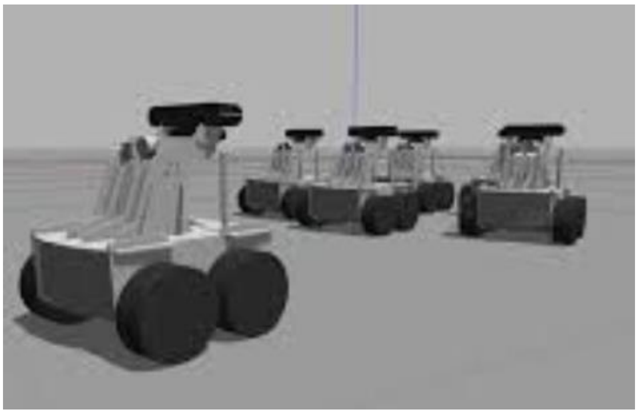

Figure 5: Robot simulator 3D in Gazebo

2.3 Simultaneous localization and mapping (SLAM)

SLAM which also known as simultaneous localization and mapping is to predict or estimate the angle or pose of the robot to map the path of robot. Localization is referred to the location of the robot itself which it can give a map. Then, mapping is referred to the map from the given location of robot. Hence, this why it named, SLAM because it works together between map and location robot simultaneously. To be specific, algorithm SLAM is needed to work simultaneously within creating a map of the environment while also locating itself inside it as stated in the research Simultaneous Localization and Mapping Part I(H. Durrant-Whyte, and Tim Bailey, 2006).

Incorporated into robotics as well as artificial intelligence (AI), a number of experts, including Peter Cheeseman, Jim Crowley, and Hugh Durrant-Whyte, had been investigating the application of estimation-theoretic approaches to mapping and localization issues. Then, the idea from Smith and Cheesman, Durrant-Whyte which was reported about the relationships of landmark correlations and controlling geometric uncertainty.(Randall C. Smith, 1987) (H. F. Durrant-Whyte, 1988). Regardless of the new method, SLAM researchers had minimal progress in tackling the problem. Due to the difficulties of successfully performing both at the same time, most researchers focused their research to either localization or mapping. The SLAM method offers quantitative information on the distance of landmark correlations. They then discovered the convergent nature of the SLAM problem and discovered that the correlations they had previously tried to eliminate were an integral element of the SLAM problem solution. (Naminski, 2013)

SLAM is one of the important algorithms to obtain accurate position estimate when it combines between odometry data and the laser scan data as in the research **(**Zhi, 2018**).** Also, it has been proved in the research (Zhaojun Meng, 2015) that this algorithm has succeed to be applied in navigation and improve in increasing its accuracy of mapping robot position.

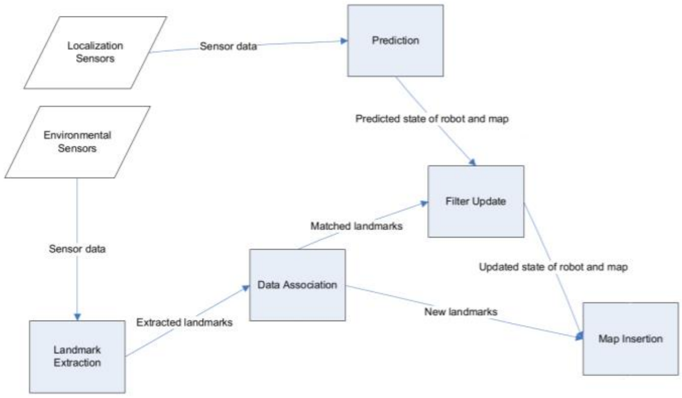

Figure 6: Flow process of SLAM in mobile robot

2.4 Kalman Filter

Rudolf E. Kalman had implemented Kalman Filter (Kalman, 1960)as an approach of estimation in hidden state variable by observing the variable where it might have error in measurement. To be specific, the KF works on state dynamic linear system. The Kalman Filter has the modest storage requirements with wide range of applications, compared to the other estimate algorithms. However, influenced from the environment, inaccuracies from measuring equipment, and erroneous parameter selection are common causes of system errors in real-world applications.(Mandi Wang, 2017).

Kalman filter is an efficient algorithm for estimating the state of system from noisy measurement. Kalman filter is commonly known in a simple form and only used on small computational power. It is used to estimate states based on the linear dynamical system which in its format as in the research of **(**Nikoukhah**,** 2017**).** Kalman Filter is proved to have an easy and simple calculation to be applied in any application of mobile robot which stated in the research of (Ahmad, 2014). This Kalman filter is clarified can be utilized in application of mobile robot navigation and control in vehicles. For Kalman Filter, it has four types, which are Kalman filter, extended (EKF), Unscented Kalman filter (UKF) and Particle Filter (PF). Kalman filter is used for linear system model, the distribution is gaussian and the computational cost is low. For EKF is used for non-linear system, the distribution is gaussian and the computational cost is low. However, there are article stated that EKF is locally linear where it denominated that EKF is partially linear. (Claudio Urrea, 2021). While for UKF it is nonlinear system, and the distribution is gaussian while the computational cost is medium. Lastly, the PF it is nonlinear, non-gaussian and medium computational cost.(Maqsood, 2019)

2.5 Obstacle Avoidance in mobile robot

To evaluate the successful accurate navigation, one of the essential tools is obstacle avoidance. Therefore, it has been tested in the research of (Wu, Hong, & Pan, 2015) by using EKF. It clarifies that EKF perform better in filtering the noise especially in moving robot. This indicates that the mobile robot is successfully navigate itself. In this research, the data is tabulated by listing its collision warnings when the robot is near the obstacle, less than 15cm.

TABLE II
COLLISION WARNINGS ($\leq$ 15CM)

Method	Left	Right	Front
none	12	0	2
KF	42	0	40
EKF	11	0	3

Figure 7: number of collisions warning,(Wu et al., 2015)

While in ROS, the research of(Murat Köseoğlu 2017). The research has been proven to be successful when the mobile robot based on ROS follows all the given direction that will be use in navigation planning where the path plan also includes obstacle. The 2D map were created by the robot where it helps to show the path of the mobile robot itself in order to avoid in any obstacle as in figure 7. In other view, from the(Muhammad Lutfi bin Hamdan, 2018) based on ROS there are packages that has been called navigation stack where it comprises of algorithm for the sensors of the robot in order to perform the navigation process. Hence, it enables the user to control the navigation of mobile robot.

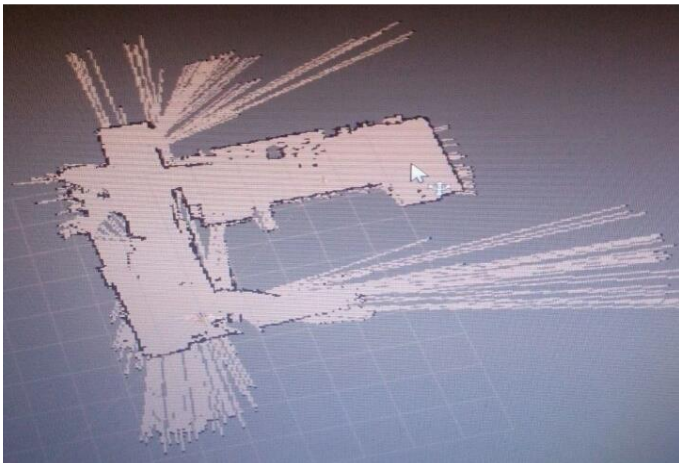

Figure 8: 2D map of mobile robot(Muhammad Lutfi bin Hamdan, 2018)

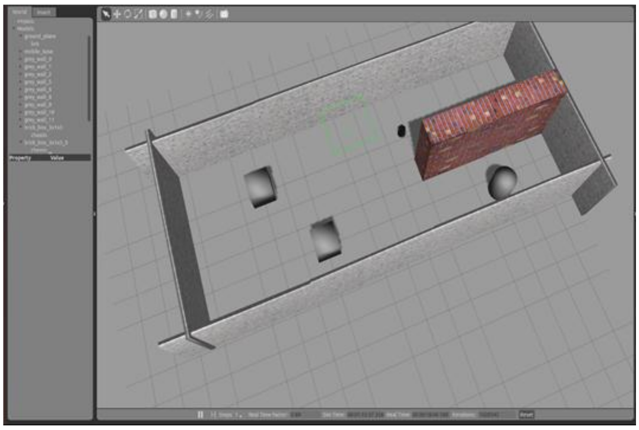

Figure 9: Turtle Bot in Gazebo simulator(Muhammad Lutfi bin Hamdan, 2018)

2.6 Localization mobile robot using Kalman Filter

In various condition, the main problem occurs in robot is usually when they do not know where is the next relative environment. (Negenborn, 2003). A smart algorithm can minimise uncertainty while maintaining essential information. The Kalman filter (KF) is a set of mathematical technique for estimation in a variety of processes. In practise, this sort of filter works quite well. In the research of Mobile Robot Position Estimation Using the Kalman Filter, they observed the position of robot in terms of x, y coordinates and its orientation. These three parameters are together combined to perform a variable vector. They used a camera in order to extract the information the distance of robot travelling in order to compute its position. Hence, using Kalman Filter can be a smarter method to provide estimate path for the robot. The works are simulated in the MATLAB and displays the estimated path and its actual path of the robot. The result show that estimated path by using KF is closer to their real path.

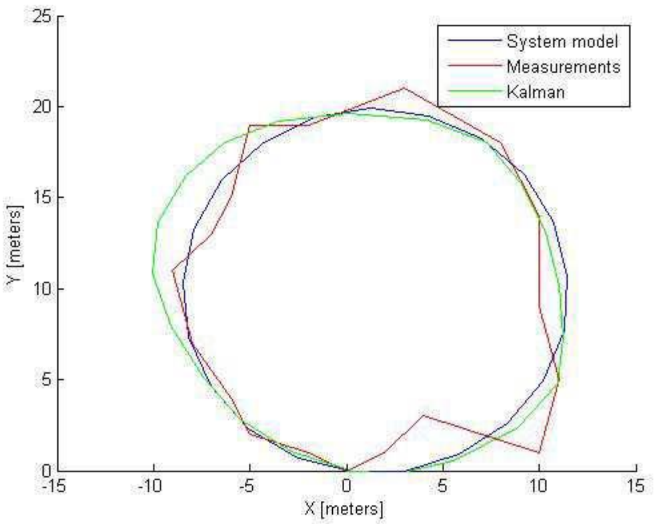

Figure 10:Trajectory estimation with the KF.(Suliman, Cruceru, & Moldoveanu, 2010)

2.7 Cross-correlation and state covariance in mobile robot

In most application, Kalman filter are suitable algorithm in mobile robot as its estimation can be converge into a specific value based on the observation that have been made by the robot as stated in research(Ahmad, 2014). However, as a result of updating process of state covariance mobile robot, there are issues arise, which is its computational cost increased. Therefore, researchers have come up with the solution which is covariance inflation using decorrelation techniques.(Guivant & Nebot, 2003). The correlation between mobile robot and landmark proves that we can obtain better performance.(Castellanos, Tardos, & Schmidt, 1997),(Hébert, Betgé-Brezetz, & Chatila, 1995) In research, (Ahmad, Othman, & Systems, 2015), they claimed that mobile robot and landmark depends to each other in order to obtain better estimation and it results to bigger uncertainties when the robot independently to the landmark.

2.8 Analysis of state covariance mobile robot

In navigation, the limitation such as the mathematical complexity, high computational cost and erroneous is one of the challenges in SLAM. Hence, Kalman Filter approach is one of the solutions, where the Kalman Filter has its update and predict stage for state covariance. To guarantee a good estimation, the state covariance must be converged as in the research of (Huang & Dissanayake, 2007). EKF is one of the good choices especially in solving SLAM limitations. Hence, the state covariance in EKF need to be observe. The state covariance is associated to estimate errors, supporting the fact that either the estimation is accurate or not. In this research, it states that the higher initial state can be resulted to the higher erroneous in estimation. Then, they proposed the lower initial state of covariance, for better estimation(Ahmad, Xian, Othman, Ramli, & Saari, 2020).

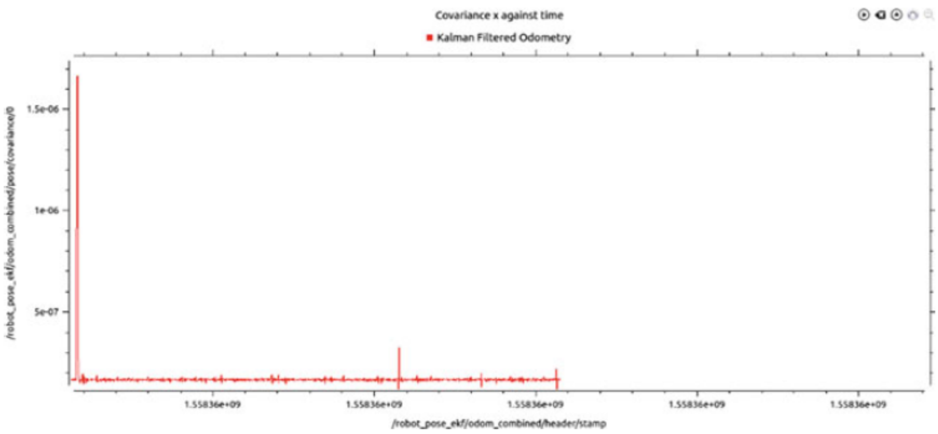

Figure 11: covariance against x-position(Ahmad et al., 2020)

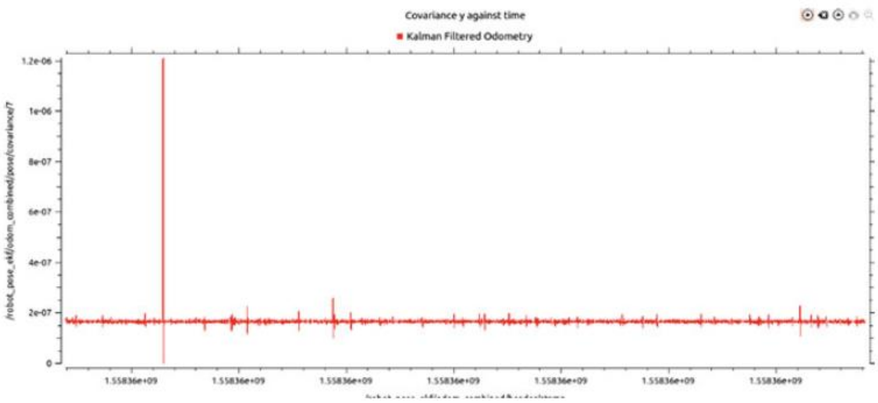

Figure 12:Covariance against y-position(Ahmad et al., 2020)

2.9 Summary

There are several findings can be concluded from this literature review. In conjunction with this, from the articles we obtain that the performance of mobile robot can be determined by investigate and analyse its position and orientation where it known as localization, to improve the error position mobile robot, to track or trajectory of mobile robot because the researcher highlighted that the accuracy in localization mobile robot is referred as an indicator of successful in mobile robot. In navigation, one of the essential tools to be analyse is when the robot overcome its collision avoidance when there are obstacles. In view of fact that all of this is aim to accomplish the autonomous, dependable and sturdy navigation. SLAM has been presented and resolved as a theoretical issue in a variety of ways where the mobile robot can create a map of its surroundings and use that map to determine its location. In SLAM, there are some limitations that needed Kalman filter to be utilize in our thesis. Kalman Filter play role in linked together the measurements and predictions to determine the best state. The Kalman filter is widely recognized as a better optimum estimation for a system with includes uncertainties. Hence, using the SLAM approach with the Kalman Filter method we can briefly analyse the performance of mobile robot. Other than that, to ensure better estimation of mobile robot the state covariance behaviour of mobile robot should be observed. The state covariance through decorrelation approach or can be defined as covariance inflation been used. By using this approach, the weak states and subsets of the state will be eliminated for solving the limitation in this thesis. Hence, the proposing method can be applied to guarantee the performance of mobile robot especially in navigation

CHAPTER 3

METHODOLOGY

3.1 Introduction

In this chapter, we discussed on the procedure to attain all the objectives of this project. Evidently, we will briefly review about the methodology of analysing the state covariance behaviour. There are two covariances that will be measured between variables. The matrix is form from the covariance matrices of mobile robot and landmark, and mainly correlation between robot and landmark which can be denominated as covariance matrix, P.

$$P = \begin{bmatrix} P_{RR} & P_{RM} \\ {P_{RM}}^T & P_{MM} \end{bmatrix}$$

Figure 13: covariance matrix form

From the above figure, P_{RR}, refer to covariance matrix. P_{MM} refer to the covariance matrix of the landmark itself. While, in other words P_{RM} it can be referred as cross-covariance matrix between the robot and landmark. In the case of landmark, the dimension of state covariance matrix is $(3 + 2m) \times (3 + 2m)$, where m is landmark. In this thesis, we set up the landmark to be stationary. Commonly the erroneous will always associated between robot and reference point. The status or state error covariance is one of the indicators for the efficiency and consistency of estimation because the error is being observed with comparison of covariance value. In condition of the actual value is larger than the covariance value, it indicates that the estimation is leading to inaccuracy. Hence, by utilizing the EKF-based SLAM we can estimated the position of robot and relative point towards the landmark in order to ensure the better estimation by observing the decrement or increment of uncertainties. Therefore, this thesis aims to analyse the state covariance behaviour by testing it on two conditions with existence of landmark and absence of landmark because it is non-trivial issues in mobile robot localization. Below figure illustrate the flowchart of simulation on analysing the pattern of state covariance behaviour and its convergence.

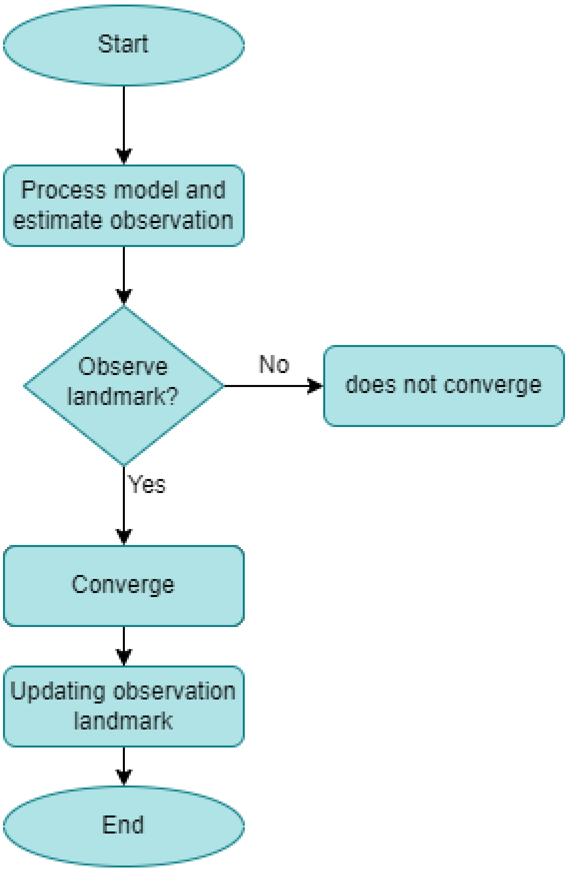

Figure 14: research progress simulation

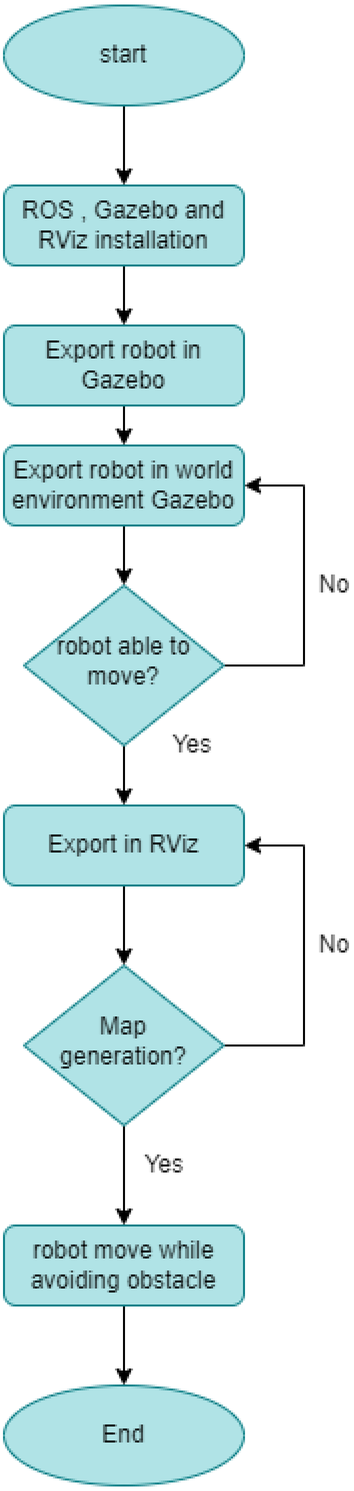

Figure 15:ROS flowchart

Above is the flowchart of ROS simulation which involves two tools, Gazebo simulation and RViz visualization. After analysing the method and overcoming computational cost issues, the robot then is being simulated in Gazebo to test its performance in term of localization. By exporting robot type which are Turltebot3 Burger in Gazebo to observe the ability of robot to move and avoid the obstacles. While in RViz, the map will be generated and robot will explore its position and localize itself.

3.2 An Implementation of Kalman Filter

The Kalman Filter is an optimum estimator, which means that it derives from indirect, imprecise, and uncertain observations. KF is recursive, which means that newer measurements can be evaluated as they come in. Kalman Filter were used in this project. This is the step for predict and update stage.

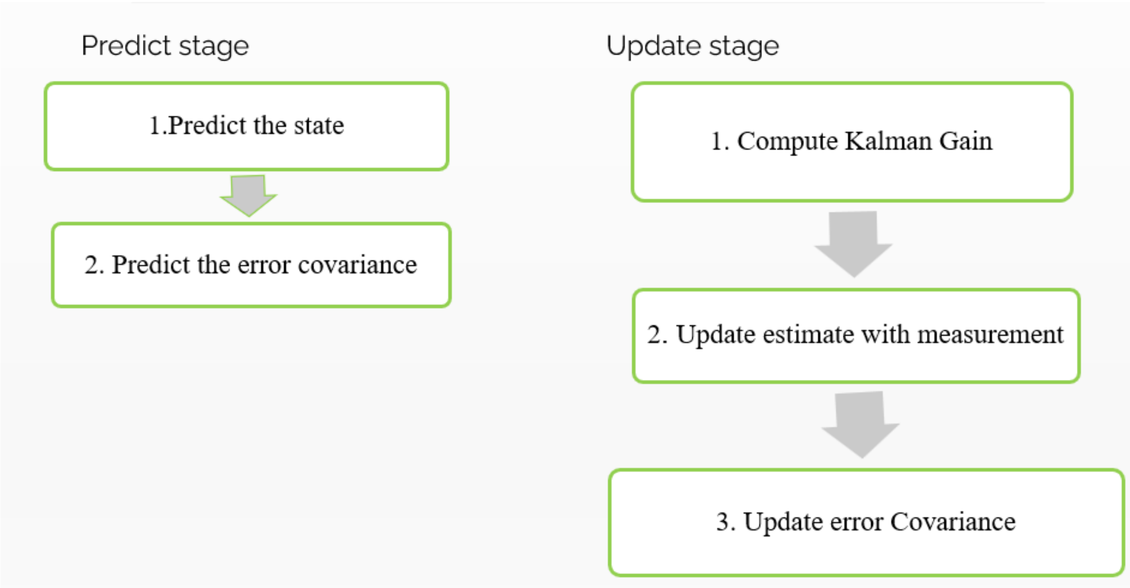

Figure 16: Process Kalman Filter

The gain will decide how much weight to put in new measurement. The Kalman gain come from the error in estimate and error in data measurement. Then goes to current estimate, this is the update estimate. The current estimate comes from the previous estimate and the measured value. The measured value can be considered come from the data input. Then, these two stages are repeated iteratively until the actual measurement is obtained. As were discussed in literature review, the Kalman Filter is proved that it is linear system. Literally, it refers a progression begins with time k-1.

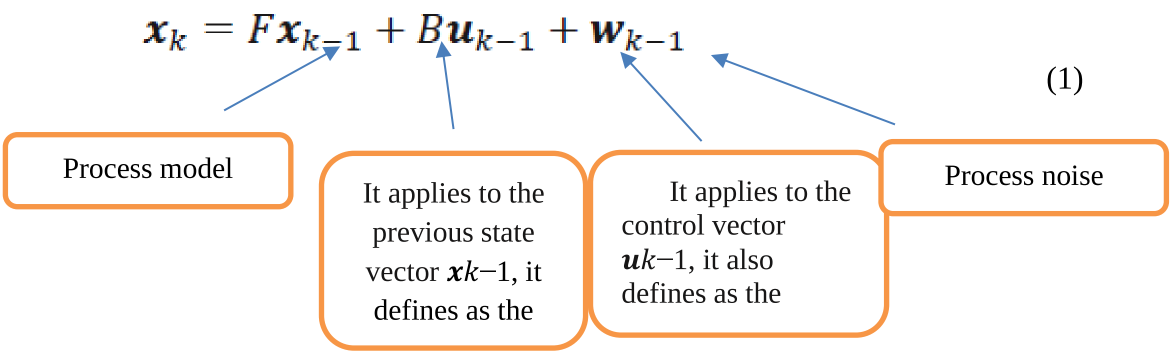

Figure 17: Description variable process model

X is an input value. By then, the filter will predict the input value. To be more specific, it is a state variable where it observed, controlled and determine its location or path of the object, in our cases it will be the mobile robot information of its velocity, position and acceleration. And it matches with the measurement model

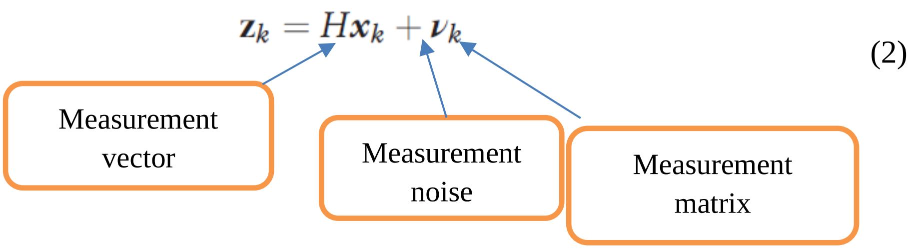

Figure 18: Description measurement

The process model is partner up with the measurement equation in order to defines the relation between the state and measurement at time k. Z is a vector of measurement. The noise is added to come up with the updated measurement. The aim of Kalman filter is to predict the approximate of xk at time. In some cases, the variable of Q and R is modulating value in order to ease the user obtain the desired performance.

Kalman filter algorithm consists of two stages which are prediction and update stage. Its stages have their own equation.

Prediction:

State estimate	$\hat{x}_k^- = F\hat{x}_{k-1}^+ + Bu_{k-1}$
Error covariance	$P_k^- = FP_{k-1}^+F^T + Q$

Table 1: Prediction equation

Update:

State estimate	$\hat{x}_k^+ = \hat{x}_k^- + K_k\tilde{y}$
Error covariance	$P_k^+ = (I - K_kH)P_k^-$
Measurement residual	$\tilde{y}_k = z_k - H\hat{x}_k^-$
Kalman gain	$K_k = P_k^-H^T(R + HP_k^-H^T)^{-1}$

Table 2: Update equation

The hat operator define that it is estimate of a variable. The – sign means that it is predict stage where + sign is update stage.

Prediction stage:

$$P_k^- = FP_{k-1}^+F^T + Q \tag{3}$$

Predicted state come from the previous update state estimate. The error covariance increases during the prediction stage as a result of the summation with Q, indicating that the filter is increasing. The state estimate is unpredictability after the stage of prediction. In estimation process, it could have some errors, noise or uncertainties. So, we have to add to the state covariance due to the predicted value of our parameters such as position, velocity may be different from the actual. In case there are other parameters interfere, there may be some noises in input. The noises can be wind or any obstacle. Q is process covariance matrix where we need to keep the state covariance matrix from becoming too small or zero because Kalman gain, $K_k = P_k^-H^T(R + HP_k^-H^T)^{-1}$ only works when we have reasonable expectation of the error in estimation. Covariance is a range of prediction. The accuracy will be increased if the value of covariance is decreased and instead. Generally, uncertainties a lot occurs in predict stage.

Update stage

When the value of updated error covariance is smaller compared to the predicted error covariance. This indicates that KF is more definite with the state estimate thereafter the measurement. A user of KF is suggested to used large value of error covariance matrix in order to obtain faster convergence. Hence, Kalman filter is implemented between the predict and update stage. The update stage is aim to provide the range of prediction estimate smaller until its closer to the true value.

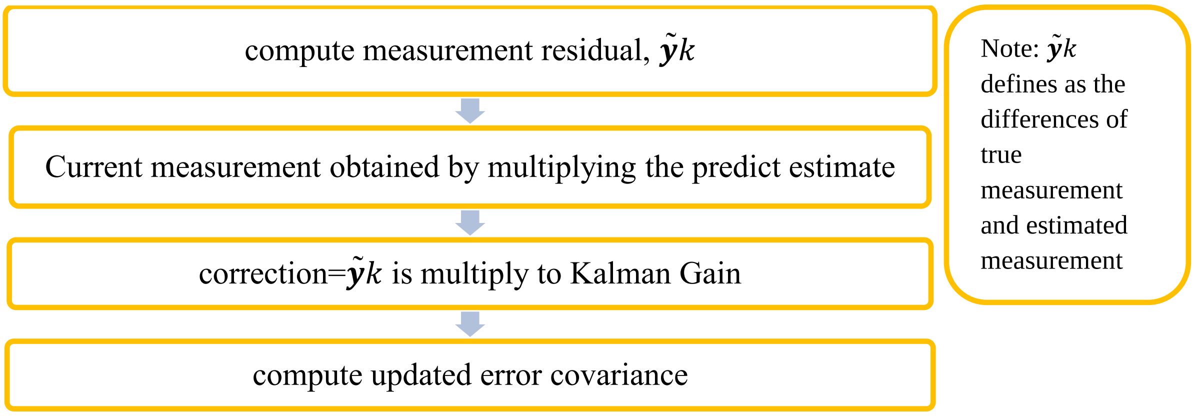

Figure 19: Process of update stage KF

Firstly, the measurement residual $\tilde{y}k$, also defines as innovation are calculated. By multiplying the predicted state, we can obtain current measurement. The measurement residual $\tilde{y}k$ is multiplied by the Kalman Gain K_k where then we will obtain the updated value to the predicted estimate $\hat{x}_k^-$. Lastly, the updated error covariance P_k^+ is calculated where then will be used for the next iteration.

ADVANTAGES OF KALMAN FILTER

As predicted, may greatly lower the steady-state error level related with random plant and measurement noise. This reduction in error appears to be somewhat robust to errors in the model used to create the Kalman filter, including both model dynamics parameters and assumptions regarding noise statistics.(Benjamas Panomruttanarug, 2008). In addition, KF offers a well-designed and efficient explanation for linear systems. The Kalman filter is a best technique to integrate measurement results into an estimate because it recognises that readings are noisy and sometimes should be discarded or have only a minimal impact on the state estimate. It helps to balance out the effects of noise in the estimated state variable by integrating more information from relevant data.(Suliman, Cruceru, & Moldoveanu, 2010). Besides, it is the best least square method in mobile robot which means that by using the KF technique it can find the best fit in a set data which it helps to narrow down to the true value.

3.3 Mathematical Formulation

The state of mobile robot is assumed as x_k . Mobile robot position includes as x, y position and heading angle with respect to a landmark. Mathematical process involves in mobile robot is kinematic model which are: $x_{k+1} = f(x_k, u_k, \omega)$. u_k can be denominated as control input which can be defined as mobile robot velocity and angular acceleration. ω can be defined as noise or uncertainties. In order to overcome with the problem of EKF-SLAM mobile robot needs to gather the information regarding the surrounding by using sensors. The measurement model can be described as $z_{k+1} = h(x_k, \upsilon)$ where zk is measurement matrix which comprises of distances and angle between mobile robot and landmarks.

3.3.1 Decorrelation algorithm

In EKF algorithm covariance matrix can be defined as the uncertainties occurs during the observation. In covariance matrix there are also cross-correlation where it is denominated as relationship between mobile robot and landmark during computation. It involves positive definite matrix $P > 0, P \in \ R^{2\times2}$.

$$\begin{aligned} P &= \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & P_{22} \end{bmatrix} \\ &= \begin{bmatrix} p_{11} + k|p_{12}| & 0 \\ 0 & p_{22} + \frac{|p_{12}|}{k} \end{bmatrix} - \begin{bmatrix} k|p_{12} & -p_{12} \\ -p_{21} & \frac{|p_{12}|}{k} \end{bmatrix} \\ &= D - \tau \leq \begin{bmatrix} p_{11} + k|p_{12}| & 0 \\ 0 & p_{22} + \frac{|p_{12}|}{k} \end{bmatrix} = D \end{aligned} \quad (4)$$

Should be k>0 and τ can be defined as positive definite matrix.

$$\tau = \begin{bmatrix} k \cdot |p_{12} & -p_{12} \\ -p_{21} & \frac{|p_{12}|}{k} \end{bmatrix} \quad (5)$$

The equation of decorrelation will be

$$
\begin{aligned}
\begin{bmatrix} A & C \\ C^T & B \end{bmatrix} &= \begin{bmatrix} A & 0 \\ 0 & B \end{bmatrix} - \begin{bmatrix} \tilde{A} & -C \\ -C^T & \tilde{B} \end{bmatrix} + \begin{bmatrix} \tilde{A} & 0 \\ 0 & \tilde{B} \end{bmatrix} \\
&= \begin{bmatrix} A+\tilde{A} & 0 \\ 0 & B+\tilde{B} \end{bmatrix} - \begin{bmatrix} \tilde{A} & -C \\ -C^T & \tilde{B} \end{bmatrix} \\
&\leq \begin{bmatrix} A+\tilde{A} & 0 \\ 0 & B+\tilde{B} \end{bmatrix} \frac{\tilde{A}\tilde{B}}{\begin{bmatrix} \tilde{A} & -C \\ -C^T & \tilde{B} \end{bmatrix}}
\end{aligned}
\tag{6}
$$

Then it will be

$$
P = \begin{bmatrix} A & C & D \\ C^T & B & E \\ D^T & E^T & M \end{bmatrix} \leq \begin{bmatrix} A+\tilde{A} & 0 & D \\ 0 & B+\tilde{B} & E \\ D^T & E^T & M \end{bmatrix}
\tag{7}
$$

If A and B will be compute according to this cases

$$
\begin{aligned}
\frac{\tilde{A}}{\tilde{A_{i,j}}} &= \begin{cases} \Sigma_{k=1}^{m} k_{i,k} \cdot |C_{i,k}| & , \quad i=j \\ 0 & , \quad i \neq j \end{cases} \\
\frac{\tilde{B}}{\tilde{B_{i,j}}} &= \begin{cases} \Sigma_{k=1}^{m} \frac{|C_{i,k}|}{k_{i,k}} & , \quad i=j \\ 0 & , \quad i \neq j \end{cases} \\
& k_{i,k} > 0 \forall i,k
\end{aligned}
\tag{8}
$$

Then, with all equation the covariance matrix will be decorrelated.

3.3.2 Kalman Filter and State covariance

There two stages of KF which are update and predict stages. Prediction stages is obtained from the kinematic model process which refer to the position of mobile robot based from its movement. While the update stages are one of the improvements in the process model from the prediction stage via Kalman gain. The technique of inversion matrix is utilized by analysing the behaviour of estimation where it inverses the state covariance. The calculation is proven to be faster when it has only value in diagonal elements. In the scenario of cross-diagonal element, the calculation will be faster to compute to real time.

3.4 Analysis state covariance with two conditions

In this thesis, we analysis the relationship between mobile robot and landmark. By then, we estimate the position of mobile robot and landmark using EKF because localization is a nonlinear process, EKF is used to give estimation regarding its position of robot and the landmark. By using EKF algorithm, it provides update state vector, and state covariance matrix where we can define it as estimation error. In localization, dimension of the state covariance matrix can be described as (3+2m) x (3+2m). This size will enlarge as much as the robot move based on the new landmark. By observing the state covariance matrix, we aim to evaluate the status of uncertainties in estimation because, state covariance matrix implies the error in state estimation between robot and landmark.

In MATLAB, simulation of command coding is being modified from the predicted and update covariance in order to see the state covariance behaviour and the pattern of its convergence. The behaviour of state covariance is being observe in condition where the mobile robot has landmark and without landmark. The parameter that was used in simulation is:

PARAMETER	VALUE
Sampling time	100s
Process noise covariance	0.02
Measurement noise covariance	0.06

Table 3:Parameter simulation

In command, we are using predict and update state in order to implement EKF estimation together. The corrected value of states together with the state estimation error covariance can be returned at every time step k. Below figure, can be defined as the function of discrete-approximation. The functions in the system imply an additive process and measurement noise. While, [1;0] can be referred as the starting state values for the two states.

```
obj = extendedKalmanFilter(@vdpStateFcn,@vdpMeasurementFcn,[1;0]);
load vdp_data.mat y
```

Figure 20: command code for EKF

```
obj.ProcessNoise = 0.02;
obj.MeasurementNoise = 0.16;
```

Figure 21:Process noise and measurement noise

In above figure, we can declare the process noise and measurement noise as our parameter. To imitate real-time data measurements, we need to take one time step at a time. Then we need to construct the predict and actual measurement so that the EKF filter can be converge. In addition, figure below is the command of predict and update state covariance over the predict and update values.

```
[CorrectedState,CorrectedStateCovariance] = correct(obj,y(k));
[PredictedState,PredictedStateCovariance] = predict(obj);
```

Figure 22:Correct and Predict command

3.5 Reduction of Computational Cost

This algorithm works when the mobile robot is referring to a landmark. The Jacobian matrix will be:

$$h_A = [-e \quad -A \quad A] \tag{9}$$

The e is denominated as:

$$e = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{10}$$

while A is:

$$A = \begin{bmatrix} \frac{dx_A}{r_A} & \frac{dy_A}{r_A} \\ -\frac{dy_A}{r_A^2} & \frac{dx_A}{r_A^2} \end{bmatrix} \tag{11}$$

Then,

$$\begin{aligned} dx_A &= [x_i - x_A] \\ dy_A &= [y_i - y_A] \\ r_A &= \sqrt{dx_A^2 + dy_A^2} \end{aligned} \tag{12}$$

Then the characteristics of process noise covariances $Q_k > 0$ and the measurement noise covariances should be $R_k > 0$. Hence, when the robot observing landmark. The state estimation and state error covariance given by:

$$\begin{aligned} \hat{X}_{k+1}^{+} &= [\theta_k \quad x_k \quad y_k \quad x_1 \quad y_1]^T \\ P_{k+1} &= \begin{bmatrix} P_{\theta v} & * & * & * & * \\ * & P_{xv} & * & * & * \\ * & * & P_{yv} & * & * \\ * & * & * & P_{x1} & * \\ * & * & * & * & P_{y1} \end{bmatrix} \end{aligned} . \tag{13}$$

The $P_{\theta v}, P_{xv}, P_{yv}$ refer to the angle of heading robot, x position of robot and y position of robot. x_1, y_1 refer to the position of landmark and * refer to the correlation of all state. P_{x1}, P_{y1} refer to its state covariance. The covariance matrix will enlarge as the robot detect another landmark.

3.6 Trajectory of Mobile Robot with two conditions

To navigate successfully, mobile robot should be capable of to move from its starting point to the desired point. This process named as localization. Different cases have been conducted to test its performance. In first condition, to mobile robot localize its position based on landmark. In simulation we construct command of mobile robot based landmark SLAM using EKF using MATLAB.

```
load("racetrackDataset.mat","initialState","initialStateCovariance"
     "processNoise","controllerInputs","timeStep", ...
     "measurements","measCovar","validationGate");
```

Figure 23:Track of dataset

Figure above shows that we construct command of tracking data set regarding its initial vehicle state, initial state covariance, process noise covariance, measurement covariance and control input. Then, we construct the predict by utilizing its control input and time step size that were used for transition function. Figure below is the command of corrected state by observe landmark and covariance measurement. By then, we can observe the trajectory of Robot path using landmark and without landmark.

```
% Get the landmarks in the environment
   observedLandmarks = measurements{count};

   % Correct the state
   if ~isempty(observedLandmarks)
       correct(ekfSlamObj,observedLandmarks,
               measCovar,validationGate);
   end
```

Figure 24: Correct state

3.7 ROS with Gazebo simulator

Significantly, for Gazebo is one of the tools for ROS which are free and open source for robot environment. The purpose of Gazebo is to design robot models, creating an algorithm for prototyping and testing, simulating indoor and outdoor environments of robot and simulating the data of sensor obtain from the laser range finders, equipped with 2D/3D cameras, Kinect style sensors and force torque. To test Gazebo, we can start run command Roslaunch. We need to run the command $export turtlebot3_burger in order to execute the turtlebot in gazebo in simulator.

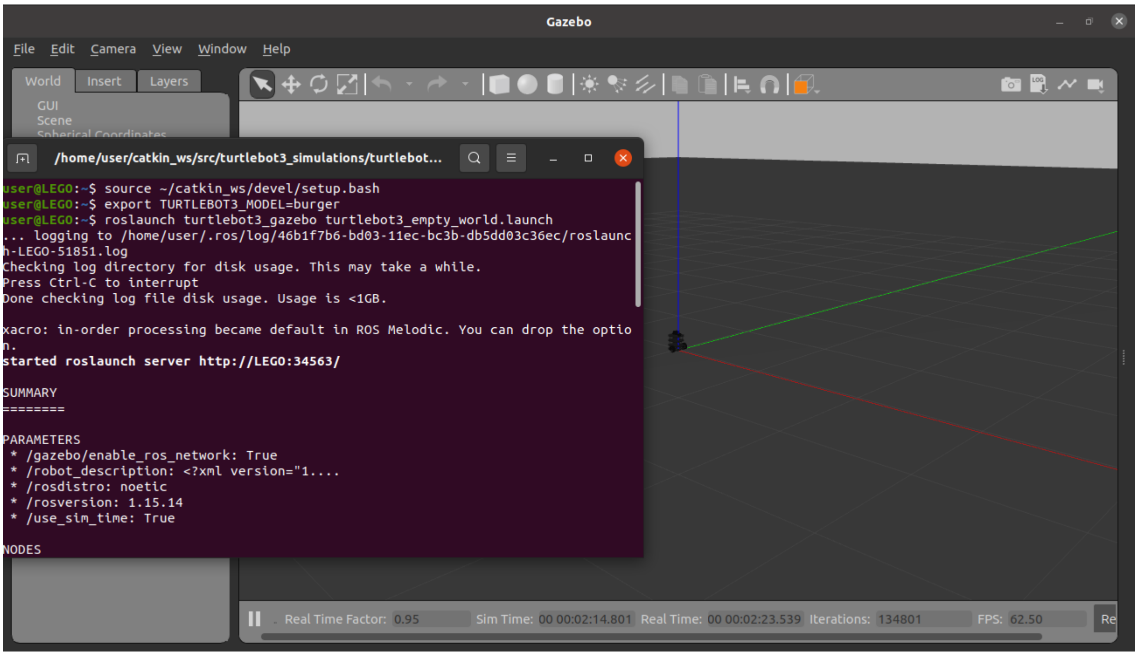

Figure 25: execute robot in Gazebo

Then, we need to launch the indoor or outdoor environment in order to test the ability of the turtlebot.

3.8 Simulating obstacle Avoidance using ROS Gazebo and mapping in RVIZ

In ROS ubuntu, in order to simulate mobile robot, we use terminal in ubuntu to execute command of mobile robot. First of all, we need to create a workspace to install the package of mobile robot. The command that we use to create package is catkin.

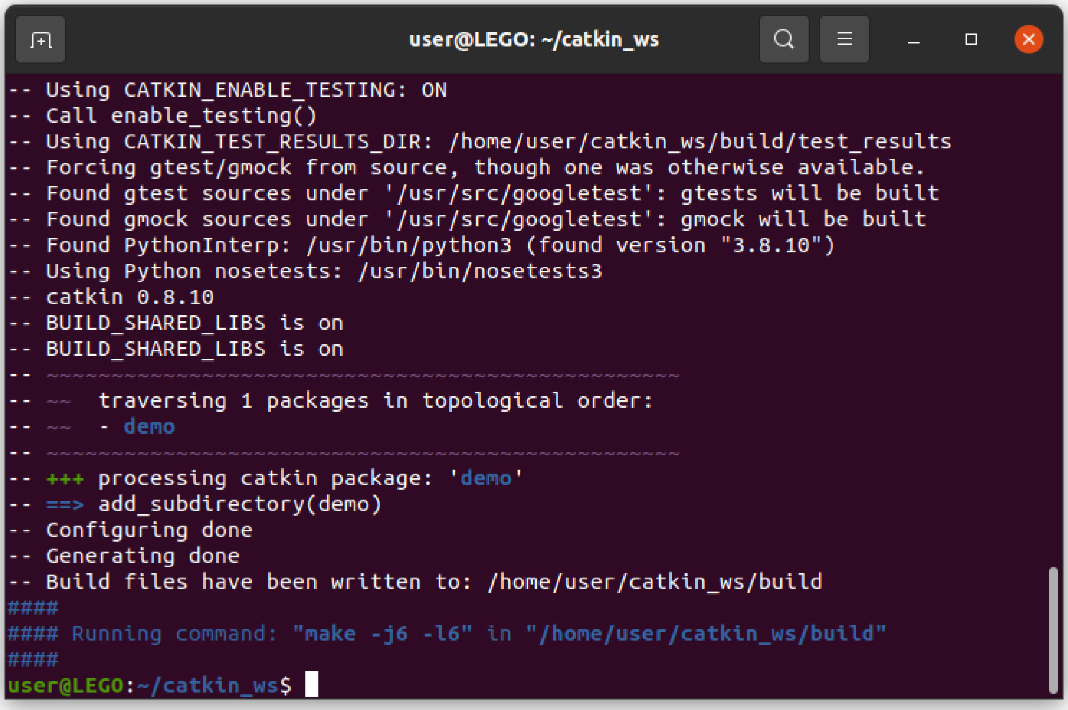

Figure 26: Catkin package

When creating the catkin package, it will then provide dependencies. After creating the package, we need to build package and source the environment in every new terminal. Then, to start simulate the mobile robot, refer to the website e-manual robotics, we need to source our package of catkin, export the Turtlebot, and launch the environment world in Gazebo. Hence, it will simulate the Turtlebot in Gazebo simulator using the environment that we execute in command. Then, we run the command $ roslaunch turtlebot3_teleop turtlebot3_teleop_key.launch in order to move the robot by just control using keyboard.

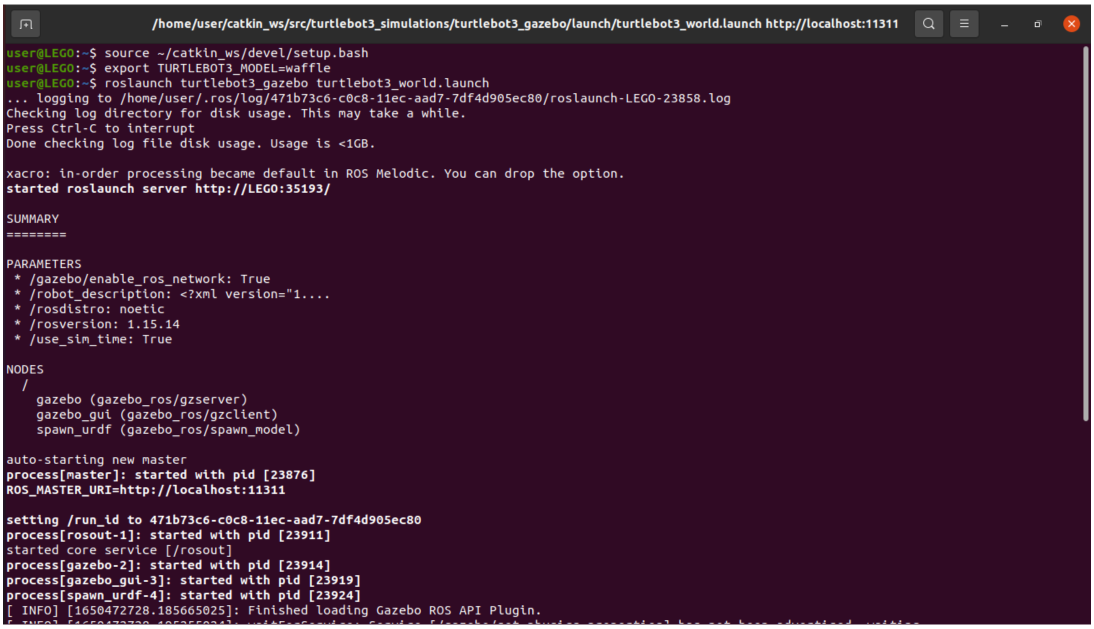

Figure 27:execute command in Gazebo

In term of map generation for robot, the robot should be able to move along the environment, and it will progressively updating the occupancy grid using its laser distance sensor by importing the robot in Gazebo simulator, and map itself on RViz.

Similarly, RViz is the abbreviation from the ROS visualization. It is 3D visualization software where it includes all the tool for robot, such as it algorithms, sensors and mapping resolution. The aim of RViz is to visualize our state and position of robot by using the data from sensor and displaying accurately the environment of robot. On that account, the Turtlebot itself equipped with 360 degree of laser distance sensor, where it can be called as LDS-01. Hence, with this we can use the gmapping package. Gmapping package includes laser-based SLAM to gives 2D occupancy grid map which are collected from the data of laser-scan. First of all, we need to run $roscore command in terminal. Next, we need to source the mapping environment. Then, export the turtlebot in new terminal and run the command of $roslaunch turtlebot3_slam. launchslam_methods=gmapping. Subsequently, after all command has been run, then the turtlebot will move, by then its laser scan will scan the environment of the robot and the map will be created on the RViz. At the top of screen RViz, there are button for 2D pose in order to set the initial position of the robot. We clicked the button and put on the robot that we have already launch. We then drag the arrow pointing to the robot heading angle.

Later on, the robot will localize itself in the map. In order to run autonomously, the 2D nav goal button at the top of the screen was clicked and then we drag to the path that we desired.

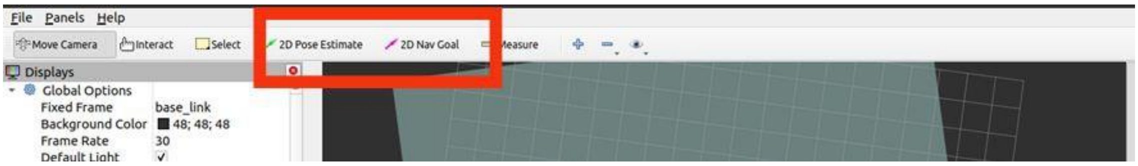

Figure 28: Button 2D pose estimate and 2D nav

At the corner of RViz, the specification that was chosen is Costmap Planner, and Planner Plan. These two buttons aim for the robot can continuously auto-navigate itself.

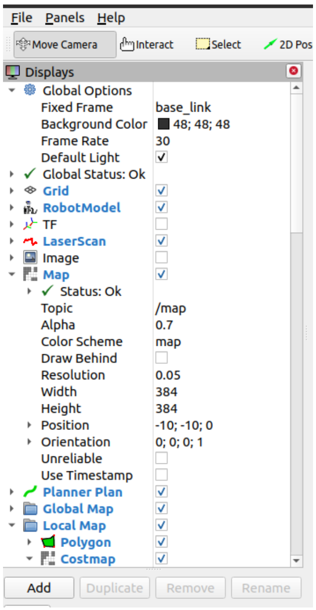

Figure 29: Specification RViz

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

In this chapter review about the data obtain from the procedure that were discussed in methodology. It includes all the result from simulation via MATLAB and ROS

4.2 Result

4.2.1 MATLAB Simulation

In this chapter review about the data obtain from the procedure that were discussed in methodology. The result is obtained from the simulation of pattern state covariance behaviour, and robot localization with existence of landmark and absence of landmark. In particular, ROS simulation result is obtained from Gazebo simulator and RViz visualization.

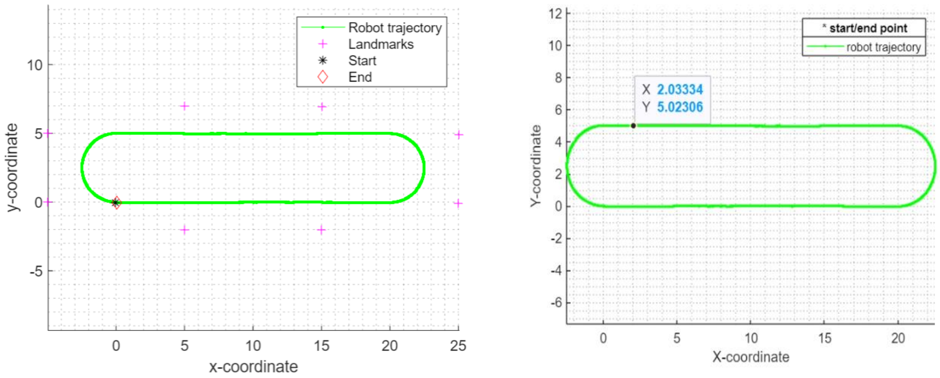

Figure 30:Comparison trajectory with and without landmark

In this simulation the speed of robot is assumed to move with a constant speed. The above figure depicts the localization of mobile robot. The green line indicates the trajectory of robot, '+' sign refer as landmark, * shape is defined as start point and diamond shape depicts as end point. In the case of absence of landmark, the robot only depends on the initial state position compared to the case with dependent of landmark. It illustrates that with the case of absence landmark, the trajectory of robot seems to be deviate from the actual path and the estimation leads to erroneous.

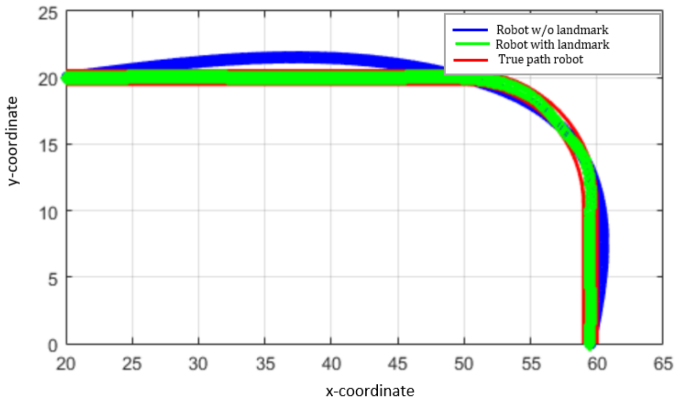

Figure 31:Comparison of the estimation robot path between with and without landmark

Figure above shows comparison of estimation robot with and without landmark and true path robot. The blue line is the estimation robot path without landmark and green line indicates the estimation path of robot with landmark, while red is the true path of robot. While observing the data, it shows that the estimated robot path (blue line) is diverge from the true path of robot because the robot without landmark is only depend on its initial position. Hence, by comparing these results, the mobile robot with landmark yield better estimation with smaller error. It does not deviate from the actual path. This explains that the correlation between mobile robot and landmark is crucial in order to obtain the most accurate especially in localization. However, when the robot is independent towards landmark, the robot will deviate from its actual path and the state covariance will be smaller as it proves that the estimation is inaccurate because it will lead the mobile robot to get disoriented.

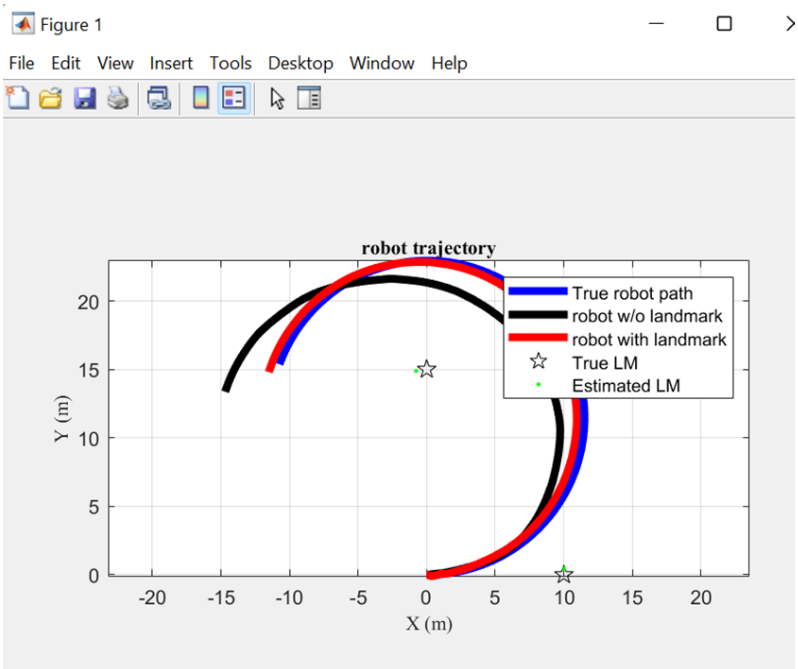

Figure 32:Estimation of robot path between with and without landmark when the robot change its path

In order to obtain the consistent result, this is the cases when the robot changes its movement. The blue line depicts that the true path of robot while the red line depicts the path of mobile robot with landmark and the black line indicates the robot path without landmark. In the cases of the robot without landmark when the robot changes its direction also shows that they are deviate from the true path of mobile robot compared with the robot with landmark illustrates approximately followed the true path of robot.

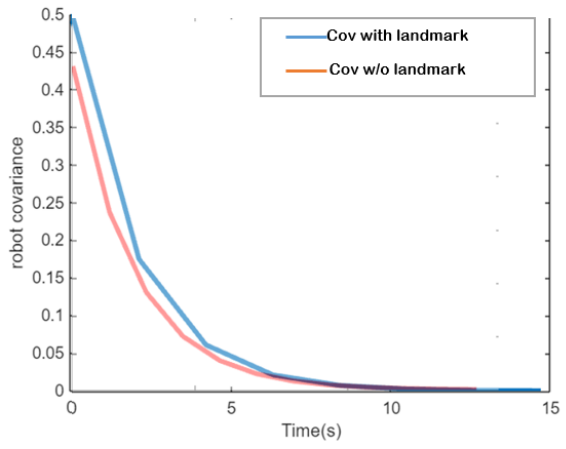

Figure 33: state covariance matrix between estimated robot with and without landmark when the robot change its path

Above figure, the update state covariance shows are bigger than the state covariance of cases without landmark. As claimed in the research(Ahmad et al., 2015) where we can observe that the behaviour of state covariance can be increase or decrease when the mobile robot moves while observing landmark.

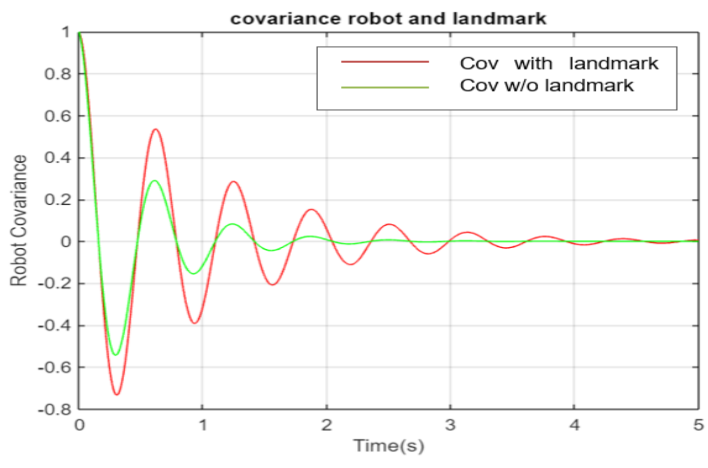

Figure 34:Comparison State covariance with and without landmark

Depicts that the red line is state covariance with existence landmark and green line is state covariance with absence landmark. From figure above, when the mobile robot is only depends on its initial position compared to that when the robot is depends on the landmark, the update state error has smaller uncertainties. We can observe that, the state covariance with landmark yield bigger than the state covariance with absence landmark. As been mentioned in research paper(Ahmad et al., 2015), when the mobile robot constantly observing and updating landmark, the state covariance will be continously converged as in the figure where the line goes to one value. Refer to this analysis, it goes to 0 value.

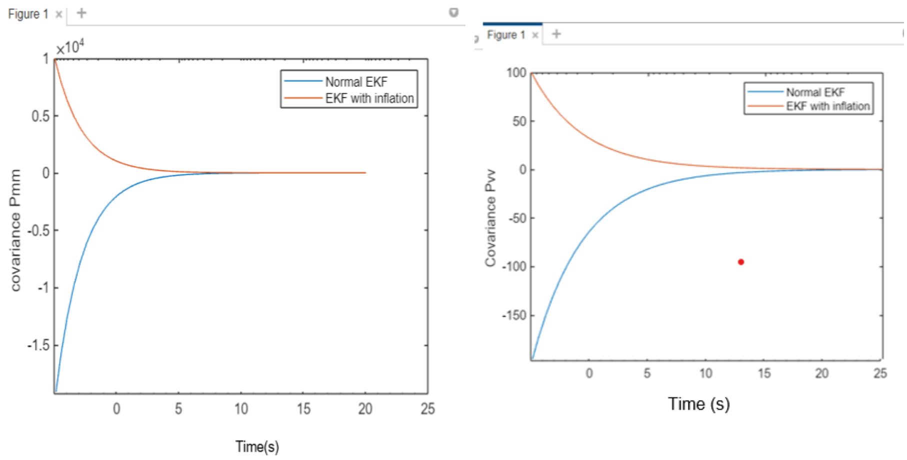

Figure 35:State error covariance normal EKF and EKF with inflation

Moreover, as been analysed from previous research (Hamzah Ahmad, 2011),EKF with inflation technique can give better performance than normal EKF as there are non-negative definite covariance during observation. From this research, where they analyse performance of normal HF and HF with covariance inflation, also depicts that Inflation can prevent finite escape time (FET) where state of unstable linearly time goes to infinity and can avoid from resulting to faulty estimation.

4.2.2 ROS simulation in Gazebo and RViz

By using command $ roslaunch turtlebot3_gazebo turtlebot3_world.launch in terminal, the robot then will be display in Gazebo simulator. Next, the command $ roslaunch turtlebot3_teleop turtlebot3_teleop_key. Launch. Then, the robot can move by using keyboard.

In RViz, after launching the command of export the turtlebot type, the mapping generation in RViz is initiated. Below also include the figure of data of map generation in gmapping process where the robot is trying to scan the map that they need to move. With 2D pose estimated then were used to define its initial position. Then, the 2D nav goal will instruct the robot to move all around in order to move to the position that we desired by using the created map.

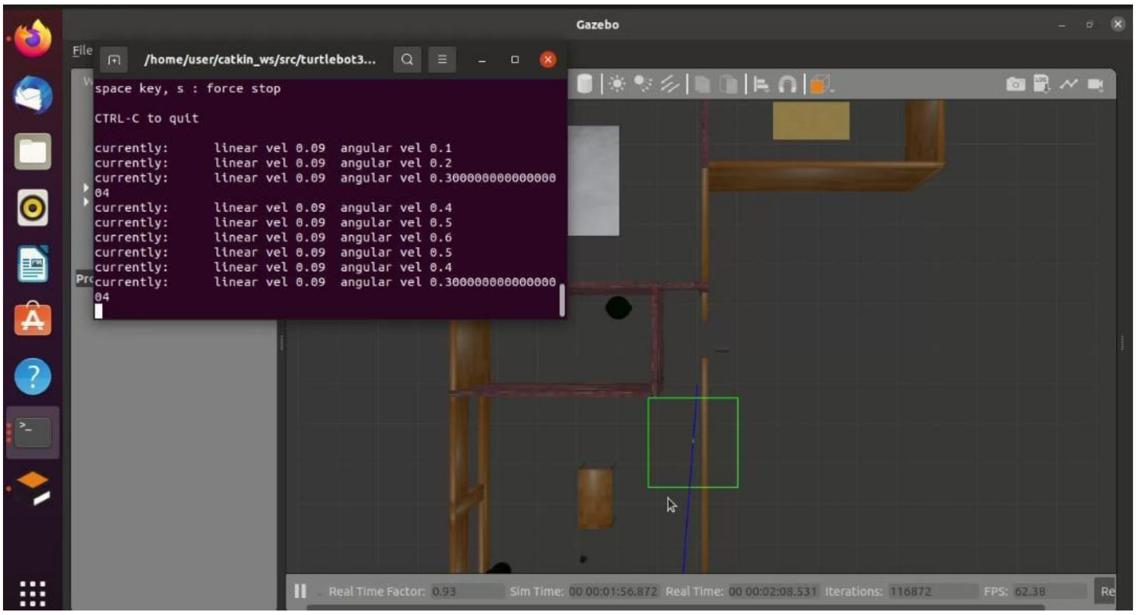

Figure 36 :Turtlebot in house world

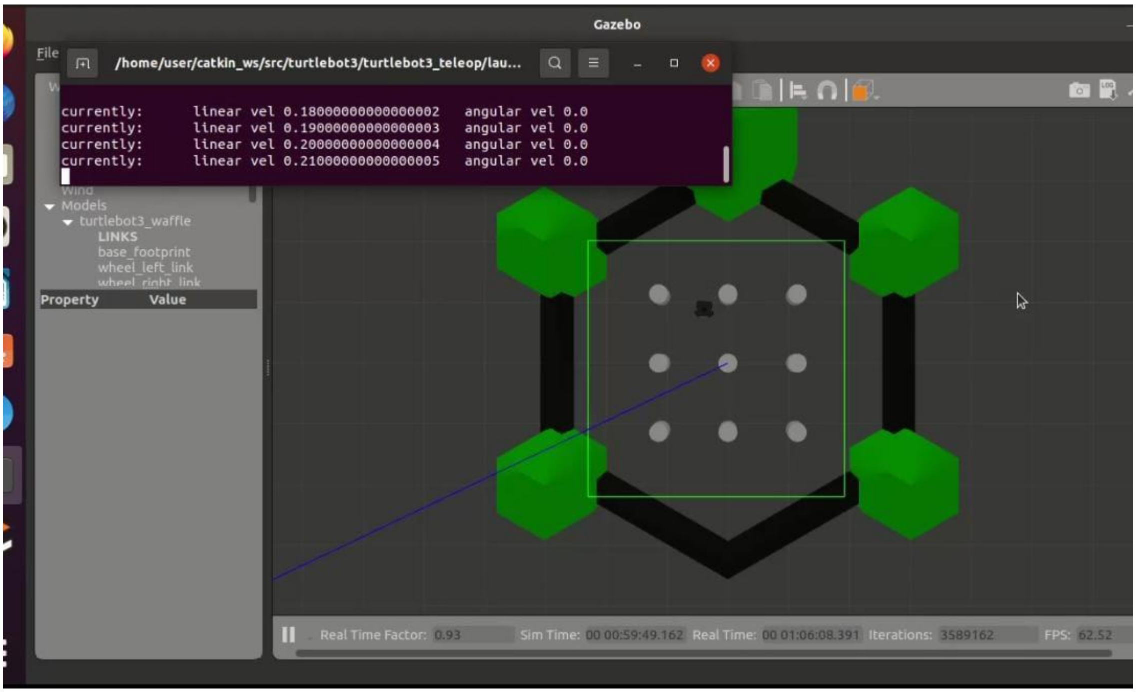

Figure 37:Turtlebot simulator in outdoor environment

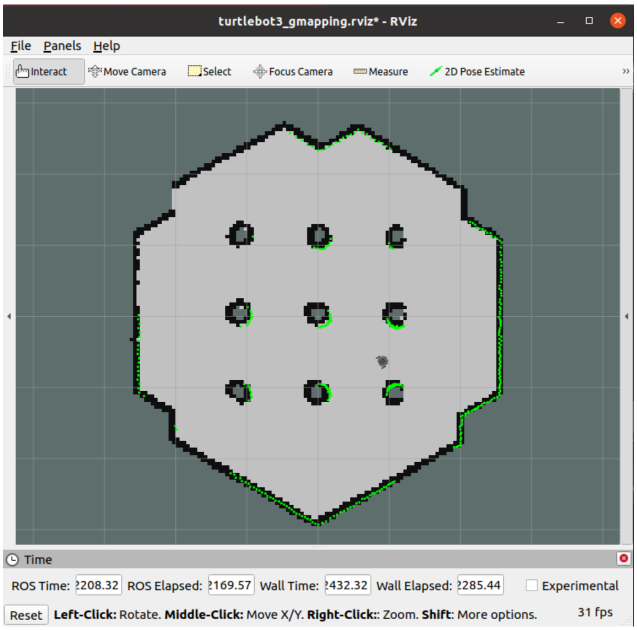

Figure 38:Turtlebot in RViz

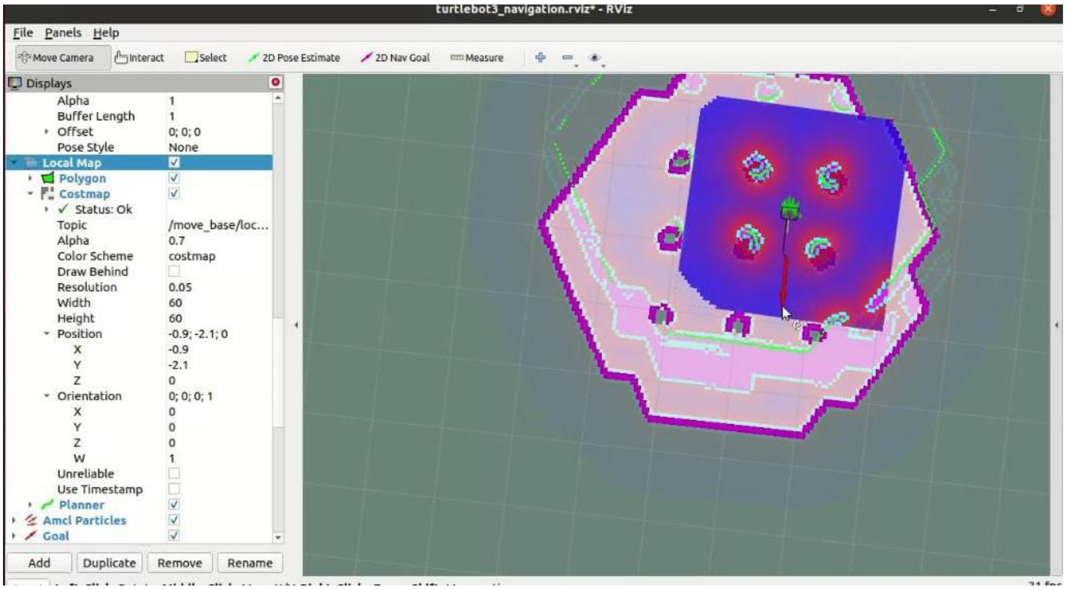

Figure 39:2D nav in RViz

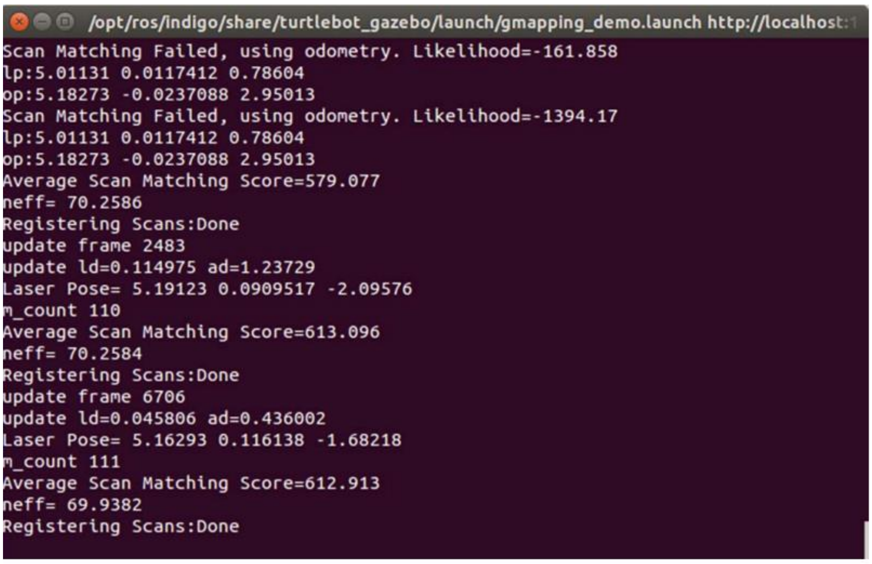

Figure 40:Data information of map creation in process gmapping

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CHAPTER 5

CONCLUSION

5.1 Introduction

In this chapter we will conclude all the research and simulation that have been done for this project. The aim of this project is an analysis of state covariance and evaluating the performance of mobile robot using technique of covariance inflation method. This technique is applied in mobile robot specifically in navigation. This simulation is also involved ROS. All the collected data has been analysed to support the theoretical behind.

5.2 Conclusion

In conclusion, this thesis aims to review the relationship between mobile robot and landmark. It briefly discusses the impact of decorrelation approach with cross-correlation of state covariance. The experiment and comparison based two case studies has been conducted which are with existence landmark and absence of landmark. The simulation in MATLAB illustrates the trajectory of mobile robot with and without landmark where then it shows in the state covariance graph. In MATLAB simulation, it shows that state covariance refers to a landmark is larger than the state covariance with the absence of landmark. This indicates that smaller uncertainties produce when the robot has landmark. Theoretically, it is stated that in previous research paper the state covariance of mobile robot will be smaller if there are no error or faulty estimation. Meaning that, the higher the state covariance, the estimation becoming more lose confidence. As in our simulation, the result a bit differs from the theoretical study. Thus, compared between this simulation and theoretical study from previous study we can conclude that cross-correlation between mobile robot and landmark is very significant. As there are simulation was conducted during normal EKF with EKF with Covariance inflation indicates that this technique helps estimation gain better confidence. Through this scenario, in mobile robot localization, covariance inflation which involves cross - correlation is one of the crucial cases. In order to perform task, the robot need to know its localization with the assists of landmark to identify its initial position with environment. Therefore, to test its performance, the mobile robot was simulated in ROS in outdoor or indoor environment. The simulation was conducted in Gazebo simulator and the RVIz. In RViz, it generates map through the gmapping process and it is proved where the robot can start to move from the start point to the end point. All the simulation conducted has been proved and referred from the theoretical analysis from previous study.

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APPENDIX A

No	Title	Week													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Construct case study														
2	Comparison method analysis														
3	Simulation on MATLAB														
4	Setup software on PC														
5	Analysis error ROS														
6	3D simulator Mobile Robot in Gazebo														
7	Simulation on RVIZ														
8	Python nodes developing and testing														
9	Improvement set of data														
10	Data analysis														
11	Thesis writing														
12	Submission slide for PSM 2 Ekselen														
13	PSM 2 Ekselen														
14	PSM 2 thesis and logbook submission														