Navigation of a Mobile Agribot by using Multi-sensor “SLAM”

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Aug, 2021

Declaration

I certify that this research work titled "Navigation of a Mobile Agribot by using Multi-sensor "SLAM"" is my own work. The work has not been presented elsewhere for assessment. I have properly acknowledged / referred the material that has been used from other sources.

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Copyright Statement

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Abstract

Applications of mobile robots are continuously capturing importance in numerous areas such as agriculture, surveillance, defense and planetary exploration to name a few. Accurate navigation of a mobile robot is highly significant for its uninterrupted operation. Simultaneous localization and mapping (SLAM) is one of the widely used techniques in mobile robots for localization and navigation. SLAM consists of front and back end processes, wherein, the front end includes SLAM sensors. These sensors play signification role in acquiring accurate environmental information for further processing and mapping. Therefore, understanding the operational limits of the available SLAM sensors and accurate data collection techniques from single or multi-sensors is noteworthy. In this work, we optimize selection of SLAM sensors, and implemented multisensory SLAM. The performance of SLAM sensors is compared using the analytical hierarchy process (AHP) based on various key indicators such as accuracy, range, cost, working environment and computational cost.

Simulation were performed gazebo environment using ROS for simultaneous localization and mapping (SLAM) with the key focus on navigation of the agribot in the indoor agricultural field. The SLAM was performed by fusion of data from multiple sensors. Obstacle avoidance and handling of computational cost was performed by using the sonar sensor. Localization of the landmarks was solved with using 2D LiDAR and Microsoft Kinect (RGBD) sensor without prior knowledge of the environment. A well-known SLAM technique (Extended Kalman Filter) was used for solving localization issues and building the map for the environment. Extended Kalman filter (EKF) based SLAM was implemented on a two-wheeled mobile robot with encoders (for localization of robot). The robot was programmed to autonomously navigate inside the indoor static environment. Sonar sensor was used for minimizing the time duration and computational cost during obstacle avoidance. In experiments, localization of landmarks and mapping are achieved with sonar sensor and LiDAR using EKF. The accuracy mapping were 93% and 97% during experimentation and simulation, respectively (with LiDAR). In RGBD-SLAM, accuracy of localization and mapping was 95% and 80%, respectively (from experiment). The accuracy of localization and mapping was 98% and 85% in RGBD SLAM with multi-sensors SLAM which include LiDAR, Microsoft Kinect, sonar and odometry sensor (in Gazebo simulation).

Key Words: SLAM, Agribot, Computational Cost, SLAM sensors, Analytical Hierarchy Process

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Acronyms

SLAM	Simultaneous localization and mapping
AHP	Analytical hierarchy process
P	Probability distribution
U	Robot odometry
Z	Sensor measurement
M	Map
X	State of Robot
GPS	Global Positioning System
UFASTSLAM	Unscented Fast SLAM
LiDAR	Light Detection and Ranging
RADAR	Radio detection and ranging
SONAR	Sound navigation ranging
SL	Structure light
TOP	Time of flight
RGB-D	Red Green Blue- Depth
CNN	Convolutional neural network
FMCW	Frequency Modulated Continuous Wave
RANSAC	Random Sample consensus
SIFT	Scale-invariant feature transform
ICP	Iterative Closest Point

CHAPTER 1: INTRODUCTION

Simultaneous Localization and Mapping (SLAM) is a modern approach in which mobile robot can localize the landmarks, localize themself and build the map. Mobile robot has been programmed for exploring the environment without prior knowledge of environment in which it operates. We can note that these mobile robot projects are mostly used for limited applications, especially used for agriculture [1], dangerous places, surveillance, planetary exploration [2] and others. But mostly used for navigating the place where it's very hardly reachable for human operations. Advantages of mobile robots are their operation for complex processes which reduces the range of labor for time-consuming tasks such as in the field of agriculture, hospital and industries (mostly used for shifting material from one place to other places). Different types of robots and drones are presented in robotic field for the ease of humans such as unmanned grounded vehicles (UGVs), unmanned aerial vehicles (UAVs) and autonomous underwater vehicles (AUVs) [3, 4]. We called a robot autonomous when it can execute its operations without human interference. An autonomous mobile robot should have the capability to localize itself, estimate the behavior of the surrounding environment, make perception according to environmental stimulus and path planning [5]. Different techniques are used for executing the robot autonomously like SLAM, fuzzy logic [6] and neural networks [7].

Simultaneous localization and mapping (SLAM) is one of the widely used techniques in artificial intelligence mobile robots for localization and mapping. It is a union of various disciplines such as computer vision, range sensor, graph theory, mathematical modeling, and probabilistic estimation [8]. SLAM is used in mobile robots for solving the complexities related to self-explore the unknown environment, localize the landmarks, build the map and avoids the obstacle within an environment. This algorithm is also used for resolving complex challenges such as navigation and odometry of mobile robots.

SLAM consist of front-end and back-end process, front-end consists of sensors like encoder, Inertial Measurement Unit (IMU), Ultrasonic, LiDAR and visual sensor (monocular, stereo and Kinect sensor) [9]. SLAM-based robots are largely dependent on sensing capabilities and are equipped with multiple sensors because of localization of the landmarks and themselves, build the map and exploring the unknown environment is a very complex challenge. A robot is called a reliable autonomous mobile robot when it has capabilities to sense its environment condition precisely, which is depended on characteristics of the SLAM sensor such as range, reliability in every condition (rainy, smoke and dust environment) and accuracy as well as other factors computational cost and cost of the individual sensor.

Front end, SLAM sensors are employed for measuring the position, velocity and direction of the robot as well as observe and localize the landmarks. This paper also discussed the SLAM sensor and provides the best SLAM sensors for localization of landmarks such as acoustic sensor, camera, LiDAR, RADAR and RGB-D sensors. However, GPS and rotary encoders determine the position, location and velocity of the robot.

In SLAM algorithms, front-end comprises of sensors (details given in section 3) which are mostly used to estimate the position and pose of the robot. The widely used SLAM sensors encompass Global Positioning System (GPS), rotary encoders, infrared (IR), acoustic sensors (ultrasound, microphone, sonar sensor), camera, LiDAR, RADAR, and RGB-D. GPS, rotary encoder and inertial measurement unit (IMU) are employed for location extraction of landmarks and estimation of position, velocity and direction of a mobile robot. Acoustic, camera, LiDAR, RADAR and Kinect sensors are utilized for tracing and tracking environmental landmarks.

Back-end consists of various techniques such as kalman filter family, particle filter [10], neural network (RATSLAM), graph SLAM, RGBD-SLAM (RANSAC and SIFT) [11] and ORB-SLAM (vision-based SLAM). These are used for address as a current state estimation in which prediction and correction of uncertainties are performed. It is consisting of one or couple of techniques used to estimate the pose, position of the robot and the locations of environmental landmarks with the help of front-end sensors.

The research on SLAM raised greatly in few decades, with multiple algorithms, various sensors and different environments (indoor and outdoor). If we talk about pros and cons of sensor used for SLAM-based robot then Ultrasonic, monocular cameras, stereo camera, Microsoft Kinect sensors and LiDAR are mostly used to solve the SLAM issue [12]. A visual sensor such as monocular and stereo needs a very extraordinary algorithm for mapping because of lack in-depth measuring and also took high computational cost. These drawbacks decrease the accuracy of building the mapping of the environment. On the other hand, LiDAR and Microsoft Kinect sensor are mostly used for mapping [13], these sensors deliver much more information in the form of point cloud data and faster. LiDAR gives the point cloud data of full terrain around the mobile robot as well as RGBD camera gives the point cloud data and video stream in the front side of the mobile robot. The price of LiDAR is very high for the middle-end solution which makes it less superior than another sensor.

The purpose of research is to accumulate an autonomous mobile robot with the SLAM technique for build a map of the indoor environment and outdoor in the agriculture field. LiDAR and Kinect sensor are the priorities for this because of their robustness and novel characteristics. Extended Kalman filter has been used for LiDAR sensor and RGBD-SLAM has been used for Kinect sensor because of versatile and accurate solution for the respective sensor. After an experiment in ROS, we find a very good experimental accuracy.

1.1 Functions of robot

This autonomous mobile robot has the following capabilities to complete efficiently its tasks in any environment (Our result is only for indoor constant environment for real-time as well as gazebo based result is also simulated in agriculture field).

1.1.1 Human Machine Interfacing

The user gives instructions to the robot about the location and the task to be done with the help of a user interface consists of an Android Smart Phone or Laptop. With the help of the camera user can use a robot as a telepresence agent for localization and mapping.

1.1.2 Movement and Motion Control

It consists of a wheeled mobile base so that it can move in the office, go to the desired location and perform the operation which is requested by a user. DC geared motors are used as actuators and rotary Encoders are used to count rotations and angular position of wheels. Encoders send pulses to the controller to count the number of rotations of motors' shaft and the decision is taken when a particular position is achieved by robot.

1.1.3 Localization, Mapping, Obstacle avoidance and Path planning

Robot must determine its location and orientation in office indoor environment and agriculture field by using sensors and determination of location not only based on the signal sent by the sensor but also decided by the Microcontroller based on the previous history of location and current direction. Ultrasonic sensors are used to detect an obstacle in its path, and a map has been built with the help of LiDAR and Microsoft Kinect sensor (RGBD).

1.2 Working

Autonomous robots are widely used in different fields to make human life easy and reliable. Ultrasonic sensors are used to avoid obstacles, camera is used to capturing pictures for mapping with RANSAC and SIFT as well a LiDAR sensor is also used for mapping. So that it knows its location, a Rotary encoder is used to measure linear acceleration, Velocity and Position along X and Y.

1.2.1 Gazebo/ROS/Robots:

A SLAM-based mobile robot should have capabilities that store information regarding situations that are going to achieve, so the robot can choose among multiple possibilities for building map, selecting the one which reaches the next state according to obstacles. Office Assistant Robot is a goal-based agent which uses its sensors to acquire knowledge about its environment and after imaging its final position it will act upon its surrounding through its actuators

1.3 Motivation

Autonomous mobile robots are increasing their popularity recently because of their application, but there are many fields where there is no prior knowledge of the environment so that is why robot need their expertise in technology which allows the robots to move and navigate in the environment and build a mapping simultaneously. The most popular field used for doing these is SLAM, which is used to localize the location of landmarks and build the map. These algorithms can be used for natural disasters like earthquakes, agriculture and rescue, which can give any information that how many people are traps in an earthquake environment. Figure 1.1 shows an example earthquake and SLAM-based mobile robot can rescue and give information about the environment that how we can rescue.

SLAM-based robots can have used in agriculture action for determining the yield of crops as well as for finding the disease that's an attack on crops. Mobile robots are also spraying and picking the food from the field. Figure 1.3 shows Mobile robots in the agriculture field.

SLAM-based robots can use in military actions shown in Figure 1.2. A small mobile robot could be used for navigating the enemy places and report the base of enemy and prison soldiers. SLAM-based robots can also create a map of the cave where there is any danger of snakes and scorpions or any dangerous animal like lions, tigers, etc.

Figure 1.1: The collapsed building of PGC [14]

Figure 1.2: SLAM possible used in the military [15].

Figure 1.3: SLAM possible used in Agriculture [152]

1.4 Objectives

The objectives of this project is to research the best SLAM sensor for every environment and computational cost, optimize SLAM sensor selection process and implement multi-sensor SLAM for robust localization which accumulate on small mobile robot that can move around freely without the knowledge of a map. It should give good accuracy for localization of landmarks and itself and build the map of these landmarks for future planning. For achieving these, some of the goal are listed below.

1) Implementation SLAM by using Multi-sensor, Fusion of multisensory data.
2) Select the best SLAM sensor based on characteristics such as accuracy, measuring range, computational cost and environmental situation.
3) Implement a robust SLAM technique for better localization and Mapping
4) Handle the computational complexity by using loop Closure problem.

1.5 Scope

This project has been designed for implementation of SLAM algorithm (EKF, RGBD-SLAM) in the indoor environment as well as gazebo based agriculture environment. There are many algorithms used for SLAM but these procedures have focused only on EKF SLAM and RGBD-SLAM algorithms, more detail are given in literature review.

CHAPTER 2: LITERATURE REVIEW

In this chapter, we review the progress on SLAM (filter based SLAM and RGBD SLAM), sensors used for SLAM (such as LiDAR, RADAR, monocular camera, acoustic sensor and Microsoft Kinect sensor) and background of SLAM history. Catogiries (single sensor and multi-sensor based SLAM) of SLAM sensor is also discussed in this section.

2.1 Background

SLAM is being popularity and made remarkable signs of progress in the past 30 years to work in the real-world applications, and applicable in the industry for different tasks [8]. The history of SLAM is divided into different ages, classical age, algorithmic-analysis age as well as robust-perception age. The classical age is from 1986 to 2004 [8]. Initially SLAM was proposed by R.C Smith and P. Cheeseman in 1986; it is one of the broadly used techniques in mobile robots for localization, mapping and navigation [16]. Over time numerous improvements were integrated with SLAM. In 1991, a probability technique (Kalman filter) was introduced which takes a series of measurements (sensor data) over time to optimize the control input and resolve the sensor noise [17]. Kalman filter was upgraded to Extended Kalman Filter (EKF) to deal with the non-linear behavior of the system by linearizing a series of measurements from the sensor. Early research focuses on visual SLAM for navigation [18, 19, 20] with ultrasonic sensor by Kalman filter algorithms, that result after soon by [21]. Localization and mapping have been done with Kalman filter-based SLAM [22]. In the algorithmic-analysis age, the different researchers worked on increasing the efficiency of the algorithm and increase the exactness of localizing and mapping of mobile robots, in this age different types of the new algorithms were built by the researchers. In 2002, Fast-SLAM was introduced which measures individual landmarks independently so that robots could explore its environment [23]. Subsequently, UFastSLAM based on an unscented transformation matrix was developed [24]. Various new filters were also implemented after the extended Kalman filters, such as the extended information filter, and the unscented Kalman filter [25].

This algorithmic-analysis period from 2004 and 2015 [8], in this age period, consistency, accuracy and a new method was introduced; As we can predict by name, age characterize productivity in the analysis of established SLAM technique. In this age other essential properties of SLAM includes observation and convergence of mobile robots and obstacles. Observation of mobile robots is the ability to manage the control vector and arrangement of control actions and explanations of location of landmarks [26]. In these sensors, specific sensors are also targeted to manage the mobile for increasing the accuracy of localization and mapping [27]. Convergence is the estimation of robot movement can be observed by a rotary encoder, Inertial measurement unit (IMU) and Global Positioning System in a specific time, then convergence is accomplished [26]. For this purpose, Kalman filter has been introduced that use linear movement, then the Kalman filter was upgraded to Extended Kalman Filter (EKF) to deal with the non-linear behavior of the system by linearizing a series of measurements from the sensor. Consistency or loop closures are introduced by Bar-Shalom, Y et al [28]. In EKF SLAM, irregularity is a drawback that can occur when Jacobians are not estimated [26]. For this purpose, visual SLAM is widely used, in which image processing plays a vital role, and can predict the pose, location of landmarks by using input image(s) from visual sensors like monocular camera, stereo camera and Microsoft Kinect sensor [29]. In visual sensor, motion can be detected by variations in the received images by RANSAC and SIFT algorithm in machine vision. These sensor needs to have enough illumination in an environment for increasing accuracy and operative results of the algorithm [30, 31, 32].

RGBD-SLAM is a SLAM technique used for a visual sensors such as monocular, stereo and Microsoft Kinect sensors (RGB-D). RGBD-SLAM is used to computing the 3D-construction map (RTAB map in ROS) of the environment and trajectory planning of the visual sensor [33]. The map can be range from a small rooms to several building blocks environment. Monocular cameras, Stereo cameras or RGB-D cameras in [34, 35] and 3D LiDAR in [36], are widely used for localizing the cited algorithm and constructing the 3D map.

Robust Perception Age is a period starting in 2015 to now the question is that "has SLAM been solved?" Such types of questions are very complex to answer; because SLAM is a combination of multiple fields such as algebra, matrix, machine vision, graphical studies, geometry, artificial intelligence, mechanical, image processing, robotics, etc. For example, SLAM algorithm fails up to now for motion in a complex environment or give poor performance in such types of the environment [8]. During this period, researcher on robustness in performance, good level of understanding and perception of motion is working on. RADAR-based SLAM is an emerging field in SLAM, medium ranges RADARs were also introduced for autonomous mobile robots; RADAR-based robots are mostly short-ranged machines systems [37, 12]. The RADAR-based SLAM problem is an emerging technology which has been done in 2014 by DICKMANN and Juergen et al [38].

From all of the background, we are focus on robust perception age. EKF and RGBD SLAM algorithm has been used because of its novelty as discussed in this section. Currently, research on SLAM is focused on increasing the accuracy in localization and mapping. In this research, our goal is to increase the accuracy in localization and mapping for the indoor environments.

Simultaneous planning, localization and mapping (SPLAM) is an emerging area used for autonomous navigation with the combination of SLAM and path planning techniques (see figure 2.1). One of the best approaches used for SPLAM is Bellman and shooting methods [39]. Bellman's approach shows signs of progress in terms of smoothness and accuracy in localization, map building and optimal path planning. Optimal path planning is used for finding the shortest, accurate and robust path. Path planning is carried out using multiple search techniques such as A* STAR, Breathe First Search, Depth-First Search and Dijkstra's algorithm. The robot must locate and have access to the map for route planning.

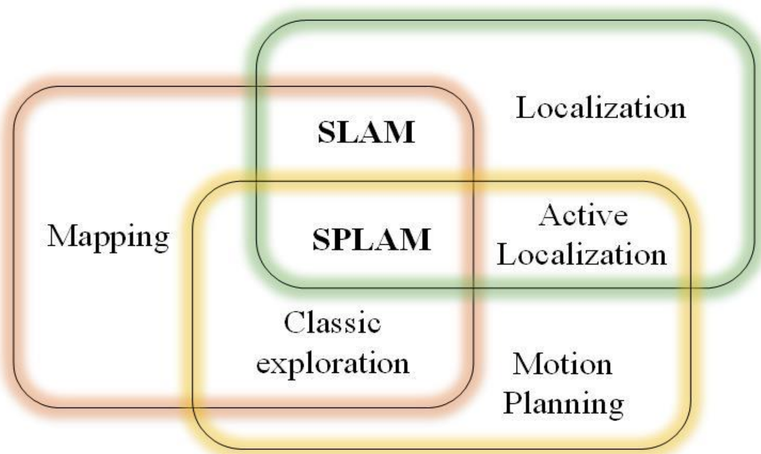


Figure 2.1: Difference between SLAM and SPLAM based on their working and autonomous behavior, Reproduced with permission from [40].

2.2 SLAM based Sensors

In the early SLAM system, acoustic and LiDAR sensors were used as range sensors. Acoustic sensors are generally used for underwater (sonar sensor) and short-range applications. LIDAR-based SLAM was introduced by Nguyen et al. in 2005 [51], this sensor is used for measuring distance at long ranges, however, lack of visual information and feature extraction is their main drawbacks. Cameras are used as a vision sensor for resolving this issue; these sensors are used in mobile robot since the early 1990s, however, dedicated visual-sensor-based SLAM has been done in 2011 by H. Lategahn et al. [52]. Furthermore, the monocular camera lacks depth measurement which is essentially required to estimate the distance from the location of the object. In the last few years, stereo camera and RGB-D [53,54] sensors are introduced in SLAM-based robots, which are compatible with depth measurements. RGB-D sensor is an advanced version of the camera with depth measurement. The first RGB-D SLAM system was introduced by Henry et al in 2012 [55]. Medium ranges RADARs were also introduced for autonomous mobile robots; RADAR-based robots are mostly short-ranged machines systems [56,57]. The RADAR-based SLAM problem is an emerging technology which has been done in 2014 by DICKMANN and Juergen et al [58].

2.3 Categorization of SLAM based sensor

SLAM-based sensors are classified into multiple front-end sensors these are classified into two to multiple sensors such as GPS, rotary encoders and IMU for localization of mobile robots as well as sonar sensors, LIDAR, RADAR, Microsoft Kinect sensor and Camera used for localization of landmarks and mapping. In this section combination of the different or single sensor has been discussed for localization and mapping.

2.3.1 Single Sensor

SLAM-based Single sensor are widely used for low-cost robots. It has been seen that it is not possible that a single sensor can be used for both localization and mapping. But encoder or GPS has been used for localization. Localization of landmarks such sonar sensor, LiDAR and visual sensor are mostly used for an autonomous robot. Advantages of single sensor SLAM based robots are less costly, low computational complexity and easy to handle. Table 2.1 shows the only approaches, pros and cons focus based on a single SLAM sensor.

Table 2.1: A literature review of single sensor-based SLAM

SLAM Sensors	Approach	Pros	Cons
Acoustic sensor	EKF [59]	Increase the return for estimation of pose and orientation	Error in building a map up to 7% due to large area
	Particle Filter [60]	Computational complexity and better accuracy in a dynamic environment.	Ignore Previous location, Orientation of mobile robot
	Kalman Filter [61]	Use of three sonar sensors, Grid-based mapping, Low cost, Low computational	Stack of the followed path, Manual operation, Discrete motion
Camera	EKF(Probabilistic)	Single-camera, probabilistic map, low cost, advanced robot	Static environment, Fast motion
	Particle Filter [62]	Multiple robots, More information, Use of corner detector for build precise map	Computational cost, Corresponding is low but occur
LiDAR	SVM classifier [63]	Build a map in three-layer, good obstacle detection, good accuracy and better real-time performance	Unable to distinguished items, high speed
	Coordinate Nodding on sensor data [64]	Developed 3D sensor with 2D LiDAR, 40-degree vertical movement	Complexity, accuracy, Mobile odometry error.
Kinect sensor	ORB SLAM (Smoothing based SLAM) [65]	Uniform speed model tracking, Path accuracy, lower computational complexity, Loop closure	Change of environment, Blur and track improvement
	R-CNN [66]	Identify a different kinds of objects, Dynamics environment, Semantic mapping, Fast algorithm	During the second phase, create an error during the dynamic error of static items

2.3.2 Multi-Sensors

As in the previous section, single sensor-based SLAM has been used by the different researchers. Multiple sensor-based sensors are also widely used for increasing precision and accuracy of the SLAM algorithms. One of the main reason for using multisensory, that every sensor has strengths and issues based on their parameter. Like sonar sensor and 2D LiDAR sensors are the best sensor for obstacle avoidance in SLAM but the drawback of these sensors are they cannot build 3D map and give more information about physical properties of landmarks. For this purpose, camera and Microsoft Kinect sensor are mostly used. But a drawback of these sensors is computational cost. Table 2.2 shows the advantages in SLAM based on Multi sensor.

Table 2.2: Literature review of Multi sensor-based SLAM

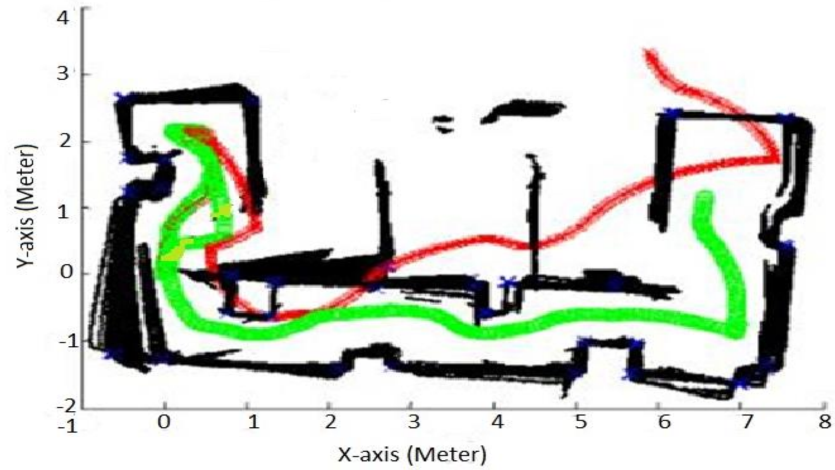
Sensors	Approach	Pros	Cons
2D LiDAR, camera	Particle filter [67]	Build a map for static environment, as well as dynamic observations, have been researched for detected with better reliability, Unmapped items.	Slow due to calculating particle weight, large data
Sonar and a CCD camera.	Hough transform, Kalman filter [68]	localization precision is highly improved	Dynamics environment, error in dead reckoning [estimation]
Kinect sensor and Sonar array	Rat SLAM [69]	Self-motion calibration, Place recognition, Unknown places (forest and building of college)	Online preprocessing of sensor and estimation of robot take 80% power of computer processor, Robot odometry
Lidar and Sonar sensors	Extended Kalman Filter [70]	Closure loop, low cost and computation complexity, static environment and	Manual interaction, Small environment
2D laser sensor,	Fast SLAM [71]	Creating of Image by laser sensor values, Low cost and computational	Range measurement, Edge detection

Acoustic sensor		complexity, Grid map generation	

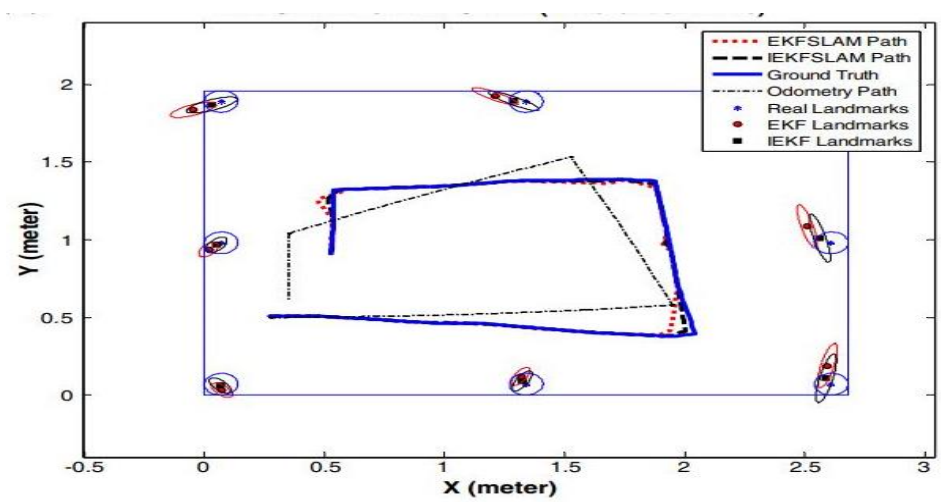
A humanoid robot was designed for SLAM that moves autonomously [72]. An omnidirectional robot was used for this purpose [73]. A two-wheel mobile robot was used for SLAM that is almost similar to this robot with EKF for localizing and mapping [74]. Four-wheel robots were used for SLAM using multisensory for improving accuracy of localization and mapping [75,76].

Different platforms are used for handling complex environment with average accuracy [73], such as maintenance, and robotic competition [77], soil sampling [76]. Ubuntu is used for Robotics operating system (ROS) [72] and Gazebo environment [73,76,77].

The laser range (LiDAR) is one popular choice among SLAM sensor [72, 74, 75, 76, 77]. On the other hand, RGB-D is also used for creating 3D map. EKF SLAM used for SLAM was completed with an indoor environment [74, 75, 78]. Santhanakrishnan et al. have implemented SLAM with EKF along with point features to increase accuracy with an average error of ±0.11m in map building and find 98% in localization as shown in Figure 2.2 (a). Shojaei et al. [80] have implemented SLAM with EKF with an Iterative kalman filter for better accuracy in map building. Localization was done with 83.82% accuracy. Mapping errors up to 0.2746 m in X and 0.4121 m in the Y direction shown in figure 2.2 (b).



(a)



(b)

Figure 2.2: Filter based SLAM (a) Build a map using Filter based SLAM for robot's trajectory [74] (b) EKF and IKF has been compared with each other

In [79] 2D and 3D map was generated by RGBD SLAM in ROS gazebo environment using ideal situation. The result was extraordinary because noise was negligible in the ideal situation shown in figure 2.3. In [81] fusion of Visual SLAM Algorithm and robot Odometry by encoders was performed by comparing based on the Kalman filter. Whenever, localization and mapping was carried for indoor environment with a distance of 43.47 m. Relative error of visual RGBD SLAM was 2.7%, as well as relative error of wheel odometry was 1.04%. Real-time indoor environment was used for performing visual SLAM as shown in figure 2.4.

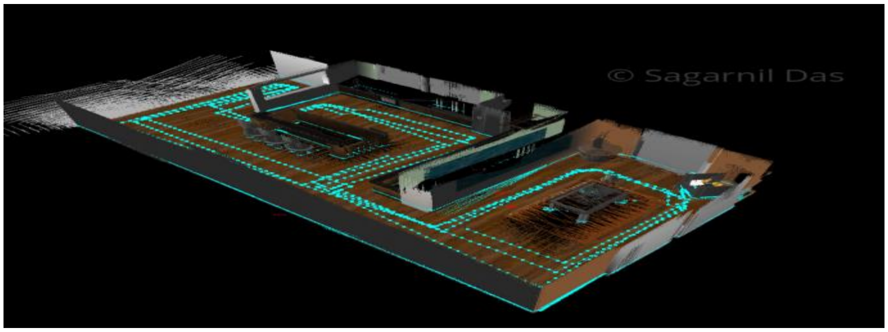


Figure 2.3: Robot localization with mapping in ROS (indoor gazebo environment) [79]

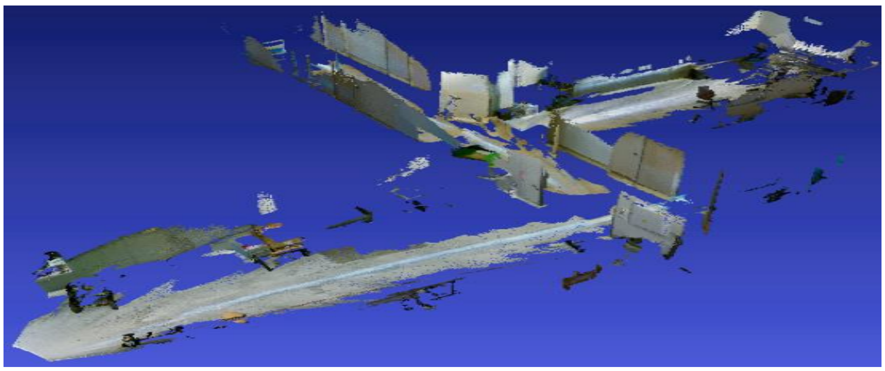


Figure 2.4: Real-time visual SLAM was implemented [81]

2.4 Literature Review related to Agribot based SLAM

In agriculture, a Mobile robot conduct different tasks such as chemical spray, checking of field, an inspection of fruit as well as picking of fruits. some of them are in the field of navigation and control, object tracking, and field monitoring. Unmanned Aerial vehicles (UAV) are also useful robots for agriculture. Novel sensor was used with fusion technique for navigating of sprayer robot. SLAM-based mobile robot are also widely used as agribot for localization and mapping by using multisensory fusion. Even, probabilistic robot was used same pattern by using the extended Kalman filter for distinguish between trees with the help of a laser scanner and camera. Reina et.al. worked on agricultural robot by using four sensors RADAR, LiDAR, stereo vision, and thermography for obstacle avoidance and mapping.

Autonomous agri-robots are intensively used to implement for agriculture for chemical spraying, planting, inspection and harvesting. Global revenue statistics of agribot system in the agricultural range up to \$7.4 billion in 2020 to \$ 20.6 billion by 2025. Robot are the best option for these activities in the field of crops. Another necessary option is also required that can possible for former to do in a field like harvesting and inspection show in table 2.3.

Table 2.3: Different research work on spray, inspection, harvesting and planting

Object	Parameter	Ref	Objective
Spray	Volume rate, Target location	[82]	Green House crop detection
	Detect weed species by a camera	[83]	Weed detection in carrot farm as well also remove disease
Harvesting	The visual camera has been used to determining target by feature (color, shape)	[84]	Low cost and simplest design for achieving the object
	Laser sensor has been used for determining features of 3D object	[85]	On the base of object obtain 3D feature, decide on the base of features

The main purpose of this literature is to implement SLAM for the indoor agricultural environment and localization and mapping. SLAM has been implemented in a simulated Gazebo environment using ROS. In this work, multisensory data has been used to implement SLAM for the agricultural environment. Different categories of sensors (Sonar sensors, LiDAR, Microsoft Kinect Sensor and build in Odomtery sensor) has been implemented for localization of landmarks and build a map of unknown environment.

CHAPTER 3: OPTIMIZATION OF SENSOR SELECTION PROCESS FOR SLAM

This section provides a holistic review of the SLAM-sensors which are widely employed in autonomous mobile robots. SLAM-based robots are largely dependent on sensing capabilities, therefore subject to their varied functionality; these robots are equipped with single or multiple sensors. In the front end of SLAM, different sensors like acoustic, Infrared (IR), camera, LiDAR, RADAR and RGB-D are used for sensing the landmarks of the environment. The selection of appropriate sensor plays an important role in the accurate measurement of landmarks during robot navigation. With the help of front-end sensors, the back-end algorithm constructs an artificial map, which is used for path planning and navigation. Obstacle avoidance during the autonomous operation of a mobile robot is one of the widely researched areas. One of the criteria for a reliable autonomous robot is the ability to sense its environment precisely and transmits the environmental conditions into the required signal for mobile robot actuation.

3.1 Characteristic of sensors

A variety of sensors are used for obstacle detection, landmark exposure, finding the robot's location concerning landmarks, pose and orientation. However, few major sensors have been discussed here which include acoustic sensors, cameras, RADAR, LiDAR, and RGB-D [86].

3.1.1 Acoustic sensor

The acoustic sensor is widely exploited in solving the SLAM problem because of its properties such as accuracy, simplicity, low power consumption (0.01-1 W), low computational and economical cost [87]. Sonar and ultrasonic sensors (also regarded as a subcategory of sonar stream sensors) are widely used acoustic sensors. Sonar transmits sound waves in the underwater environment [88] while ultrasonic sensor emits the ultrasonic waves on the ground surfaces and their measurements are characterized by frequency and wavelength. The sensor transmits an acoustic wave at a specific frequency and locates the object by sensing the echo signals from the object. In the case of the ultrasonic sensor, the waves travel in the air at the speed of light and bounce back after striking the landmark with the same speed. An object's distance can be measured by calculating the time of the signal from signal emission to echo reception [89]. Likewise, the position and location of landmarks can be estimated from sensor data using a back-end algorithm such as Particle filters and EKF [90, 91], more details are given in table 4.1 and table 4.2.

The measurement of the sonar sensors is more accurate in the underwater environment in comparison to the LiDAR and vision sensors [92]. Limited range is the only drawback of these sensors which is normally 2 to 10 meters. Due to their restricted range, these sensors are comparatively rare in industrial applications [93]. As microphones and speakers are also used as acoustic sensor, therefore, acoustic sensors are very cheap and they are useful for localizing landmarks, obstacle avoidance, and measuring the distance from a nearby object. Usually, sonar sensor actuates in an underwater environment at low-frequency [94] and ultrasonic sensors operate at high frequency.

3.1.2 Light Detection and Ranging (LiDAR)

Light Detection and Ranging (LiDAR) is a preferable sensor for mobile and aerial robotic platforms because of low computational cost, better measurement range, omnidirectional detection and environmental compatibility [95]. Robots can measure distance in 2-D and 3-D using LiDAR [96]. Feature and module of different LiDAR sensor in the literature review are given in table 4.1. LiDAR measures depth by sending and receiving laser light. Displacement and rotation of the robot is calculated by detecting the laser light line; these lines give information about the surface topography. The depth of an object can be measure by flight time [97]. Kalman filter is used to measure the position of multiple objects from LiDAR data. Ground filtration, surface extraction, and model construction of an urban building are performed by morphological transformation, Hogg transformation, RANSAC [98], CNN [99] and deep learning algorithms [100], more details are given in the table 4.2.

In the case of LiDAR, scanning angle, accuracy in measuring distance, angle and depth are important parameters used for detecting the landmarks [101, 92]. The sensor parameters are used for map creation and obstacle avoidance. In addition, LiDAR has high accuracy (even in environmental disturbances such as fog, storm and rain) as compared to camera and RGB-D. Similarly, while LiDAR has omnidirectional detection (360 degrees) as compared to the line of sight sensors such as camera, acoustic, RGB-D and infrared. LIDARs are generally classified as solid-state, mechanical and hybrid LiDAR [103], and they can provide 360^{o} visibility with high accuracy while measuring remote landmarks with a measurement range from 20-300 meters (with an accuracy of 15 mm). However, the power consumption of LiDAR sensors is very high (50-200 W).

3.1.3 Camera

Visual-based SLAM has increased its popularity in the last few decades and the camera is the most popular sensor used for SLAM. In the literature review, vision sensors are commonly used in SLAM-based robot because of simple configuration, and comparatively easy programmable techniques are used [104]. Two types of cameras are used for SLAM-based mobile robots such as mono-camera and stereo camera [105]. The first-time monocular camera is used in 2003 for the SLAM problem named as mono-Slam [106]. In the mono-camera, the main advantages are their simple hardware, economical, distance measuring, and smaller size but the disadvantage of these sensors is computation cost for measuring depth. However, a stereo camera can be used for reducing the computational cost while measuring depth because two cameras are used as one camera [107].

Feature-based and direct approaches are two techniques used for solving V-SLAM problems. A feature-based filter is used in feature-based approaches with the help of the Kalman filter [108]. The problem of this method is computational cost because it can increase the size of a state vector for a large environment. The loop closures problem can be solved proficiently with the help of a feature-based technique [109]. Another technique used for V-SLAM is the direct method; it uses images directly without using any feature. In this technique direct tracking, mapping method and LSD method are used. The dense technique is also used as a direct method and is generally used for measuring depth pixels by pixels in each frame [110]. Calibration of cameras (stereo camera, monocular camera) is always a requirement for measuring the accurate depth of landmarks. The intrinsic and extrinsic parameters of the camera are required to exploit the calibration. The pose of a camera can be found by an extrinsic parameter of the camera. The intrinsic parameter consists of focal length, focal point, principle points and pixel per unit length [111]. In machine learning and deep learning, CNN and regression is a technique used for solving visual-based SLAM, more details are given in table 4.2. The range of a monocular camera is dependent on the resolution of pixels and electronics of the camera with the combination of intrinsic and extrinsic properties of the camera. Power consumption for a monocular and stereo camera is 0.01-10 W and 2-15 W respectively.

3.1.4 Microsoft Kinect sensor (RGB-D)

Microsoft Kinect sensor is one of the widely used sensor in SLAM because of the combination of vision and range sensors as well as simple configuration, small and useful for 3-D and average cost-effectiveness. The digital value of this sensor is identical to the monocular camera with the inclusion of depth factor. The main feature of this sensor is the IR transmitter and receiver along with a monocular camera and works on SL (structure light) and TOF (time of flight) techniques. RGB-D sensor is released in November 2010 [112]. The hardware of RGB-D is compatible and needs low computational cost for working on it. It is mostly used in an indoor environment because the IR emitter and receiver don't make a fine pattern in the outdoor environment and generates noise. Feature and module of RGB-D sensors from the literature review are given in table 4.2.

RGB-D camera is an advanced technology in V-SLAM. It is similar to a camera that generates RGB color-based pixels, but the novelty of this sensor is depth. Methods studied for this sensor are Kinect fusion, SLAM++, and segmentation. The Kinect fusion method is used for representing a 3D environment with the help of voxel space. The SLAM++ method is used for recognizing the 3D object. Segmentation is used by the segmented object from each other according to their feature and depth [110, 113]. The general use of the Kinect sensor is segmentation. It is comparatively cheaper than LiDAR but is expensive than the camera. The measuring range of it is not very good. The power consumption of this sensor is ranging from 2-5 W. The procedure of measuring distance is very simple and accurate.

3.1.5 RADAR

RADAR technique is an emerging technology in the SLAM used for measuring long-range distance. A rotating antenna is used in RADAR for localizing the landmarks by emitting the radio waves. RADAR is a robust sensor and can work in every environment such as dust, rainy, day and night. A moveable antenna is stroked in RADAR and this antenna can rotate up to 360° degrees for environment data acquisition [114]. The RADAR used for mobile robots is smaller in size; its range varies from 3m to 40 m [115]. Range depends on the power of the emitted RADAR radio waves. The price of RADAR depends on its size; people design RADAR by IR, radio and UV wave [116]. Since the RADAR sensor lacks angular resolution as compared to LiDAR, therefore it is cheap. If we compare two different types of RADAR and LiDAR, such as MPR (RADAR) and Velodyne VLP-16 (LiDAR), the linear range of MRP is up to 20 m and Velodyne VLP-16 LiDAR can measure up to 40 m. Moreover, the angular resolution of LiDAR and RADAR is 0.4° and 1.8° respectively [117].

RADAR is a new sensor in the SLAM-based robot; some methods used for this sensor are identical with LiDAR. It is acquiring the data from each side in the environment, transmitting the radio signal while rotating the antenna and monitors the signal from these echoes. Its working principle relies on FMCW. The feature-based method [118], RANSAC, Kalman filter, and particle filter are used for processing the sensor data [119,120]. One of the other methods is used especially for RADAR is panorama for combining the whole side in one image for localizing landmarks [121]. Table 4.1, show sensors which were used previously for solving SLAM based robot; range, pros and cons along with the model of the individual sensors are discussed.

Table 3.1: Evaluation of SLAM sensors based on their features are discussed, such as pros and cons and model of individual sensor

Sensor Name	Type of Sensor	Operating range	Bias of Sensor
Acoustic	Ultrasonic or Sonar	Up to 4.5 m [122]	Low
Camera	Vision	up to 5m for Kinect camera	Low
LiDAR	Laser based	up to 20m ahead [117]	Medium
Radar	Electromagnetic	up to 20m ahead	High

The SLAM algorithm consists of various parameters such as sensors, generated maps and environment. These parameters are integrated employing varied methods such as extended Kalman filter (EKF) and particle filter. These algorithms are used to minimize errors in robot parameters such as sensor artifacts, robot status, and landmark positions. Through literature review, the most commonly used sensors are acoustic sensors, LiDAR, vision sensors, RADAR and RGB-D. These sensors can work in multiple environments such as underwater, indoor, dynamic and ground. Errors in sensors are very common, these include caused by man-made, random errors, corresponding errors and imprecision. Due to a similar location in the environment, the closure loop can produce errors. In the literature review, people have been solving these errors by using

SLAM-based algorithms (EKF, particle filter, and Fast SLAM) and also generate maps and locate landmarks as shown in Table 4.2.

Table 3.2: Uses of the sensor with different methods/approaches are deliberated like EKF, particle filter and others

Sensors	Approach Implemented	Loop Closure
Acoustic sensor	EKF [122]	No
	Particle Filter [60]	No
Camera	EKF [123,124]	Yes
	Particle Filter [125]	No
Lidar	EKF [126]	No
	Particle Filter+ scan matching [127]	Yes
	PCA line feature [128]	No
Radar	EKF+ICP [129]	No
	Particle Filter [116]	No
Kinect Sensor	EKF [117]	Yes
	Particle Filter [130,133]	Yes

Table 3.3 show the sensors, the feature of the specific model of the individual sensors is discussed.

Table 3.3: Evaluation of SLAM sensors by different models

Sensors	**Features**
Acoustic sensor	An acoustic sensor is a range sensor used for obstacle avoidance in mobile robots such as ultrasonic and sonar sensors. These sensors are the cheapest for measuring distance. HC - SR04 is an ultrasonic sensor rarely used for measuring range purposes. The ranging accuracy of these sensors is up to 3mm and resolution is much better, but the range of this sensor is not good. The range of this sensor is up to 4m [94]. IS JSN-SR04T is a sonar sensor used for mobile robot underwater. It is ordinarily used for underwater sensor; it can find distance underwater up to 4.5m. But linearity of it is not very excellent. It gives 35% when used up to 130cm.

Camera	Camera is a vision-based sensor used to acquiring more information about environment. It used image capture used for measuring accuracy of parts, orientation, and presence of obstacles. Computer vision is vital for self-driving in which vision sensors are used to capture an image of the environment. Two types of vision sensors are used for SLAM, which is the monocular and stereo camera. Vision sensors create a problem for measuring the accurate depth because of the different pixel values. The measuring distance range is depending on pixel value and its high resolution [124].
LiDAR	2D and 3D LIDAR are used for obstacle avoidance, a 3D Lidar sensor is detecting in a horizontal and vertical direction, Velodyne LiDAR Puck is mostly used as 3D LIDAR, it detects 360 degrees in left to right 15 degrees up and down. Range accuracy is round about 3cm. The range of this sensor is 100m. It is mostly used for design 3D modeling and mapping as well as for autonomous vehicle navigation. It is rotating parts are not available, so that why take resistance in challenge environments. YDLIDAR TX20 LIDAR is used as 2D Lidar, It detects information on the environment and acquires the angle information constantly. The range of this sensor is 20m. It has a precise and stable performance. It is a much expensive sensor for design cheap sensors and also it is a two-dimensional Lidar [53].
Radar	Radar used electromagnetic waves for detecting, tracking, recognizing and localizing the object. Radar used for a mobile robots is small and portable. MRP is radar used for short-range. The range of this sensor is 20m. It can encode more complex and partial evaluation signals; it can operate at a different frequency for short and long-range purposes. It is mostly used for long-range and specifically used for military purposes [57]. UWB Radar is also used for a mobile robots. The range of this sensor is also 20m. It can operate well in smoky and dusty weather, also can filter dielectric material due to low frequencies. Availability, dynamics range and time stability are very good. Localization and positioning accuracy with the help of UWB Radar is mostly achieved by the advanced algorithm. Overall, it is computationally complex and expensive.

Microsoft Kinect sensor	RGB-D Xbox 360 sensor gives 640x480 full sensor resolutions at the video frame rate 30Hz. It needs a high GPU system, needs so much computational complexity [19]. Kinect v2 is an upgraded version sensor Its function works on the Time-of-Flight camera. It gives good resolution up to 1920x1080. Due to high resolution, it requires more time to solve and needs more computational complexity [155].

3.2 A Comparison of SLAM Sensors based on parameters

Every sensor has unique properties, which empowers the specific sensor with most significance over other competitive sensors. Depending upon that specific novelty, sensor selection depends upon cost, environment (workspace), computational cost, accuracy and measuring range (space requires during sensing). Each system has a different priority; it should not be too much expensive and sometimes accuracy is the requirement. Among multiple sensors, the sensor's ability to perform well in the desired environment and range measurement are the top priorities.

3.2.1 Computational Cost

The computational cost plays an essential role in the selection of the SLAM sensor. The computational cost is an important aspect while working on SLAM based mobile robot. The calculations performed on SLAM-based mobile robot are very complex because of complex acquisition signals; therefore, sensor data requires high specification computer hardware for solving such data. To achieve high accuracy in localization, the computer's microprocessor should be very fast. Implementing such a demanding process on the embedded microcomputers is the real task. For example, a vision sensor camera provides abundant information in the form of a pixel. A camera with 1024x840x3 pixels provides 2.5 megabytes' data in one count, for running the process smoothly computer or microcontroller should have good processing speed, which is very hard for microcontrollers to handle. The camera gets all data in digital form, i.e. big matrix, which increases the computational cost in comparison to other sensors. RADAR rotates 360^o during landmarks localization, panoramic method is used to integrate all direction data in one image or matrix; this needs a remarkably high capacity RAM and processor. On the other hand, LiDAR is a good sensor for use in average computer hardware or microcontroller. It provides the required information in every possible direction of the robot and the required signal of the sensor needs a low microprocessor system. The acoustic sensor is also a good choice because of its low computational cost. Camera-based systems give blur images during movement.

Most visual SLAM sensors are solved by two methods i.e. feature-based and direct method. The feature-based method depends on features, for solving such methods demands less computational cost. On the other hand, the direct method needs high computation cost because of a lot of mathematics. However, during movement, the feature-based method doesn't perform well, it is possible to miss features during landmarks localization as well as direct method needs high computation cost, therefore mostly LiDAR or sonar sensors are used in the SLAM field while computational cost is a superior factor. RGB-D sensor properties are also related to a monocular and stereo camera without distance measure (like RGB-D, RGB is a parametric factor as in-camera and stereo but D is a distance measure extra factor used for range measuring). Based on these parameters and literature reviews, I assign priorities (for every cited sensor) on AHP. The result of AHP is shown in figure 3.1.

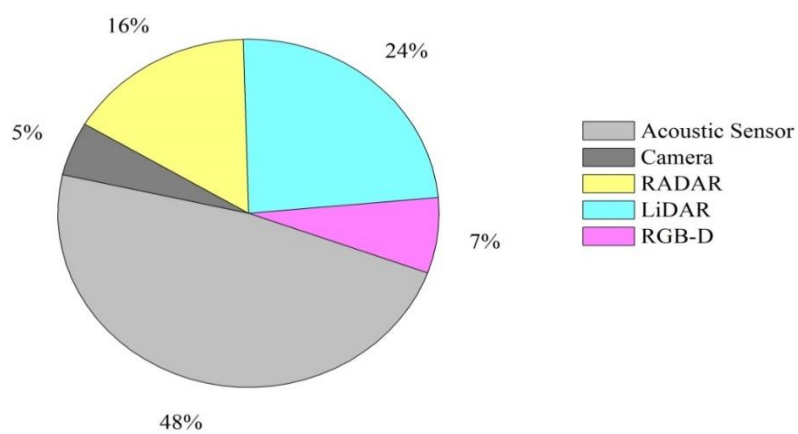


Figure 3.1: This figure illustrates computational cost for different SLAM sensors (Calculate from AHP), higher values show lower computational complexity.

Figure 3.1 shows the computational cost for SLAM sensor's higher values with lower computation cost based on the Analytical hierarchy process (AHP). The acoustic sensor needs a minimum computer hardware system for solving that composed of one digital value like 2 to 5 m for SLAM based robots, however, all cited sensors require good computational hardware. LiDAR signal need an average microcontroller and computer hardware system for solving. The signal emitted from LiDAR consists of 25 to 360 digital values depend on the angular resolution. The computer can solve these numbers of digital values very smoothly. RADAR comes next in priority in SLAM sensors. The signal received from RADAR is also similar to LiDAR but needs a panorama method for its integration, which increases its complexity. To solve vision sensors and RGB-D sensor signals, the system needs a very complex algorithm. For SLAM sensors, researchers used computer specifications as given in table 3.4.

Table 3.4: A survey of software systems required for sensors.

Sensor	Specification
Acoustic	Intel Core i5-3317U 1.70 GHz CPU and 16 Gb RAM with MATLAB 2017a and vision toolbox software's [132]
Camera	core i7-6700 CPU with 64 bit Ubuntu Linux [133]
LiDAR	Desktop PC with 6 GB RAM along with 64bit Operating System and 2.27 GHz Intel(R) Xeon(R) processor [134]
RADAR	An Intel i7-5557U processor, 16 GB RAM, SSD storage [135]
RGB-D	Intel Core i5-6600 CPU (four cores @ 3.30 GHz),16 GB of RAM and Raspberry Pi(4) microcontroller with 4 GB of RAM are also used [136]

3.2.2 Measuring Range

For a mobile robot, the ability to measure accurate range is an important factor and in monocular vision sensors, range measurement is a major issue. Usually, a stereo camera sensor is utilized for range measurements; however, its accuracy is low as compare to LiDAR, sonar, and RADAR. In RGB-D, data acquisition raises complexities for range measurement and needs the best computer for solving range measurement algorithm but depth measuring parameter (RGB-D D is a parameter for measuring depth) superlative as compare mono-camera and a stereo camera. Sonar sensors are low cost and they possess a lower measurement range (2 – 5 m), which is insufficient for an industrial mobile robot. RADAR sensors are popular in mobile robots for long-range measurements. LiDAR (20-300 m) is the preferred choice for range measurement in comparison to other sensors because of low computational cost as compared to the stereo camera, RADAR and RGB-D. Figure 3.2 shows the bar chart of measurement ranges of the individual sensor.

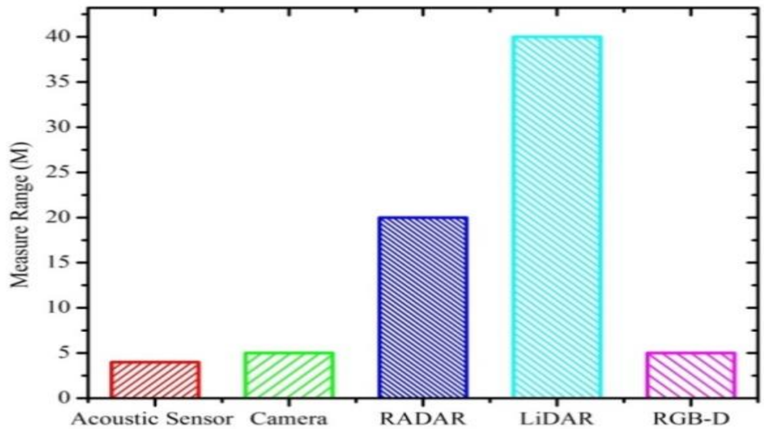


Figure 3.2: The average measurement range limits are based on the literature for autonomous mobile robot, in which LiDAR is superior for mobile robots with a given range and the camera is not cool for range measuring

3.2.3 Environment

A self-exploring mobile robot encounters number of environmental-related challenges such as complex geographical features and obstacles. Every SLAM sensors has certain limitations in different environmental conditions. Ideal SLAM sensors should be robust enough to work perfectly in different environmental conditions such as during a bright and sunny day, dust, rain, or smoke. The performance of camera is heavily compromised in the previously cited conditions. This can lead to fatal errors in data acquisition and interpretation, for example, at night camera gives all-zero digital values in an image. However, IR cameras can work well in bad weather conditions with a major compromise in the accuracy in case of rain and smoke. Similarly, the Kinect sensor also has some drawbacks such as pixel by pixel digital data (can be zero while night or smoke environment condition) similar to vision sensor. LiDAR perfectly works in every environment without underwater [91]. A sonar sensor also works in every environment, but these sensors generate artifacts in data acquisition. Keeping in view the above pros and cons, RADAR is one of the best choices for working in every environment without any compromise inaccuracy. Figure 3.3 shows the efficiency and compatibility ranking of different SLAM sensors in multiple environmental conditions. Based on these parameters and literature reviews, I assign priorities (for every cited sensor) on AHP. According to the AHP results, RADAR works well in different environmental conditions while Camera and RGB-D are equally ranked and have lowest performance in case of bad environmental conditions such as smoky and rainy weather.

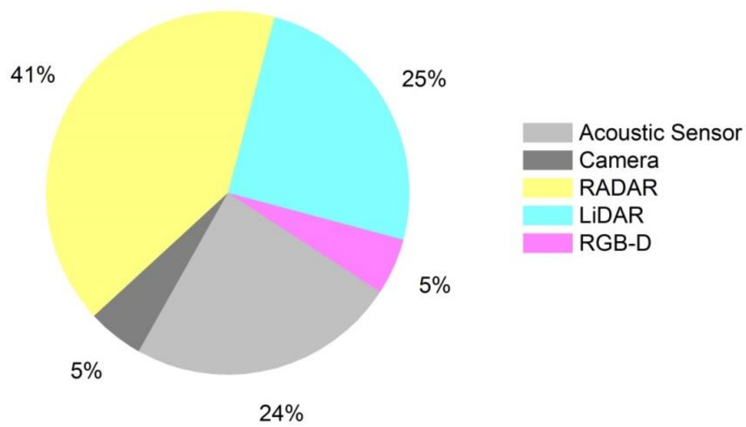


Figure 3.3: Pie chart represents compatibility ranking of the listed sensors in multiple environmental conditions; selection priority will be given to the sensor which has high compatibility indicator (value) estimated by AHP.

3.2.4 Cost-effectiveness

Cost is another major factor to keep in mind for selecting the SLAM sensor because every designer desires to make a low-cost autonomous robot. It is hard to compare the sensors while concerning cost because the cost is dependent on the properties of sensors like accuracy, size, life, range, and resolution. The acoustic sensor is one of the cheapest sensors among all SLAM sensors. Monocular camera is a little bit expensive as compare to the sonar sensor but less expensive as compare to other cited sensors. RGB-D has widely used in the field of SLAM-based robots and it is average expensive but it is good in computational complexity as compared to camera. RADAR is also a new emerging sensor and has different prices depending on the properties; RADAR used for the autonomous robot is not so much expensive as compared to ordinary RADAR because of small in size. LiDAR is the most expensive sensor used for a mobile robot, but the cost of LIDAR is drastically changed from time to time depending on their properties (Angular resolution, Range Measurement, Range resolution, Scan angle and others) [137].

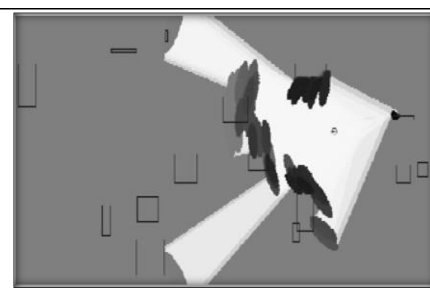
3.3 Map Building in SLAM and Sensor Used

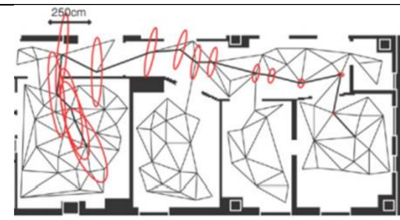
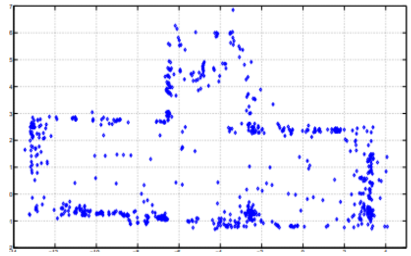
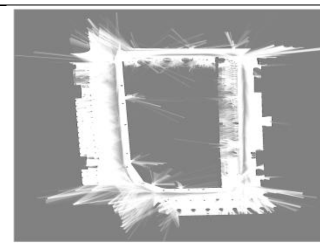
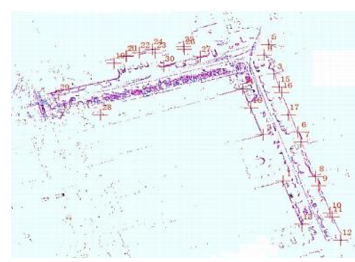
The map is a symbolic representation of the environment in SLAM, where robots localize themselves and landmarks. The map has two mediums, static and dynamics. In a static map, every object in the environment is static. The sensor output is combined after finding a proportional scale of the object to the stationary world for build a map of static environment called active mapping

[138]. In a dynamic map, objects are in movement and continuously change drastically the environment. Various classifications of SLAM have been discussed based on its work. SLAM map-based classifications are online, offline, active and full SLAM. In online SLAM, a previous and current pose of the robot is estimated in the perspective of the map. In full SLAM, it estimates both maps and completes navigated path (History of a path) by the robot in the map. In Active SLAM, the robot actuates autonomously and acquires data of the environment for mapping. On the other hand, in passive SLAM, the robot is actuated manually and receives the data with the help of sensors autonomously.

In the real-world, the static environment is not true because people, cars and animals are moving. The two types of dynamic objects are identified, such as high dynamic objects and low dynamics objects [139]. In high dynamics, objects are changing their location abruptly and sensors observe such types of objects for a short time. On the other hand, in the lower dynamic object, the object moves with low frequency even mostly sensor cannot observe the movement of objects such as movement of the door, furniture movement etc. A sensor with good accuracy can detect abrupt changes. Table 3.4 shows that different approaches have been used for building a map by using different sensors.

Table 3.5: Survey of build mapping with help of sensor in a different environments is given.

Main Features	**Mapping Output**
Acoustic Sensors	
The acoustic sensor can be used to create a 2D map of the environment while keeping track of the obstacles the robot might face during its course of action. These sensors when combined with the Gaussian random variables can minimize the mapping uncertainty significantly, shows the figure of result [140] with the permission of copyright Elsevier 2017. Another method to generate a 2D map using acoustic sensors is SONAR. However, this type of mapping is limited to the provision of grid mapping [89]	 Environment: Indoor
Camera	

Vision-equipped robots proved to be very useful in carrying out the task of SLAM. The use of cameras facilitates the localization of robot, camera and robot interaction networks make the exploration easier. However, these systems suffer from the challenges of camera calibrations, shows the result of copyright images with the permission of Elsevier 2006 [141]. Another advantage of using camera systems is the ease in collaboration of multiple robots and their observations which can work together to extract the visual landmarks for better loop closure [142]	 Environment: Indoor  Environment: Indoor
LiDAR	
LiDAR sensors are usually used for long-range measurements and are more accurate than ultrasonic sensors. Moreover, even with lesser accuracy, these sensors can attain highly dense observations which can easily detect special features like corners in indoor environments [143]. Despite the advantages of LiDAR sensors, loop closure is always a challenge to attain due to the difficulty in extracting key features. Therefore, these sensors are often paired with various control networks for the back end optimization [144]	 Environment: Indoor  Environment: Outdoor
RADAR	

<table>
<tr><td colspan="2">RADAR sensors proved to be substantially useful for outdoor SLAM because of the provision of relative map observations. This makes map management and data association handling easy in practical outdoor environments [145]</td></tr>
<tr><td colspan="2">Kinect</td></tr>
<tr><td>Kinect sensor belongs to a special class of vision-based sensors where the sensor can produce a 3D environment reconstruction. These sensors perform with much better accuracy as compared to the LASER sensor, however, its limited field of view makes its applications limited in many practical applications [146-147]</td><td>
Environment: Indoor</td></tr>
</table>

3.4 Optimization of Selecting SLAM Sensors process using Analytical Hierarchy Process

The AHP method is a technique used for the selection of objects based on their properties. It is a decision-making approach introduced by Thomas Satay [148]. It is used for different applications such as healthcare items, industrial sensors and government substances. It is a mathematical implementation and useful approach for dealing with decisions making of a complex problem. The goal of this technique is to select the most suitable leading category. In this technique, the decider sets priorities according to his experience and based on his priorities, this technique gives suitable decisions in the selection of categories, as in our case it will calculate the sensor value mathematically.

Multi-Criteria Decision Making (MCDM) is a method used in the normalization technique to generate an aggregate of the categories, an important point of this method is to find the best result from a set of priorities. Data normalization is a necessary part of the decision-making process, that transfers input data into numerical data to comparing the result, rate and ranks for selecting the best items. The AHP covers mathematical properties (of SLAM sensor) and required preferences such as cost, computational complexity and reliability for the environment, and range. The complexities of a problem can be reduced by converting each preference into pairwise comparison show in figure 3.5 [149].

3.4.1 Mathematical Model

AHP is an effective tool for setting the decision making the weight of evaluation criteria for alternatives and built a process for weighting design criteria in a way, the process should be consistent. After setting the criteria, assign a score to all alternatives based on decision-maker pairwise comparisons criteria. The score values are always given within a range of 1-9, which shows different categories. Higher the score of the respective alternative, the better the performance of the alternative. In the final stage, from alternative and criteria matrix find the final weight global weight score, and achieved priority ranking of alternative to each criteria shows in figure 3.4.

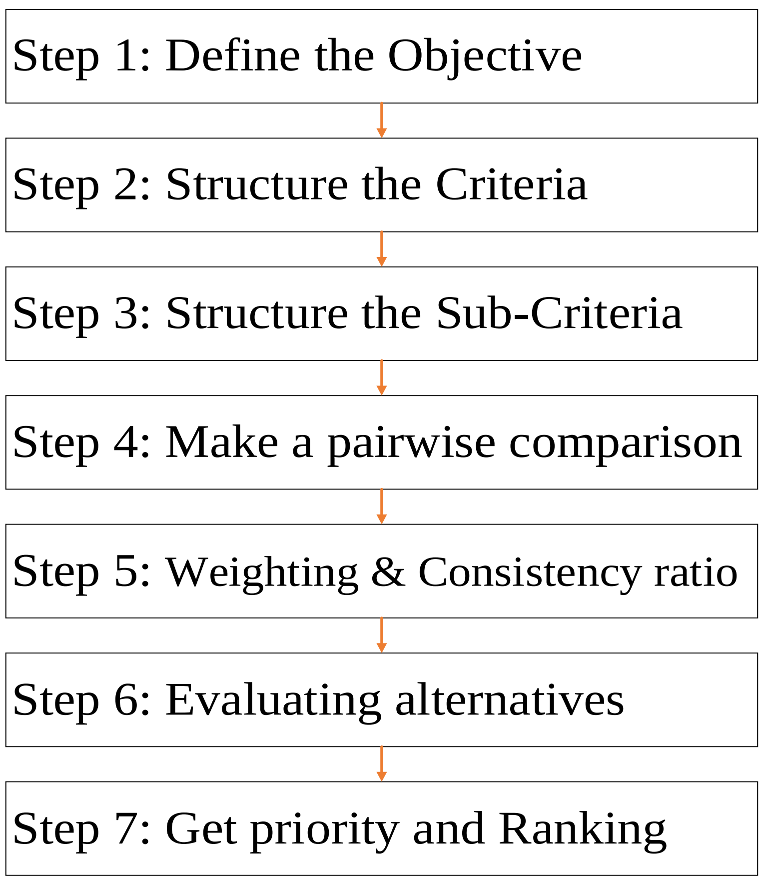


Figure 3.4: AHP block diagram

The main object of using AHP is the selection of the best sensors for SLAM, these are consisting of proximity sensors as discussed at starting of this section. Cost-effectiveness, measuring range, computational cost and environmental behavior has been set as criteria for the selection of sensor. These have been briefly discussed in section 3. Acoustic sensor, Camera, LiDAR, RADAR and Microsoft Kinect sensor have been set as sub-criteria for selection of best sensor, briefly discussed in the section this section also shown in table 3.6. Pairwise comparison has been done from the 1-9 range according to standards based on table 3.7. This table has been build based on literature review as well as figures shows in this section such as 3.1, 3.2 and 3.3.

Table 3.6: Parameter used for AHP

AHP parameters	**Selection**
Selection of goal	SLAM Sensors
Criteria	Cost-effectiveness, measuring range, computational cost and environmental behavior
Sub-criteria	Acoustic sensor, Camera, LiDAR, RADAR and Microsoft Kinect sensor

Table 3.7: Pair wise comparison for AHP matrix

Sr. no	**Sensors**	**Range(m)**	**Computer complexity**	**Environment**
1	Acoustic	2-5	Excellent	Good
2	Cameras	N-A	Very Bad	Bad
3	LiDAR	50-300	Very Good	Very Good
4	Kinect sensor	5	Bad	Very Bad
5	RADAR	Depend on Size	Good	Excellent

AHP technique verification can be found through the following parameters. Consistency ratio (CR) is a ratio of Consistency Index by corresponding random matrix. The consistency ratio must be less than .01 values for consistency of weights. Equation 3.1 shows the A is multiple stones with W weights. The multiplication result of $A.W$ is λmax. W, λmax shows the larger eigenvalues of matric. All eigenvalues are zero except one. So the sum of the eigenvector is equal to the trace of matrix A. On the other hand, to make W unique normalization has been done on its matrix by dividing its values by their sum. λmax ≥ n shows that A is consistent if it is verifying.

$$A.w = \lambda max.\, w \qquad \lambda max \geq n \tag{3.1}$$

Small changes in A implies the λmax, the deviation of latter from n make a deviation in n from consistency called consistency index (CI). The formula of CI is given in equation 3.2.

$$CI = \frac{\lambda max - n}{n-1} \tag{3.2}$$

A= Pairwise in the form of Vector

W= Normalized weight in the form of Vector

λ_{max}: Maximum eigenvalue

n: Eigenvalues of A

a_{ij}: Numerical pairwise values i and j

The average consistency of consistency index at the same matrix index is called random index (RI). Then the ratio of consistency index by the random index is called consistency ratio shown in equation 3.3. Values of CR less than .1 show the inconsistency in setting the criteria or sub-criteria.

$$CR = \frac{CI}{RI} \qquad CR \leq 10\% \tag{3.3}$$

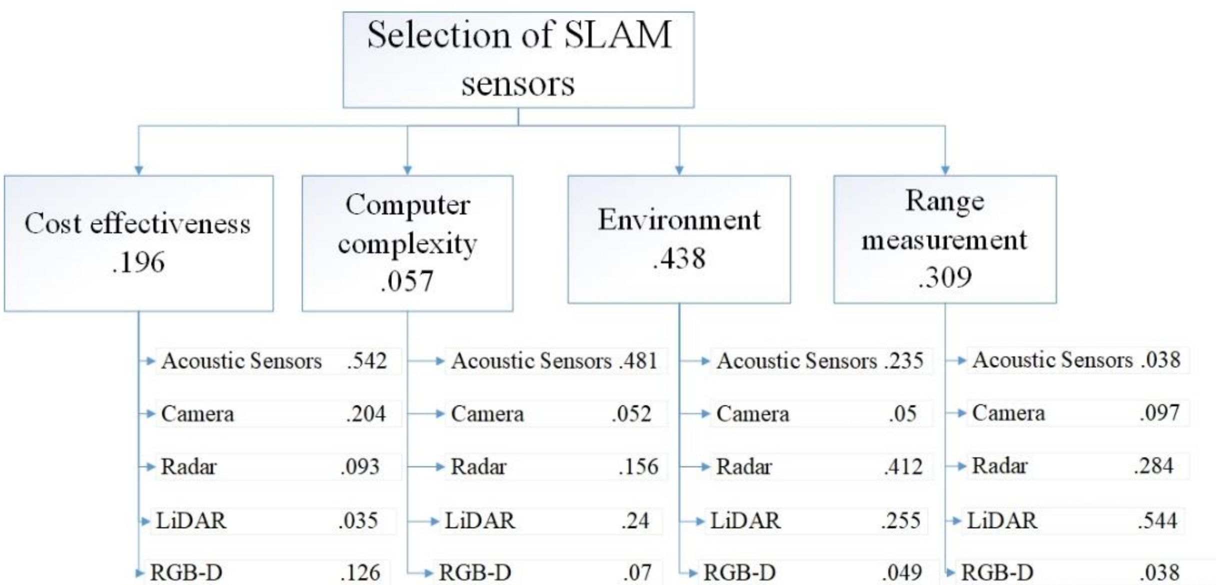


Figure 3.5: Analytical rating process (AHP) for the entire sensor is based on cost-effectiveness, computational complexity, environment and range measurement. Some of the priorities are set based on the requirements and the category is prioritized.

Our requirement for selecting SLAM sensors consists of some priorities such as cost-effectiveness, computational complexity, environment and range measurement. These priorities can be changed based on requirement depend on the user; people live in developed countries give more emphasis on accuracy, working in environment and range. However, people from underdeveloped countries give more priorities to the cost and computational complexity of sensors. According to this, we have set priorities based on literature reviews from multiple research papers, and gave more importance to the environment and range measurement for our mobile robot. SLAM sensor's priorities are also shown in figure 3.4 with the help of the AHP technique.

The analytic hierarchy process comprises five sensors (Acoustic sensor, Camera, RADAR, LiDAR, and RGB-D) that has been shown for the SLAM problem. Figure 3.4 shows the acoustic sensor is a superior sensor based on cost-effectiveness and the vision sensor ranks second. In the priorities of the environmental factor, RADAR seems one of the best sensors to counter environmental problems and LiDAR is on the second mark based on numerical value. Based on computational complexity, the acoustic sensor seems one of the reliable sensors and LiDAR can also be used for lower computer specifications. While considering range measurement as the prime factor, LiDAR is the best choice with the range capabilities of 20-100 m.

Table 3.8: Final Results based on Analytical hierarchy process (AHP).

Sensor Type	**Priority**	**Rank**
LiDAR	30.03%	1
RADAR	29.53%	2
Acoustic Sensor	24.83%	3
Camera	9.48%	4
RGB-D	6.19%	5

According to the AHP method, we can thus summarize that LiDAR can be the best sensor because of its best range measurement, good performance in every environmental condition and compatibility with average computer hardware. RGB-D is last because of its range, environmental reliability and cost-effectiveness. Our priorities (cost-effectiveness, computational complexity, and environment and range measurement) are shown in table 3.5 for SLAM sensors (acoustic sensor, vision sensor, LiDAR, RADAR, and RGB-D). This calculation has been done online in the AHP software [150].

CHAPTER 4: RGBD SLAM AND FILTER BASED SLAM

In this chapter, different step and component of robot has been described. First of all, a multisensory SLAM-based two-wheel robot has been designed for performing experimental results of SLAM, block diagram has been shown in figure 4.1.

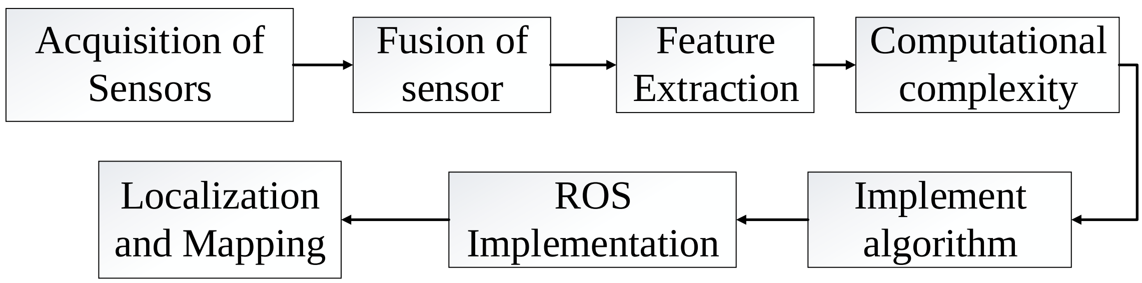


Figure 4.1: Real-time mobile robot process that has been used for an experimental result

A well-known controller has been used with an average cost microcontroller and integration of Bluetooth and WIFI called ESP 32, It is developed by espressif system (Shanghai-based Chinese company). It is a very high-speed processor 160 to 240 MHz with a single core and dual-core. The reason that has been used is because of its pin configuration and Wifi module, we can make any digital pin as interrupt and there is also two pins that we use as DAC for using analog value. Further information is including in Table 4.1.

Table 4.1: A detailed information about ESP 32 that make it more superior to another controller

Sr	Feature	Values
1	Xtensa dual-core	160-240 MHz
2	WiFi module	802.11
3	Bluetooth module	v4.2 BR/EDR and BLE
4	ADC	18 x 12
5	DAC	2 × 8
6	TX/RX	8 Channel

LiDAR and Microsoft Kinect sensors have been used for localization of landmarks and building a map of the environment. LiDAR is a well-known sensor used for SLAM-based mobile robot for building the map and obstacle avoidance as well as used for range measuring. Working of this sensor is like it emits the laser waves and received the laser waves then can measure the distance by time of flight. LiDAR is also used for 3D mapping and navigation for a mobile robot. The first time LiDAR is introduced by Hughes Aircraft Company in 1961. Hokuyo LiDAR sensor has been used with mobile robot for measuring the range.

Microsoft Kinect sensor is consisting of a depth camera, RGB camera, microphone and IR sensor for night vision. Kinect sensor is the line of motion sensing input device used for building the 3D map in SLAM. This device is produced by Microsoft and released in 2010. Mostly popular application of this sensor is gamming; people mostly used Xbox 360 for gaming purposes. From table 3.8, we can see RGBD sensor has been ranked 5^{th} number, but this sensor has been preferred to be used in SLAM experimental and simulation result due to requirement of depth values for building 3D mapping. 3D LiDAR is used for building the 3D map but is expensive. Low cost sensor such Microsoft Kinect sensor is used on the basis of literature review and requirements, they used other sensor for fulfil the requirement of LiDAR.

Ultrasonic or sonar sensors are widely used for measuring range and obstacle avoidance. It is one of the cheapest sensor that why people mostly used for a different purposes. There are three categories in this board such as a transmitter, receiver and transceiver. Working of it is, it emits the Sonar sensor wave from a transmitter and receives these waves from receiver and transceiver is used for converting these waves into an electrical wave. The main purpose of this sensor is to minimize the time duration as well as computational cost.

In the SLAM, different methods are used for finding the localization of mobile robot and landmarks and create a map of the environment. Rotary encoder and GPS sensors are frequently used for localization in indoor and outdoor environments, respectively. Rotary encoders generate the number of pulses per revolution as an output signal; to identify the position and speed of the robot as well as the location of the landmarks. The Global Positioning System (GPS) is a satellite-based radio navigation signal to estimate the position, velocity and time of a mobile robot. The signal of GPS can only be detected outdoor and it is widely used as a robust and accurate system for localization, however, it is quite expensive as compared to the rotary encoders. In a rotary encoder, the initial position of the robot is difficult to predict, whereas, in GPS, the estimation of position and speed is complicated, additionally, GPS is less accurate than encoders. Some of the properties are given in table 4.2.

Table 4.2: A brief comparison of Global positioning system (GPS) and Encoders

GPS	Encoders
The Global Positioning System (GPS) is a satellite-based radio navigation.	Encoders provide the current orientation, position and odometry information.
Provides high precision capabilities	Provide high reliability and accuracy with the advantage of being compact in size.
The GPS needs to be coupled with INS/Encoders to overcome the noisy GPS receivers [49]	Subject to direct light or radio interferences

In this project, rotary encoder has been used with high torque motors. Due to high torque and current, a Monster H-bridge is used. Monster H-bridge is used for driving the DC motors; we can see that after 3 to 4 min, due to high current IC burn. For this purpose, Monster H-Bridge has extraordinary performance for reliability. It can bear up to 30A. Its max PWM frequency is up to 20KHz.

ROS-based agriculture artificial environment has been created for inspection of crops in the simulated result and implement SLAM in indoor environment such as green house. For this purpose, Microsoft Kinect sensor, LiDAR, Sonar sensor and encoder has been used for the robust result. A holistic review of these SLAM sensors has been discussed in the early section. And the reason for choosing these sensor has been also discussed in the previous section based on the AHP process.

SLAM-based techniques are an emerging fields and lot of experimental results are going on the research side. Based on our requirement and setup of agriculture environment, mainly filter-based SLAM and RGBD SLAM has been used for indoor agriculture in indoor environment. RGBD-SLAM is the best technique using for visual 3D mapping and localization. The only visual sensor can give much more information for agriculture crops. Based on RGB camera and depth camera, a map can be generated for analyzing the quality of crops. For this purpose, RANSAC and SIFT technique has been used that is part of RGBD-SLAM technique. A method that has been used for achieving our result is given in figure 4.2. The identified point feature estimate 6D transformation by using the RANSAC method in RGBD SLAM. Rigid transform combines the rotational and translation motion, find the best optimized rigid transform T ($T_p=R_p+t_p$). Iterative closest point (ICP) is used to build a 3D map by using point cloud of LiDAR and RGBD sensors, and by using this technique localize the position of robots and accomplish optimal path planning. Initial inputs are required are classified as reference point clouds and source point clouds, initial transformation, on the behalf of these parameters ICP give output in the form refined transformation.

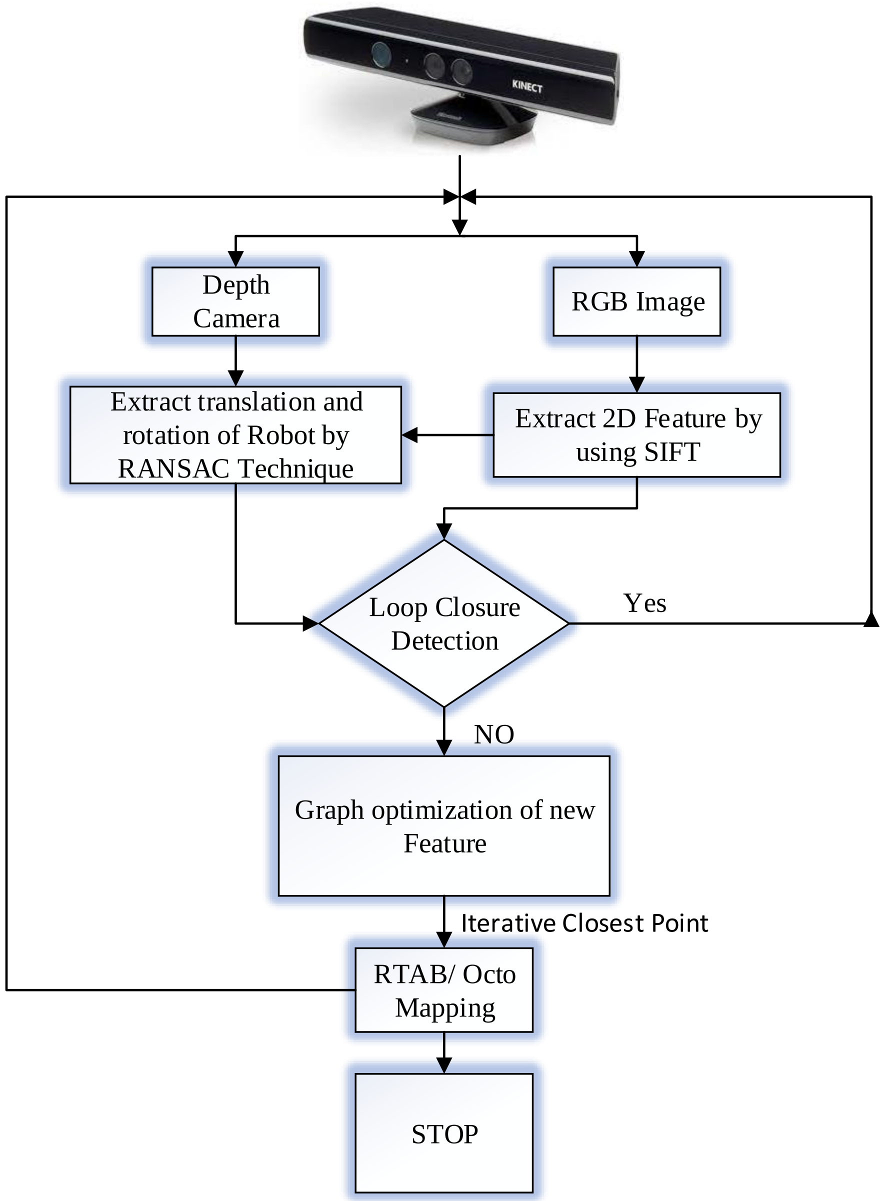


Figure 4.2: RGBD-SLAM block diagram for localization and mapping with Kinect sensor

Filter based SLAM are classified into many techniques has been discussed in the above section, but a memory robust method has been picked for completing our experimental and simulation for operating it smoothly without needing high computational performance. On the base of the literature review, a table gives detail about how much good and high-performance computer has been used for completing these high-quality methods. For this purpose, an Extended Kalman filter has been used because this method is good for compensating the average computer. A table has been given for discussing parameters for EKF used as compare to the particle filter.

Table 4.3: Difference between EKF and Particle filter

Sr no	Properties	Kalman	Particle
1	Time Duration	Fast	More time required due to particle (so time need 5000 particles)
2	Efficiency	Less than 100% but give good result	Accurate (Depend on the number of particles)
3	Computational Cost	Less	Much
4	Memory	Less memory required for storage past states	More
5	Solution	Exactly	Approximate
6	Prediction	Only signal state for correction	Multiple state due to weights
7	Implementation complexity	Fewer iterations (Simple)	More iterations (Complicated)

Extended Kalman filter is used in a different platforms other than SLAM, detail mathematical procedure and methodology is given in the next section. Robot deals with different classifications such as the present state of the robot, sensor measurement, controlling the robot and generating the map of the environment.

4.1 Extended Kalman Filter

Extended Kalman Filter (EKF) (SLAM based) is a technique used for estimating the state vector that contains the robot pose which consists of landmarks and the location of the mobile robot. EKF is the procedure, in which the nonlinear model measures the current state and the new state estimate. The reason EKF has been used is because of its simple implementation and straightforward method. EKF consists of two processes in which first we predict the next state and then correction process in which, on the basis of landmarks correction will be done with covariance vector.

In SLAM, the robot needs to deal with numerous tasks such as the current state of the robot, sensor measurement, robot control and environmental map building. Let the current state of the robot be *'X_k'* that represents its position in the *XY* plane. The robot updates its position or state according to its path and control input from $k = 0$ to k = ȸ. The input control stimulus or execution of action *'U_k'* can be measured by varying the robot's direction and position which acts as a control input (linear velocity or angular velocity of wheels). The current state can be identified from sensor data such as a rotary encoder or GPS. *'Z_k'* is another sensor measurement in SLAM and under that, the robots can distinguish objects in the environment and construct an artificial map 'm_i' of the landmarks using an obstacle avoidance sensor. Figure 5.1 shows the error between the estimated state and the real case with the SLAM algorithm.

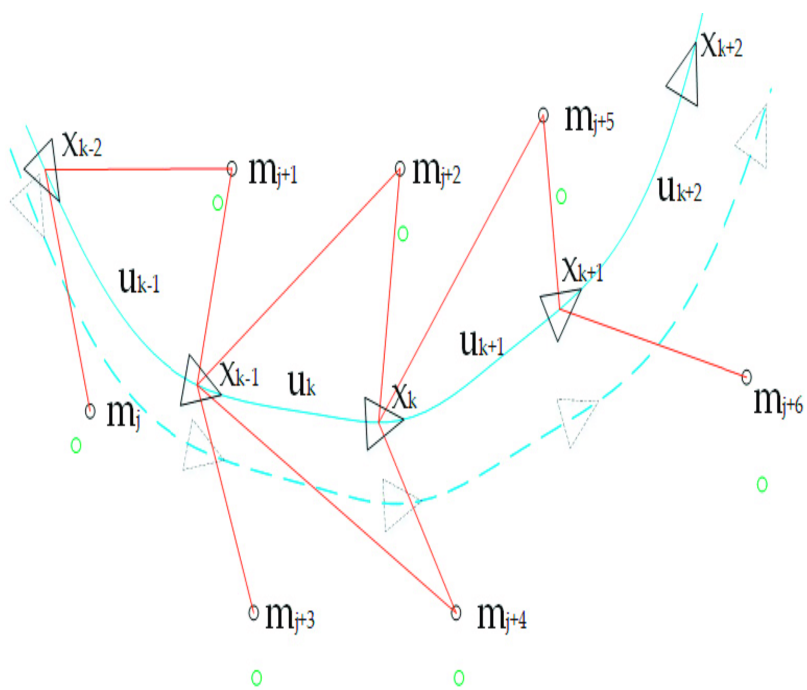


Figure 4.3: SLAM states, control, environmental mapping and sensor data acquisition used for measuring predicted location (estimated location) of landmarks and correction by using SLAM algorithm [151]

4.1.1 Prediction

The prediction process is used for kinematics and movement of a mobile robots; in which we are only discussing the next state that what will be the next state based on the control vector. The next state of the robot's odometry measurements were obtained from wheels' encoders and width and radius of mobile robot for the angular velocity of both wheels. The new pose or state of mobile can be determined by turning or moving forward. As discussed, the current pose (x, y, θ) and movement of the mobile robot depend on angular velocity of both wheels (l and r) that we can get from wheels' encoders; this kinematic-based model has been derived from [128].

The full derivation of Kinematics model for Prediction step

$$r = \alpha (R + W) \tag{5.1}$$

$$l = \alpha R \tag{5.2}$$

$$r - l = \alpha W \tag{5.3}$$

$$\alpha = r - l / W \tag{5.4}$$

$$\begin{bmatrix} C_x \\ C_y \end{bmatrix} = \begin{bmatrix} P_x \\ P_y \end{bmatrix} - (R + \frac{W}{2}) \begin{bmatrix} \sin \theta \\ -\cos \theta \end{bmatrix} \tag{5.5}$$

$$\theta' = (\theta + \alpha) \bmod 2\pi \tag{5.6}$$

$$\begin{bmatrix} P'_x \\ P'_y \end{bmatrix} = \begin{bmatrix} C_x \\ C_y \end{bmatrix} + (R + \frac{W}{2}) \begin{bmatrix} \sin \theta' \\ -\cos \theta' \end{bmatrix} \tag{5.7}$$

P'_x and P'_y are the predicted values in x and y coordinates (m).

$$\begin{bmatrix} P'_x \\ P'_y \end{bmatrix} = \begin{bmatrix} P_x \\ P_y \end{bmatrix} + l \begin{bmatrix} \cos \theta \\ \sin \theta \end{bmatrix} \tag{5.8}$$

$$(z - h(x))^T \Psi^{-1} (z - h(x)) \leq \varepsilon \tag{5.9}$$

$$\Psi = H \Sigma H^T + Q \tag{5.10}$$

z consists of landmark depth and bearing values in m, rad.

h(x) are the values of depth and bearing of added landmark (state vector) in m, rad.

Ψ^{-} is a covariance matrix of the landmark in the State vector.

H is the Jacobian derivative of the landmark.

Σ is the values of covariance of the current state?

Q is the value of measurement error.

4.1.2 Correction

The correction step is in EKF-SLAM used for a correction next state on the basis of landmarks data and covariance matric. Like bottom equation shows the current equation based on jocabian.

$$g(x, y, \theta, l, r) = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} + \begin{bmatrix} (R + \frac{W}{2})(\sin(\theta + \alpha) - \sin\theta) \\ (R + \frac{W}{2})(-\cos(\theta + \alpha) + \cos\theta) \\ \alpha \end{bmatrix} \tag{5.11}$$

g_1 and g_2 are the current values of mobile robot in x-y coordinates (m).

g_3 is the angle of the predicted pose (rad).

Equation (5.11) shows the new predicted values that we can find on the basis of the previous pose and location and new angular values which are control vectors. The Jacobian matrix (G) has been calculated with the partial derivative of g with respect to states, control vector and landmarks location. If l and r are not equal.

$$V = \begin{bmatrix} \frac{\partial g_1}{\partial l} & \frac{\partial g_1}{\partial r} \\ \frac{\partial g_2}{\partial l} & \frac{\partial g_2}{\partial r} \\ \frac{\partial g_3}{\partial l} & \frac{\partial g_3}{\partial r} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{Wr}{(r-l)^2}(\sin\theta' - \sin\theta) - \frac{r+l}{2(r-l)}\cos\theta' & \frac{-Wl}{(r-l)^2}(\sin\theta' - \sin\theta) + \frac{r+l}{2(r-l)}\cos\theta' \\ \frac{Wr}{(r-l)^2}(\cos\theta - \cos\theta') - \frac{r+l}{2(r-l)}\sin\theta' & \frac{-Wl}{(r-l)^2}(\cos\theta - \cos\theta') + \frac{r+l}{2(r-l)}\sin\theta' \\ -\frac{1}{W} & \frac{1}{W} \end{bmatrix} \quad (5.12)$$

V is also the Jacobian vector of new state. When l not equal to r:

$$V = \begin{bmatrix} \frac{1}{2}(\cos\theta + \frac{l}{W}\sin\theta) & \frac{1}{2}(\cos\theta - \frac{l}{W}\sin\theta) \\ \frac{1}{2}(\sin\theta - \frac{l}{W}\cos\theta) & \frac{1}{2}(\sin\theta + \frac{l}{W}\cos\theta) \\ -\frac{1}{W} & \frac{1}{W} \end{bmatrix} \quad (5.13)$$

The covariance of the control vector ($\Sigma_{control}$) can be calculated by then l is equal to r

$$\Sigma_{control} = \begin{bmatrix} \sigma_l^2 & 0 \\ 0 & \sigma_r^2 \end{bmatrix} = \begin{bmatrix} (\alpha_1 l)^2 + (\alpha_2(l-r))^2 & 0 \\ 0 & (\alpha_1 r)^2 + (\alpha_2(l-r))^2 \end{bmatrix} \quad (5.14)$$

The predicted covariance for next state can be calculated using equation (5.15).

$$\bar{\Sigma}_t = G_t \Sigma_{t-1} G_t^T + V_t \Sigma_{control} V_T^T \quad (5.15)$$

Value of landmarks detection plays an important role in all this scenario, this state vector is represented in the Cartesian coordinates, in which for making map we our data in polar coordinates, for converting Cartesian to polar coordinate bottom equation has been used.

$$r = (x_m - x_L)^2 + (y_m - y_l)^2 \quad (5.16)$$

$$\alpha = \left(\frac{Y_m - y_l}{x_m - x_l} \right) \tag{5.17}$$

$$x_l = x + d\cos\theta, \; y_l = y + d\sin\theta \tag{5.16}$$

r is the value of distance along with the landmark from LiDAR in the meter.

x_m and y_m are the values landmark's location in coordinates environment in meter.

x_l and y_l are the robot's current location in xy-coordinates (m).

α is the values of angle of a landmark from robot in rad.

θ is the robot's current heading in rad.

H is jacobian vector of landmarks matrix with respect to state g.

$$H = \begin{bmatrix} \frac{\partial r}{\partial x} & \frac{\partial \alpha}{\partial x} \\ \frac{\partial r}{\partial y} & \frac{\partial \alpha}{\partial y} \\ \frac{\partial r}{\partial \theta} & \frac{\partial \alpha}{\partial \theta} \end{bmatrix} = \begin{bmatrix} -\frac{\Delta x}{Q} & \frac{\Delta y}{\sqrt{q}} \\ -\frac{\Delta y}{Q} & \frac{-\Delta x}{q} \\ \frac{(\Delta x \sin\theta - \Delta y\cos\theta)}{\sqrt{q}} - d & \frac{(\Delta x\cos\theta + \Delta y\sin\theta)}{\sqrt{q}} - 1 \end{bmatrix} \tag{5.17}$$

Kalman gain (K) is used for minimizing the error by finding the factor.

$$K_t = \Sigma_t H_T^T (H_t \Sigma_t H_T^T + Q)^{-1} \tag{5.18}$$

$$Q = \begin{bmatrix} \sigma_r^2 & 0 \\ 0 & \sigma_\alpha^2 \end{bmatrix} \tag{5.19}$$

Σ_t is the predicted covariance

Q is the covariance vector of measurement.

σ^2 is the standard deviation of measurement distance.

σ_α^2 is the standard deviation of the measurement angle.

The new state and new covariance have been corrected using equations.

$$\mu_t = \mu_t + K_t(z_t - h(\mu_t)) \tag{5.20}$$

$$\Sigma_t = (I - K_t H_t)\Sigma_T \tag{5.21}$$

μ_t are the vector of new corrected state

Σ_t is the vector of new covariance.

μ_t is the vector of the predicted state.

h() is the vector of polar coordinates of landmarks.

CHAPTER 5: RESULT AND DISCUSSION

RGBDSLAM is a SLAM technique used with Microsoft Kinect sensor RGB-D. In this technique, with the help of point cloud data of the RGBD sensor, we can create an octomap and RTAB map. It is RGB-D SLAM that takes the depth camera values and RGB images for measuring all information regarding the distance and feature of an object by RGB-D cameras. In this technique, there are multiple methods used for measuring the current position of Kinect sensor and feature detection with random samples consensus RANSAC, iterative closest points (ICP) and scale-invariant feature transform (SIFT). RANSAC is used for finding the transformation matrix of Kinect sensor by using SIFT features. Depth and RGB-images data have been collected synchronously to perform this method. RANdom SAmple Consensus (RANSAC) is well known as an iterative method consists of a scientific model for experimental data. The method is characterized by three parameters of RANSAC.

1. When data is not in the model then error tolerance will be maximized.
2. The maximum number of iterations used in the algorithm.

This technique is used for constructing the 3D mapping, in which depth measuring and feature extraction technique is used. On the other hand, an extended Kalman filter has been used that is filter-based SLAM. Detail description of it has been given in the above chapter consist of the current state, building map, path and movement matrix.

5.1 Simulation-based Result

5.1.1 Simulation environment

Experiment conduct in agriculture environment in gazebo robotics operating system (ROS), and conducted in different scenarios discussed in this section. ROS and gazebo environment have been performed in Linux Ubuntu 16.04. This simulation environment runs in real-time simulation are shown in figure 5.1. As a show that simple robot has been designed for simulation with the combination of multisensory such as laser sensor, Infra-red sensor, Microsoft Kinect sensor and Odometry for localization. In this artificial agriculture robot, the ground has been designed like a mud block and the green block color has shown the field for inspection and mapping.

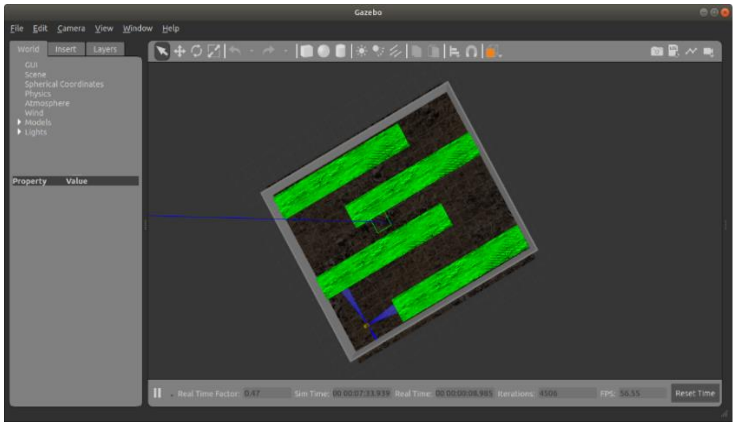


Figure 5.1: Real-time simulation environment for the result

5.1.2 Hector SLAM and Programmable map

Hector SLAM is a well-known technique used for approximation of the robot position and for building maps. It is the combination of filter-based SLAM technique and grid mapping tool for mapping in the form of graphical mapping. Graphical mapping by using hector SLAM is performed by laser sensor in Gazebo tool environment. Figure 5.2 shows the hector SLAM-based mapping result for localization and mapping by using a laser sensor (2D LiDAR). The simulation result of this hector SLAM is very holistic and some the error shown in mapping because of computational cost, because of building rtabmap (Octo mapping by using RGBD SLAM) take 340 Mb. Which makes the computer slow to process the simulation.

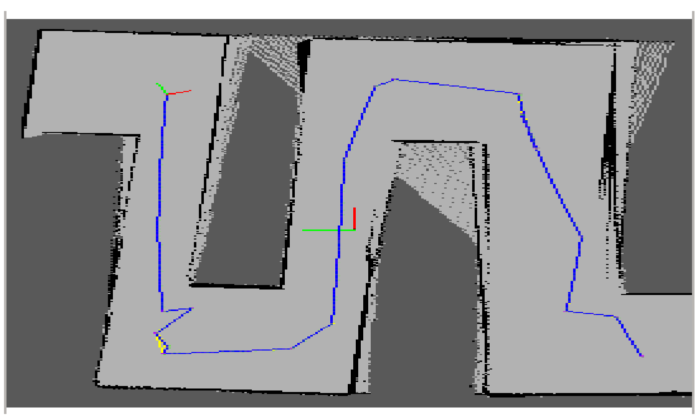


Figure 5.2: Build a map by hector SLAM based mapping result

Localization and the graphical map have been built for extracting the exact boundaries, obstacle position and trial of agribot arena. So they can differentiate between boundaries farm sides and wall sides. Odometry of agribot and localization of boundaries are exactly according to agricultural environment shown in figure 4. Accuracy of this related to localization is very good and almost up to +95% localize the position of agribot and localization of boundaries. Accuracy of mapping is also very good and robust up to +93% shown in table 1.

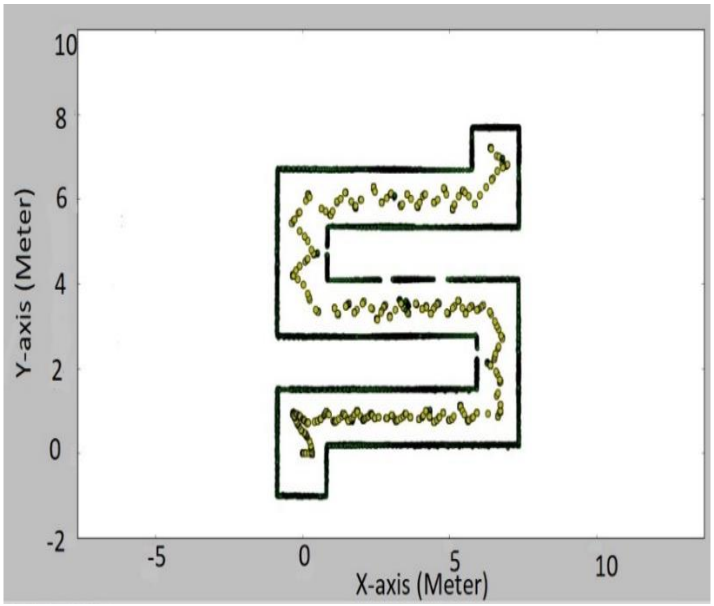


Figure 5.3: Build a map in the form of result to localization and mapping by using extended Kalman filter

5.1.3 RTAB Map for RGBDSLAM by using OPENNI platform

RTAB-Map that has been built with RGBD-SLAM in ROS, stands for Real-Time Appearance-Based Mapping (RTAB). It depends on a visual depth sensor and RGB images instead of a laser range sensor such as LiDAR, Sonar sensor and RADAR sensor for localization and mapping. It is a graph-based online SLAM technique that has been built by use of a depth image. It can settle the loop-closure in a very efficient way. RTAB-MAP is a 3D map used for the reconstruction of the indoor environment. After installing full libraries, OPENNI has been install, real-time mapping has been shown with Kinect sensor shown in figure 5.4, in which I have attached the Kinect sensor with Ubuntu and construct all the 3D maps in Gazebo.

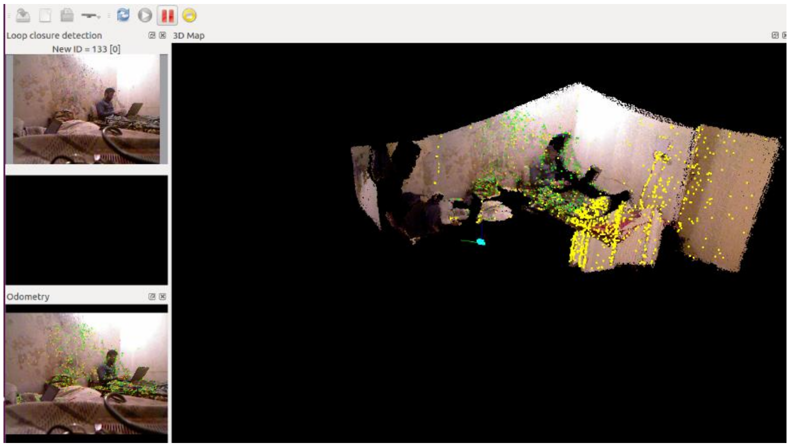


Figure 5.4: Built-up model for constructing 3D map

In chapter 3, It is suggested that LiDAR is the best choice sensor on the basis of characteristics (Range, cost, environment and computation cost) with the analytical hierarchy process. Based on AHP, LiDAR is superior sensor and the second choice is the Radar sensor, sonar sensor is ranked as 3^{rd} and monocular camera and Microsoft Kinect sensor ranked as 4^{th} and 5th. Our main focus in this project is to design a robot with multiple sensor SLAM systems. So we have to make the two different systems in which first we have designed the Sonar sensor and LiDAR-based robot in ROS environment by using real time odometry of robot. Another robot was designed with Sonar sensors and Kinect sensors in real-time as shown in figure 5.5. The result of the simulated model is given in table 5.1.

The simulation result of RGBDSLAM by using the RTAB map with the help of OPENNI has showed in figure 5.5. Localization was carried according to the movement of robot in gazebo, so localization and mapping are faultless with good accuracy. Microsoft Kinect sensor was used with build-in odometry sensor (rostopic echo /tf) for building the octomap. SIFT, RANSAC and ICP technique was used for building this octomap. SIFT was used for feature collection, RANSAC and ICP was used to an estimate the transformation to construct the 3D map and localize the position of Kinect sensor.

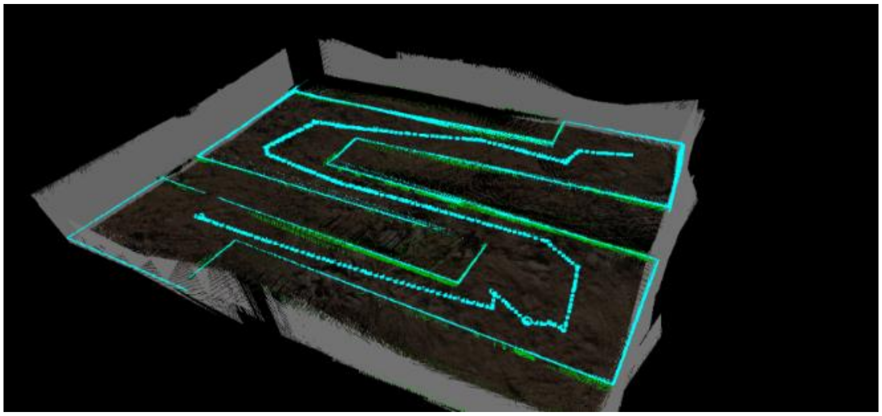


Figure 5.5: Build an RTABMAP by using RGBDSLAM

Table 5.1: Simulated agriculture environment results

Sr No	Feature	Hector SLAM	RGBD-SLAM	2D Map generation
1.	Total number of frames	1496	1496	415
2.	Loop Closure Detection	-	25	-
3.	Localization	Up to 95%	Almost 98% success rate	Localize the border almost at the same position
4.	Mapping	±0.3 m +90% (Accuracy)	+85 % (Accuracy)	±0.057 m +96% in real time

Handling the computation cost is one of the priority objective of this research. For this purpose, Sonar sensor used for obstacle avoidance instead of using Microsoft Kinect sensor and LiDAR that take so much computational cost. LiDAR and Sonar sensor, point cloud of LiDAR data was received 515-time, but data has used 11-time, which automatically save processing speed and memory. On the other hand, Microsoft Kinect sensor, Sonar and LiDAR-based sensor received the 1496-time data from each sensor. Which takes 262 MB for 13.9-meter distance from LiDAR and Kinect sensor in 240 seconds shown in figure 5.6 but in this case by using Sonar sensor it takes 340 MB in 73.8 meters in 211 seconds figure 5.6. In this case, 23.588% of memory has been saved.

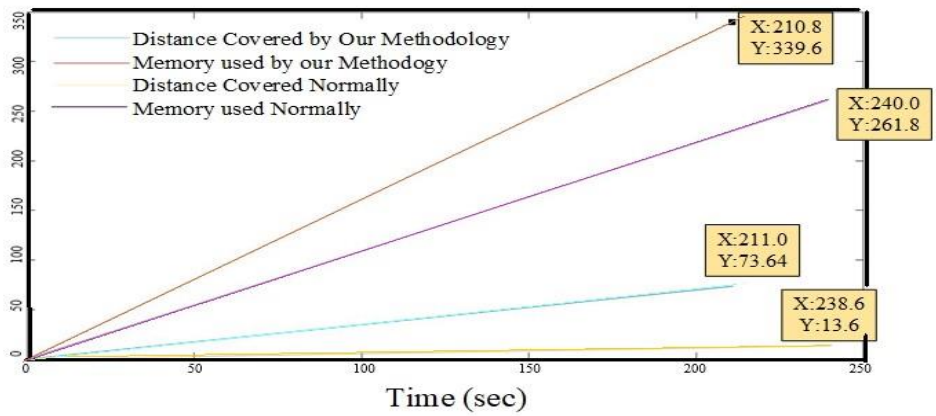


Figure 5.6: Computational complexity reduction result by proposed methodology

5.2 Experimental Results

Localization of mobile robot is the foremost step for high accuracy because with sensor measure the position of landmarks according to the location of a mobile robot for localization and mapping. Incremental encoders are utilized for this purpose to conclude the pose from the coordinate system. if initial values (x, y and theta) are known then next pose and state can be determined using rotation and translation measurement of wheel encoders as shown in figure 5.7. The current state and orientation of robot can be represented by

$$\text{Position} = [x_t \ y_t \ \theta_t]^T \tag{5.1}$$

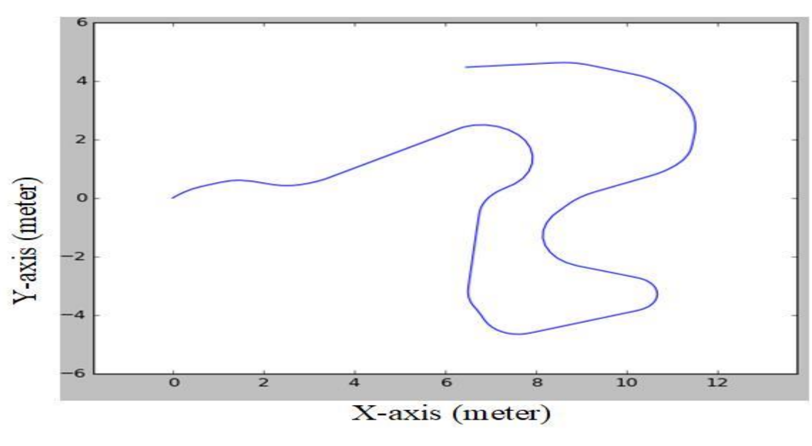


Figure 5.7: Shows the real-time path followed by robot in the x and y-direction

Every robot pose and location can be determined step by step in time interval (Δt). Δx and Δy small time interval in x and y direction that robot takes along the path in time interval Δt. $\Delta\theta$ is posed interval can be determined by the width of the mobile robot and angular velocity of the individual wheel. The next state of mobile robot can be found by simply added these interval values (Next equations Δx, Δy and $\Delta\theta$) in previous state values. In the extended Kalman filter, the previous and next state of the mobile robot are carried by the control vector (u_t that consists of ΔR and ΔL). The algorithm of EKF used for approximation the location of mobile robot shows the entire path by encoder motor based on the angular velocity of both wheels.

$$\Delta x = \Delta L \text{ cosine } (\theta + \Delta\theta / 2) \tag{5.2}$$

$$\Delta y = \Delta L \text{ sine } (\theta + \Delta\theta / 2) \tag{5.3}$$

$$\Delta\theta = (\Delta R - \Delta L) / W \tag{5.4}$$

Localization of landmarks is dependent on the state of mobile robot. The values of LiDAR or Kinect sensor are taken from the position of robot and location of the obstacle. LiDAR real-time data is given in Figures 5.8 and 5.9. During 2πΘ rotation LiDAR emits 720 rays of data points.

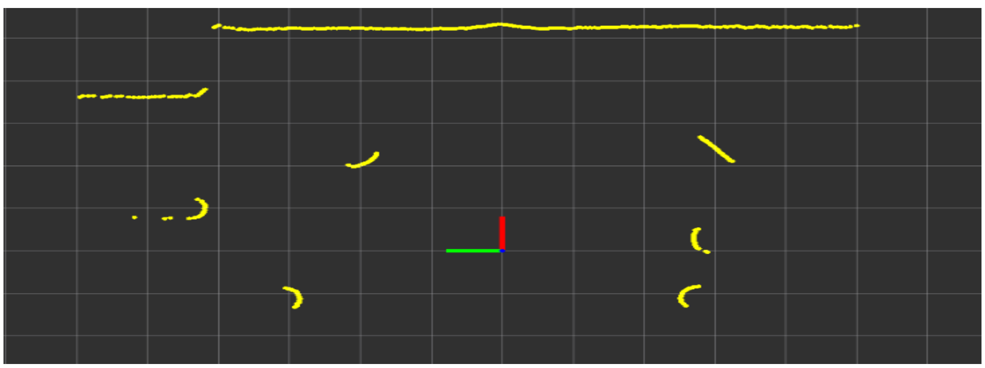


Figure 5.8: Data acquisition of LiDAR map in rviz

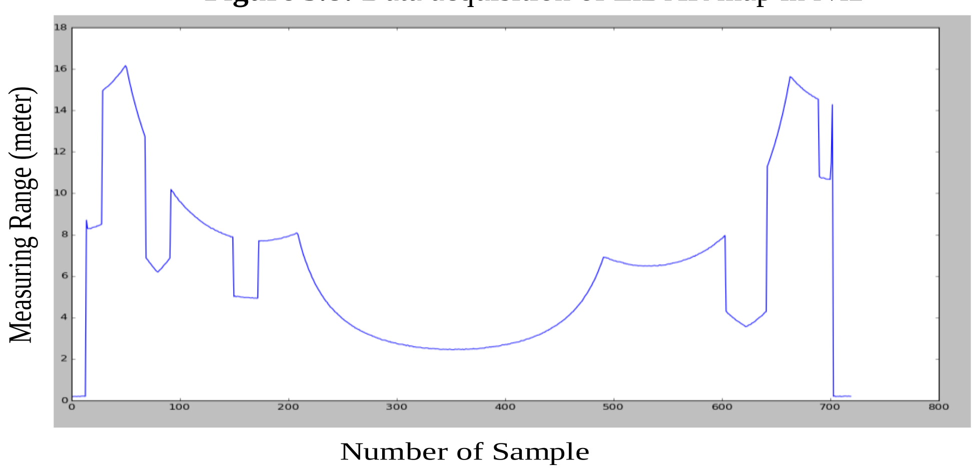


Figure 5.9: Measurement of real-time LiDAR data

The feature can be extracted by the derivative of all received values from LiDAR shown in the figure. These values have been scale from 200 for a better representation. The values of more than ±100 had shown the position of landmarks. The values shown a little bit peak values in figure 5.10 are the values of walls changing from all sides.

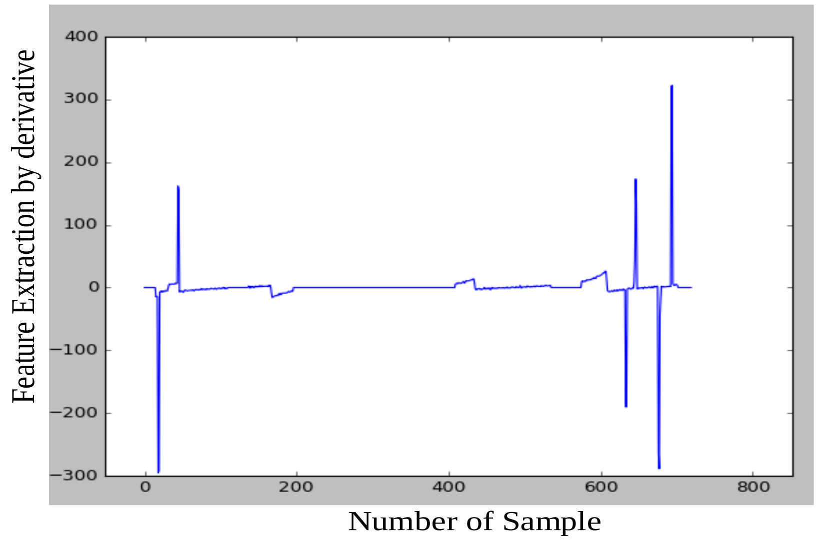


Figure 5.10: Derivative of LiDAR values for feature extraction for localizing the landmarks

To verify the accuracy, robustness, real-time efficiency of the proposed methodology, LiDAR and Kinect sensor are used in real-time and in the Gazebo environment. EKF and RGBD SLAM algorithm are used with LiDAR and Kinect sensor for localization and mapping. EKF creates a fast 2D grid map by using LiDAR with low computational cost while RGBD SLAM creates a 3D octomap by using an RGB camera and depth camera.

The map is a symbolic representation of the environment in SLAM, where robots localize themselves with landmarks. The map has two mediums, static and dynamics. SLAM map-based classifications are online, offline, active and full SLAM. Our robot moves in a static map where every obstacle is in static (no movement in an arena) and active SLAM was implemented and the robot actuates autonomously and acquires data of the environment for mapping.

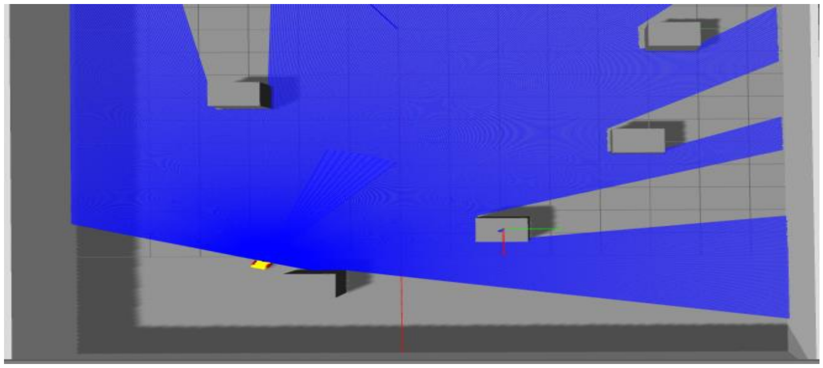


Figure 5.11: Real-time environment in which the LiDAR rays are emitted from robot to localize the landmarks in Gazebo.

Kinect Xbox sensor are mounted on the front side of the mobile robot and LiDAR sensor is mounted on the middle for minimizing the error in building the map. The movement of mobile robot was programed, the obstacle and walls were mapped in two dimensions with LiDAR and in 3 dimensions with Kinect sensor. As dependent by result is given in figure 5.12.

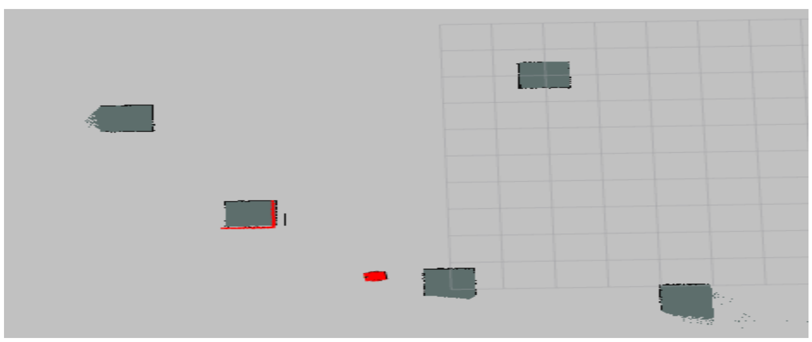


Figure 5.12: Map building in ROS using LiDAR sensor

A map was built with EKF as shown in figure 5.13. The map was built with an accuracy of more than +85%. Some of the errors in mapping are shown in the figure 5.13 which are related to spread around the actual location of landmarks, that is because of fully active SLAM procedure using EKF with robot angular pose (θ) and positional values (x and y). In figure 5.13 shows EKF filter which is implemented for a mobile robot with an accuracy of localization is 93 %.

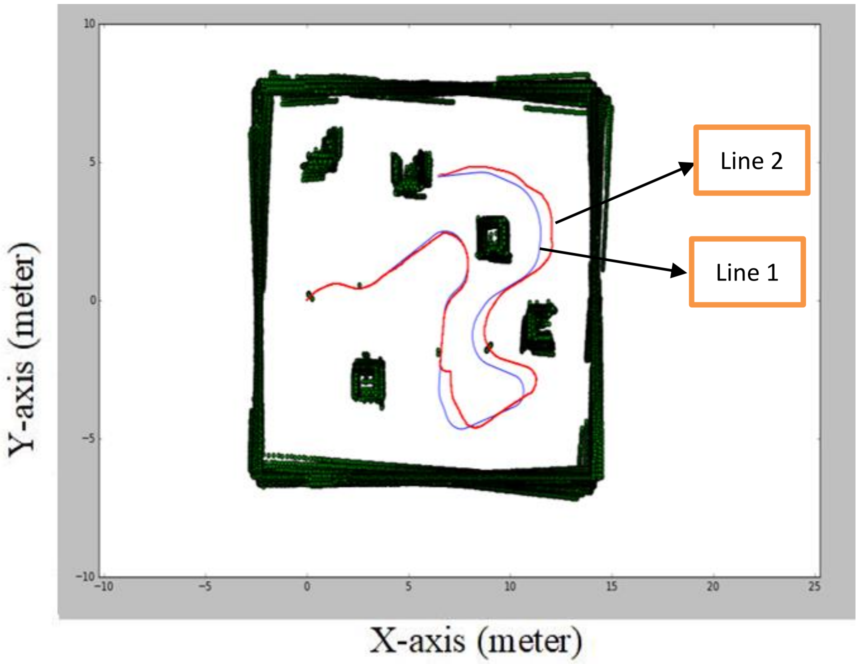


Figure 5.13: Map building with LiDAR sensor, in this first line shows the actual path of the mobile robot and the second line shows the path achieved with EKF based on control vector

In figure 6.14, these is real-time images from Microsoft Kinect sensor in which depth camera and RGB images play their role. This is a simple map form of 3D images, which can use for build 3D images with Microsoft Kinect sensor.

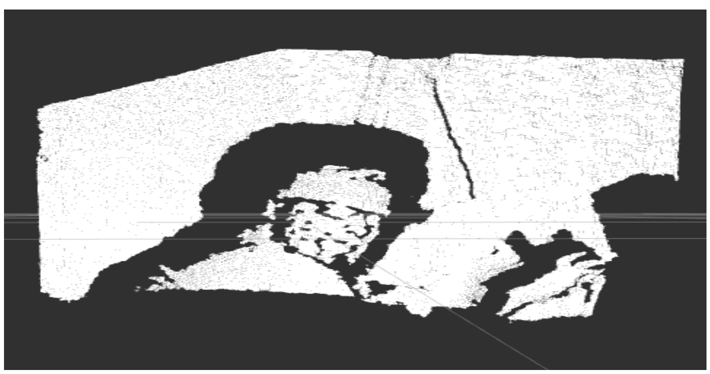


Figure 5.14: Real-time environment with Kinect sensor Xbox 360 in RVIZ

In the other SLAM-based robot system, we have merged the Sonar sensor and Kinect sensor for localization and mapping. Another RTAB map was designed with the help of RGBD-SLAM in ROS as shown in figure 5.15, Map was designed successfully with some noise due to low-quality pixel of Kinect sensor.

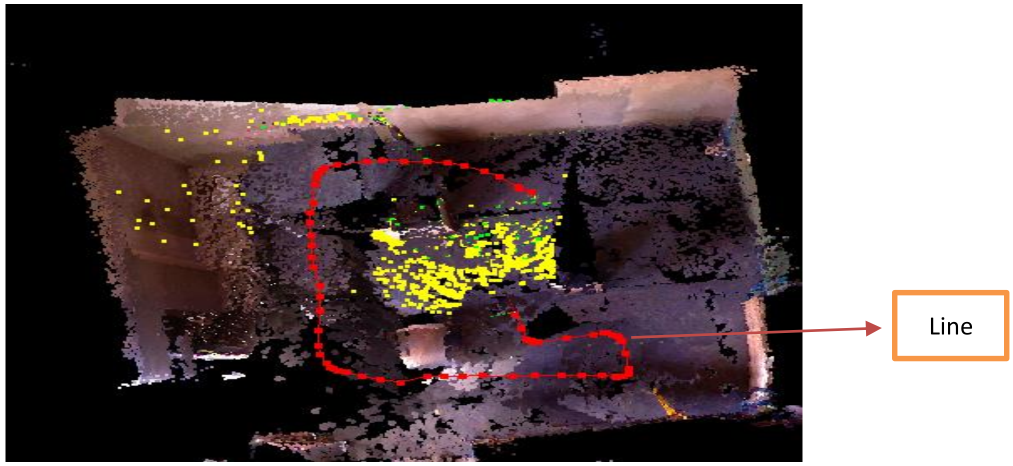


Figure 5.15: Map building with Kinect sensor in ROS, dotted line shows the path of the mobile robot and yellow dot show the feature of landmarks, this map has been achieved in a Real environment with 15x12 feet room with RGBD-SLAM.

Accuracy of loop closure in RGBD-SLAM with Kinect sensor is better than EKF LiDAR because Kinect sensor gives much more information, so it is quite simple to extract features in RGB and depth camera as compared to 2D-LiDAR. Overall the feature are discussed in table 5.2.

Table 5.2: RGBD-SLAM feature has been detected during localization and mapping.

Sr no	**Feature**	**RGBD-SLAM with Kinect sensor**	**EKF based SLAM with LiDAR**
1.	Total number of frames	1078	274
2.	Loop Closure Detection	134	3
3.	Localization	95% (Accuracy)	+93% (Accuracy)
4.	Accuracy of building a map	+80 % (Accuracy)	±0.4 m with +85% in real time & +97% in ROS environment

Multisensory SLAM based method was performed for indoor environment in real time (for a room) and in simulation based on indoor in green warehouse environment.

CHAPTER 6: CONCLUSION AND FUTURE WORK

In this work, we optimize selection of SLAM sensors, and implemented multisensory SLAM. The performance of SLAM sensors is compared using the analytical hierarchy process (AHP) based on various key indicators such as accuracy, range, cost, working environment and computational cost. Autonomous Robots are dependent on sensors data for localization, pose and location estimation of the robot and map building. Proper sensors selection for the desired application is highly important and such selection AHP based method is an appropriate choice. AHP method shows that LiDAR is the best choice for long-range applications as compared to acoustic, vision sensors, RADAR and RGB-D sensors. RADAR is widely explored for application in autonomous mobile robotics. Vision sensors provide more details about the environment; however, complex algorithms and computational complexity are limitations. Acoustic sensor cost-effective with a linear output however, the limited range is its key limitation. AHP analysis reveals that LiDAR is preferred among all the cited sensors for SLAM problems due to long-range, minimal computational complexity and capability to work in some noisy and smoke environments. The analysis further shows that RADAR can be the second choice after LiDAR due to its optimal measurement range and moral performance in diverse environmental conditions.

SLAM was carried by using EKF and RGBD-SLAM in simulation and experimental environment for indoor agricultural static conditions. EKF algorithm was programmed in ROS to navigate the robot in the Gazebo environment for mapping. Localization of landmarks and mapping of the environment is achieved with a sonar sensor and LiDAR with accuracy of 93% and 85 %, respectively (experimental result). RGBD-SLAM has been used in ROS for 3D mapping of the same environment. Accuracy of the localization and mapping was up to 95% and 80%. In simulation based environment, accuracy of localization and mapping was 98% and 85% in RGBD SLAM with multi-sensor data (Build in Odometry in ROS, LiDAR, Kinect sensor, Sonar sensor).

SLAM technique is one of the well-known techniques and still, more research is still required. We have built 2D and 3D maps from the different sensors in static environment. For future work it is recommended to perform such investigations in dynamic environment.

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Completion Certificate

It is certified that the thesis titled "***Navigation of a Mobile Agribot by using Multi-sensor "SLAM"***" submitted by CMS ID. 00000277784, NS Muhammad Shahzad Alam of MS-2018 Mechatronics Engineering is completed in all respects as per the requirements of Main Office, NUST (Exam branch).

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