INTERNATIONAL JOURNAL ON ORANGE TECHNOLOGY

https://journals.researchparks.org/index.php/IJOT e-ISSN: 2615-8140 | p-ISSN: 2615-7071

Volume: 4 Issue: 6 |Jun 2022

Design and Analysis of Mobile Locomation Approach

Shokendra Dev Verma

Student, Sat Kabir Institute of Technology and Management, Haryana, India
dev77info@gmail.com

Kirti Bhatia, Shalini Bhadola

Assistant Professor, Sat Kabir Institute of Technology and Management, Haryana, India
bhatia.kirti.it@gmail.com, shalini77info@gmail.com

Rohini Sharma

Assistatnt Professor and corresponding Author, GPGCW, Rohtak, India
rohinisharmaohlan@gmail.com

---***---

Annotation: One of the most difficult tasks for a robotic system is to determine the best path through the workspace. The main purpose is to prevent obstructions and create an optimum path. As a result, a mobile robot's free configuration space must be managed very carefully for course planning and navigation. The path planning work will be easier, faster, and more efficient if the configuration space is partitioned. In addition, the data perceived by the sensor contains some noise. As a result, we construct an approach to produce an optimal prediction state in order to build a map that aids in the effective management of the environment in order to locate the most efficient paths to target. We use the modified Kalman Filter (MKF) to determine the most reliable sensor data prediction, and then the K-means clustering method to identify the subsequent landmarks while evading barriers.

Keywords: Robot Navigation, Localization and Mapping, Kalman filter.

INTRODUCTION:

There are now mobile robots that can jump, run, walk, and perform other actions similar to their biological counterparts. Legged robots, wheeled mobile robots, artificial intelligence, flying robots, robot vision, and other branches of robotics have emerged, involving several technological fields such as mechanical, telecommunications, and computer programming. The realm of mobile robots, containing new trends, is covered in this article. Artificial intelligence, automated vehicles, network communiqué, pleasant robot-human interfaces, safe human–robot [1-3].

NAVIGATION

The most crucial aspect of a mobile robot's design is its mobility. abilities to navigate. The goal is for the robot to transfer about from one location to another in a familiar or unfamiliar environment, taking the sensor values into consideration achieving the required results This necessitates the robot's rely on its other features, like observation (the robot must be able to perceive). Employ its sensors to gather useful information), and localization (the cognition (the robot must be aware of its location anddesign). (The robot must choose what to do in order to fulfil its objectives), and (The robot should compute its input forces on) motion control. To accomplish the anticipated trajectory, the actuators must be used). While accomplishing the navigating function, the robot is equipped with multiple cognitive devices that allow it to mimic the surroundings and determine its location, control movement, recognise barriers, and evade obstructions using navigational techniques [4-6]. The most crucial function of any navigational methodology is to plan a safe route from the initial point to the destination (by recognising and

INTERNATIONAL JOURNAL ON ORANGE TECHNOLOGY
https://journals.researchparks.org/index.php/IJOT e-ISSN: 2615-8140 | p-ISSN: 2615-7071
Volume: 4 Issue: 6 |Jun 2022

avoiding obstacles). Consequently, whether working in a basic or complex environment, choosing the proper navigational method is the most important step in a robot's course design.

LOCALIZATION AND MAPPING

The robot must first determine its position in the workplace in order to navigate successfully. As a result, in robot navigation, localization, vision, and motion control are all critical. Localization and representations are inextricably linked. The challenge of robot localization would be overcome if a precise GPS system could be mounted on it. The robot would always be aware of its whereabouts. However, this system is currently unavailable or insufficiently accurate to be useful. Localization, in any event, entails not only identifying the robot's precise location on Earth, but also its relative location in relation to a target. If the robot wants to go to a precise destination, it will need an environment model or map to plot a route to get there. This means that localization is a broad concept that encompasses not only finding the robot's exact position in space, but also creating a map and measuring the robot's position in relation to it [7].

Eventually, the robot attempts to recover its position and recognise when it has arrived at the destination place by localising on a map. Representation is a crucial aspect of map localization. Actual impediments can move in the real world since it is dynamic. The topic of guessing the motion vector of transitory objects is still under investigation. Wide open spaces, like parking areas, fields, and inside halls like those found in convention centers, pose another issue. Due to their scarcity, they create a challenge. Occlusion by human crowds is a classic example. The ideal case would be for the robot's sensors and mapping method to instantly and consistently determine the robot's precise location [8].

DESIGNING A PATH, A TRAJECTORY, AND A MOTION

Path planning is associated with determining the optimum route for a mobile robot to take in order to arrive at the destination without crashing, allowing the robot to navigate via obstructions from one configuration to the next. The motion's temporal progression is ignored. There are no velocities or accelerations taken into account. The purpose of trajectory planning is to determine the force inputs that move the actuators so that the robot pursues a trajectory that permits it to progress from the beginning setup to the final one while evading obstructions. To plan the trajectory, it considers the robot's dynamics and physical features [9].

OBSTACLE AVOIDANCE

During robot motion, clashes between the robot and impediments should be prevented. Robot navigation refers to a mobile robot's capacity to travel around a previously recognized or unfamiliar area to reach a goal without crashing with any impediments. A competent motion planner should be capable of identifying robot-to-workplace obstacle collisions so that the robot can avoid them.

PROPOSED METHOD

we construct an approach to provide an efficient prediction of upcoming states in order to construct a map that aids in the effective management of the environment in order to locate the most efficient paths to destination. We use the Modified Kalman Filter (MKF) to provide an appropriate assessment of sensor data, and then the K-means clustering technique to locate the subsequent milestones while evading obstructions.

Kalman Filtering

By predicting a joint probability distribution over the variables for each time frame, Kalman filtering, also recognised as linear quadratic estimation (LQE), is a methodology that utilises a succession of assessments found over time, such as statistical noise and other inaccuracies, to produce estimates of unknown variables that typically are more credible than those rely on a specific measurement by itself [10].

INTERNATIONAL JOURNAL ON ORANGE TECHNOLOGY

https://journals.researchparks.org/index.php/IJOT e-ISSN: 2615-8140 | p-ISSN: 2615-7071

Volume: 4 Issue: 6 |Jun 2022

We may use Kalman Filtering to integrate the uncertainties about the robot's current state (i.e. where it is and which direction it is gazing) with the uncertainties about its sensor data to reduce the robot's total uncertainty. A Gaussian probability distribution or a Normal distribution is commonly used to reflect both uncertainty. The mean and variance are the two variables of a Gaussian distribution. The variance represents how uncertain we are about this mean value, while the mean expresses what value of the distribution has the highest possibility of being true.

There are two sections of this algorithm. In the forecast phase, the filter yields approximations of the current state variables and their ambiguity. After the result of the following measurement (essentially tainted with certain degree of error, especially random noise) is found, these estimations are modified by a weighted average, with greater weight given to estimations with better certainty. It's a recursive algorithm. It may operate in real time using only the present input observations and the earlier determined state and its uncertainty matrix; no prior data is required.

Extended Kalman Filter (EKF)

The state transition prototype and the measurement prototype should both be linear when using Kalman Filters. From a scientific perspective, this means that we can update the robot's state and measurements using Linear Algebra's simplicity and beauty. This indicates that the state variables and calculated values are anticipated to change linearly with time in practise. If we evaluate the robot's location in the x-direction, for example. Let the robot was at position x1 at time t1, we suppose that it will be at position x1+v*(t2–t1) at time t2. The x-direction velocity of the robot is represented by the variable v. The state transition model is slightly off if the robot is truly speeding or performing any other nonlinear motion (such as driving in a circle). In most cases, it isn't far off, but in some extreme cases, the assumption of linearity is just incorrect. Assuming a linear measurement model also has drawbacks. Assume you're travelling along a straight road with a lighthouse directly across the road in front of you. While you are a long way away, the distance between you and the lighthouse, as well as the angle at which it appears from your perspective, changes almost linearly. The angle, on the one hand, changes considerably as you go closer, especially when you drive by it, while the distance, on the other hand, remains quite constant. This is why, when Robot is exploring his 2-D environment with landmarks strewn throughout his 2-D plane, we can't apply Linear Kalman Filtering. Extended Kalman Filtering is just "Normal" Kalman Filtering with the nonlinear state transition model and measurement model linearized further [11].

Unscented Kalman filters

The unscented Kalman filter is a nonlinear Kalman filter that appears to be an improvement over the EKF (UKF). In the UKF, the underlying Gaussian distribution is represented by a deterministic sampling of points that approximates the probability density. The posterior distribution's moments can then be deduced from the transformed samples by using the nonlinear transformation of these points as an estimation of the posterior distribution. The process is referred to as the unscented transform. When estimating error in both directions, the UKF is typically more reliable and accurate than the EKF.

DEAD RECKONING

A locating technique based on the integration of an estimated or observed displacement vector is known as dead reckoning. Signal masking and outages are not an issue. However, with time, its positioning flaws build, necessitating external calibration or augmentation with other positioning devices. DR is made up of two or more sensors that measure the vehicle's heading and displacement[12].

GRID MAP

A grid map can be used to represent any indoor area, such as a house, apartment, or business. The position of a robot in the environment at any given time is relative to the map's corner (x=0, y=0). Knowing where there is open space and where there are impediments on a workshop floor allows a robot to plan the shortest, collision-free path from one spot to another.

SLAM (SIMULTANEOUS LOCALIZATION AND MAPPING)

A strategy for autonomous vehicles that allows you to simultaneously generate a map and locate your vehicle inside that map. The car can map out unknown environments using SLAM methods. Engineers use the map data to perform activities like route planning and obstacle avoidance. Figure 1 shows the workflow of SLAM[13].

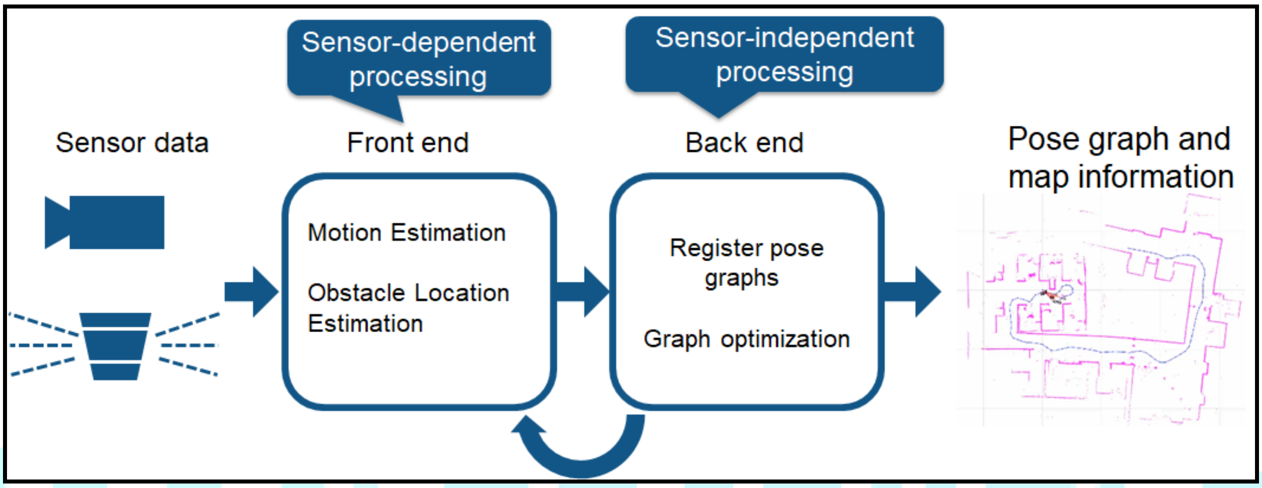


Fig 1: Workflow of SLAM

Particle filtering

The particle filtering method describes the process of locating a collection of random samples propagating in the state space to approximate the probability density function and substituting the integral operation with the sample mean to achieve the state lowest variance distribution[14].

IMPLEMENTATION ENVIORNMENT

The coordinate location of the robot in the plane is fully described by the point (x; y). However, for a stiff robot which can translate and rotate in the plane, this depiction is inadequate. The positioning of the robot at every point is being considered in this work. When the robot A travels on a workspace W, it can not access all areas of W. Because the physical state of A with regard to a static place in W is specified by the configuration c1 of robot A, a configuration c1 of robot A is said to be legitimate if robot A can access the location of W as specified by the configuration.

MODIFIED KALMAN FILTER (MKF)

A collision-free route corresponds to a curve of the free space Cfree. It makes it possible to model nonlinear systems. The MKF is made up of three phases that function together in a round. The state and covariance of robot are predicted first and then the robot then observes the environment, assigning any new observations or measurements to the accurate feature (MKF examination), and lastly correcting the robot's state and covariance (MKF update).

(k-MC) PROCEDURE

It [15] is a cluster analysis approach that divides n number of inspection data into k clusters according to which every inspection link to the cluster with the closest mean. Let's say the robot A has n positions and m orientations.

INTERNATIONAL JOURNAL ON ORANGE TECHNOLOGY
https://journals.researchparks.org/index.php/IJOT e-ISSN: 2615-8140 | p-ISSN: 2615-7071
Volume: 4 Issue: 6 |Jun 2022

According to K-MC, the goal is to split the n points into k sets (k n) in order to minimise the summation of squares within the clusters. For route optimization, we devise a clustering methodology that divides the robot's free space into a number of zones known as clusters. Cluster centres can be considered the subsequent landmark to be localised under specific assumptions.

Unidentified cell regions entirely encircled by occupied cells or obstructions Because cobs are not approachable, they are deleted from the clustering process before applying K-means. The contour of each zone is then tracked to see if it is completely limited by occupied cells. The entire territory is designated as inhabited in this example. Next, take the sensor data and run it via MKF. MKF offers us with corrected environmental measures that are more precise than sensor readings.

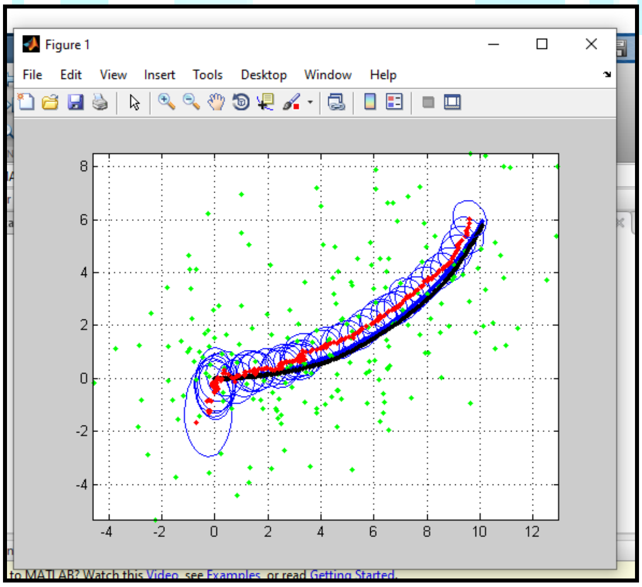
After getting the MKF outcome, we use the K-means clustering procedure. By avoiding the obstacles, K-means clustering provides us k cluster centres. Because the cluster centres are built to avoid barriers, they can be used for robot localization and map construction in this environment as a whole. After the robot has been localised, it will be much simpler for it to explore the optimal rout to its goal.

RESULTS AND ANALYSIS

The world isn't linear, and sensors aren't immune to noise. As a result, we use MKF to linearize the primary data. Consider x and y coordinates for the even arbitrary points in the range. The degree of attractiveness of the centre points is determined by the n number of these uniform random points. The higher the quantity of random numbers we generate, the better the result. It is also self-evident that the algorithm's execution duration is determined by this number, as a large n value will slow down the procedure.

First of all we linearize the surrounding enviornment by using Modified kalman Filter. Noises are removed with the help of filter. We find an estimation of path for robot as depicted in Fig 2.

Fig 3 illustrates the position error variations among Death Recokning(DR), GPS amd MKF algorithm. It has been observed that Modified Kalman filter is very close to GPS system.



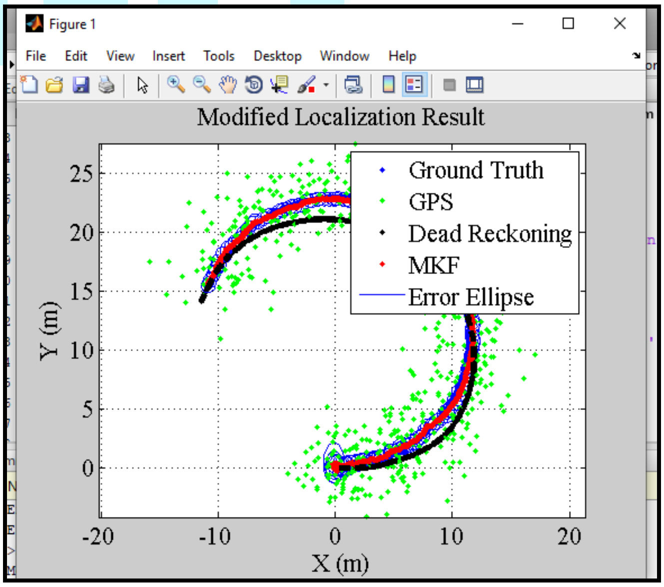


Fig 2: Linearized Trajectory Fig 3: Comparision of Position error among DR, GPS and MKF

Figure 4 shows the results of Unscented Kalman Filter. Its value is not as close to GPS as of Modified Kalman Filter. Figure 4.6 the position error between ground truth, Particle filter and DR.

INTERNATIONAL JOURNAL ON ORANGE TECHNOLOGY
https://journals.researchparks.org/index.php/IJOT e-ISSN: 2615-8140 | p-ISSN: 2615-7071
Volume: 4 Issue: 6 |Jun 2022

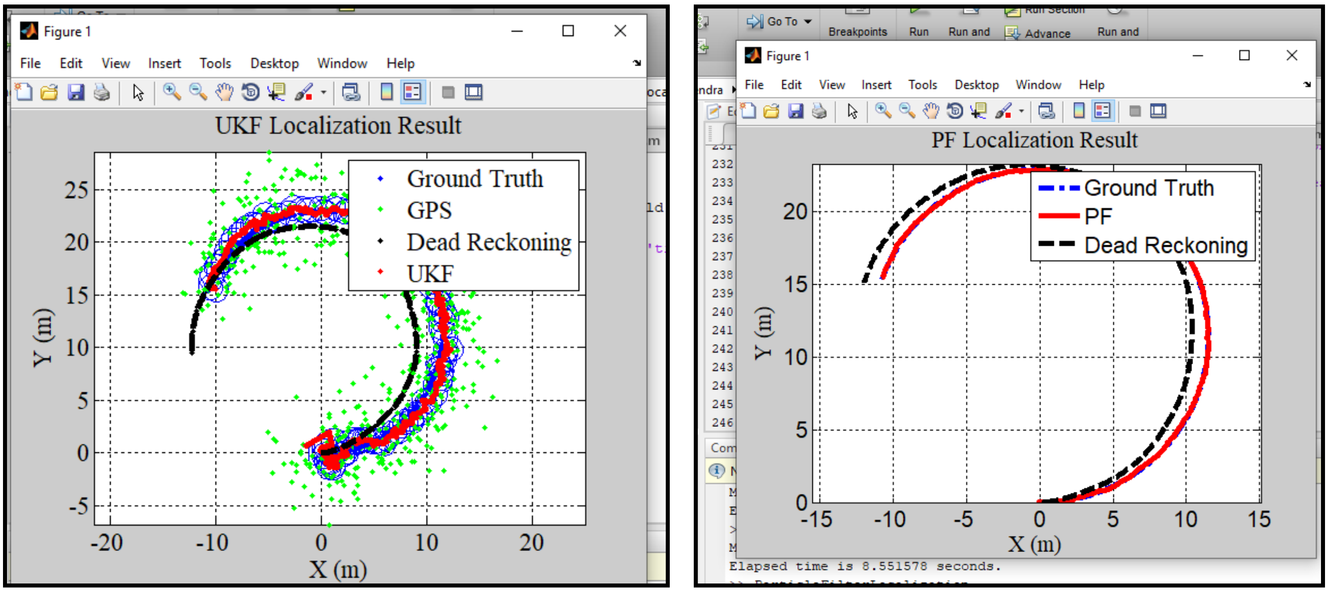


Fig 5a: Position error difference among DR, GPS and UKF & 5b: PF,GT, DR

Our technique separates the surroundings and locates the centre of every of the k partitions, correctly excluding the regions containing obstacles. Results of K-MC are shown fig 5a (before K-means sampling) and 5b (after k-means sampling).

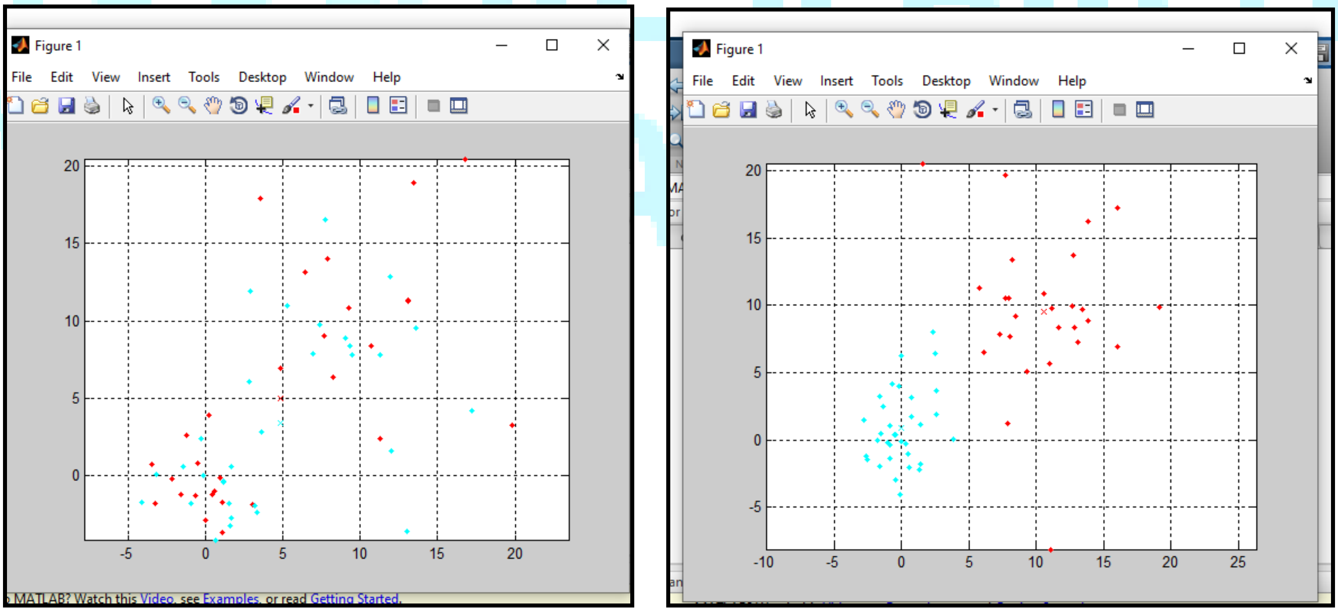


Figure 5a (before K-means sampling) and 5b (after k-means sampling).

After that we performed grid mapping, the results of grid mapping are shown in figure 6a and performed Complete coverage path planning (fig 6b).

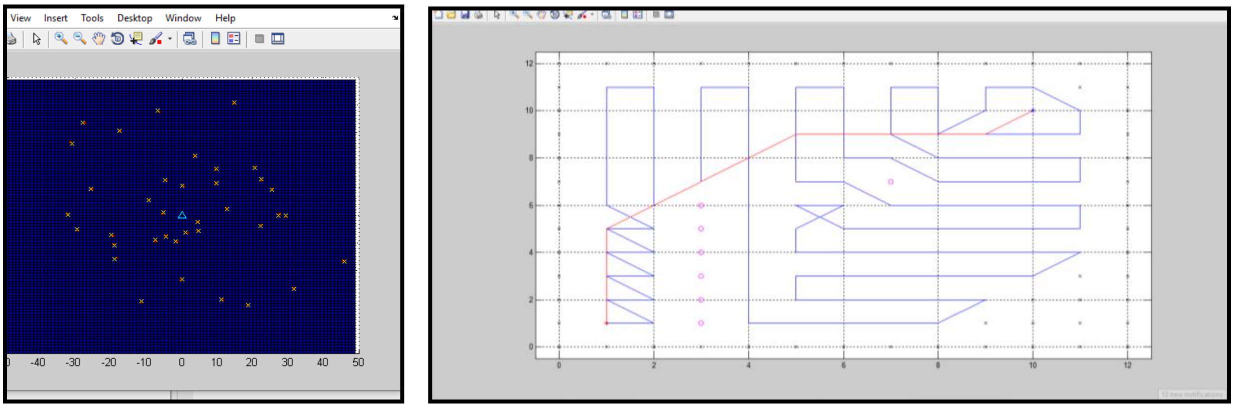


Fig 6a: Grid Mapping and Fig 6b: Path planning

Next we have integrated the MKF with SLAM and find that results are very close to ground truth, figure 7.

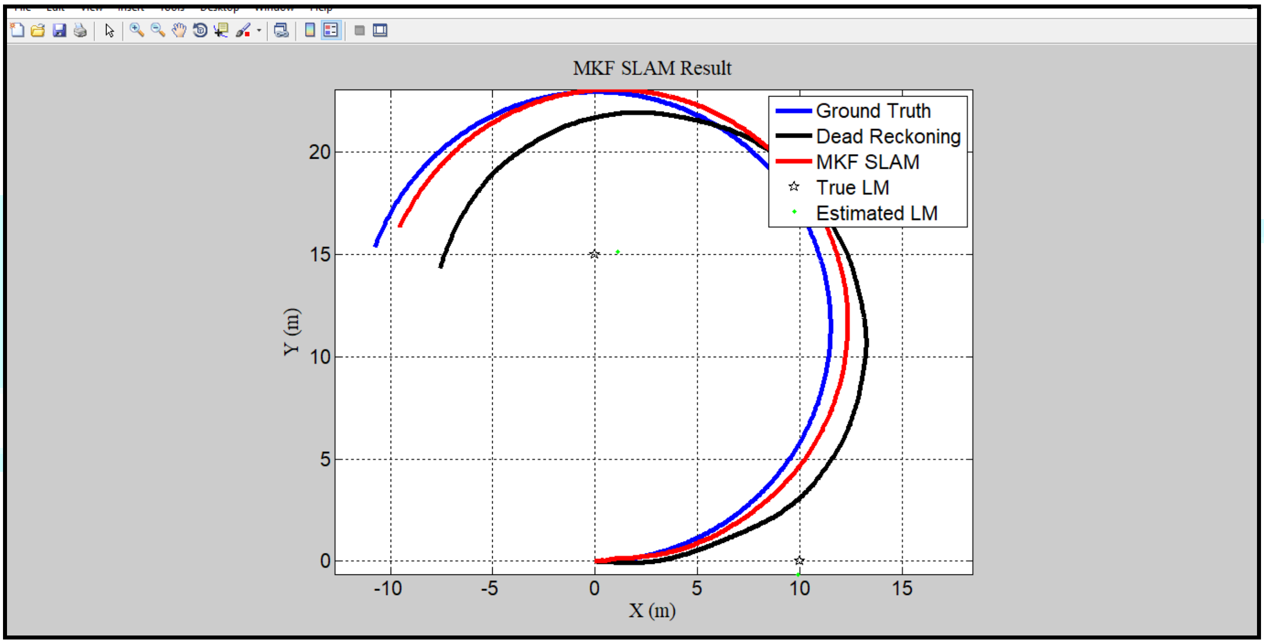


Figure 4.12: Integration of SLAM with MKF

CONCLUSION

One of the most difficult jobs for a robot is to find out the best path through the workspace. The main purpose is to eliminate obstructions and create an efficient path. Consequently, a mobile robot's free configuration space must be managed very effectively for course planning and navigation. The path planning work will be easier, faster, and more efficient if the configuration space is partitioned. We suggest a mechanism for the robot to explore its surroundins without having any previous knowledge of it. If the robot is familiar with several locations throughout the accessible region in the configuration space, it will be much easier for it to locate itself and choose the best way through the environment. A robot's sensor observations are imperfect, and it is uncertain what will happen if it performs a specific action. We take into account the noise, linearize it using MKF, and then use the K-means technique for clustering is used to locate cluster midpoints in the surroundings while evading barriers. The midpoints of the clusters can be thought of as the robot's next markers for locating itself, and these landmarks will then be utilised to discover the best path to the target.

We have also compared different filters for localization like Particle filter and Unscented Filter. We performed path planning, complete path coverage and path smoothing. We also integrated the MKF with SLAM and find that results are very close to ground truth values.

REFERENCES

1. German National Library". International classification system of the German National Library (GND).
2. Ghassaei, Amanda (20 April 2011). The Design and Optimization of a Crank-Based Leg Mechanism (PDF) (Thesis). Pomona College. Archived (PDF) from the original on 29 October 2013.
3. 3D One-Leg Hopper (1983–1984)". MIT Leg Laboratory. Retrieved 2007-10-22.
4. Miller, Gavin. "Introduction". snakerobots.com.
5. Dowling, Kevin. "Power Sources for Small Robots" (PDF). Carnegie Mellon University. Retrieved 11 May 2012.
6. Roozing, Wesley; Li, Zhibin; Tsagarakis, Nikos; Caldwell, Darwin (2016). "Design Optimisation and Control of Compliant Actuation Arrangements in Articulated Robots for Improved Energy Efficiency". IEEE Robotics and Automation Letters. 1 (2): 1110–1117.
7. https://www.roboticstomorrow.com/article/2016/06/types-of-robotic-actuators/8253
8. Wettels, Nicholas; Santos, Veronica J.; Johansson, Roland S.; Loeb, Gerald E. (January 2008). "Biomimetic Tactile Sensor Array". Advanced Robotics. 22 (8): 829–849.
9. Filliat, David, and Jean-Arcady Meyer. "Map-based navigation in mobile robots: I. a review of localization strategies." Cognitive Systems Research 4.4 (2003): 243-282.
10. https://en.wikipedia.org/wiki/Kalman_filter
11. https://en.wikipedia.org/wiki/Extended_Kalman_filter
12. https://www.sciencedirect.com/topics/computer-science/dead-reckoning
13. https://in.mathworks.com/discovery/slam.html
14. https://towardsdatascience.com/particle-filter-a-hero-in-the-world-of-non-linearity-and-non-gaussian-6d8947f4a3dc
15. D. Napoleon and P. G. Lakshmi, "An Efficient K-Means Clustering Algorithm for Reducing Time Complexity using Uniform Distribution Data Points," in Proc. of IEEE Int. Conf. on Trendz in Info. Sc. & Computing (TISC), pp. 42-45, 2010.