ISSN: 0974-5823 Vol. 7 No. 1 January, 2022

International Journal of Mechanical Engineering

Performance Evaluation of Multisensor Data Fusion Approaches for Handling Data Uncertainty and Inconsistency in Robot Localization

S. Sindhu
Data Science and Business Systems, SRM Institute of Science & Technology, India

M. Saravanan
Department of Networking and Communications, SRM Institute of Science & Technology, India

Abstract - **Robotics plays a vital role in this era, where robots are seen as a possible solution for the shortage of skilled labour. Nowadays, mobile autonomous robots are used in various applications such as Manufacturing, Military, Medical diagnosis, Agriculture, Transportation, and Home Automation systems. In many situations, Robots have to make decisions and plan accordingly which leads to major challenges, among which navigation, path planning, obstacle avoidance, and localization must be handled with the right approach. Numerous researches have been carried out to overcome the aforementioned challenges. In the present work, we have taken steps to identify and resolve the issues in Robot Localization. Localization provides a reliable solution for estimating the robot's current position. Usually, the robot position is determined through mounted sensors. The information obtained from these multiple sensors should be used in the most appropriate way to take the correct decision in estimating the robot's current position. The uncertainty and inconsistency present in the sensor data for location estimates may cause a devastating impact on sensitive applications. To overcome the drawbacks of localization, an effective method should be identified to address the problem such as errors and improper state estimation. This paper focuses on comparing the performance analysis of various types of Kalman filters used for state estimation in Robot Localization.**

Keywords - Extended kalman filter, Kalman filter, Multisensor data fusion, Robot localization, Unscented Kalman filter.

INTRODUCTION

1. Robot Localization

Robots are computer aided machine that support human actions. Nowadays robots are replacing humans in many technological fields such as Manufacturing industries, Information analysts, Medical Diagnosis, etc., The robots are classified into five types in general:

i. Pre-programmed Robot: This kind of robot can be used in repetitive tasks. Pre-programmed robots are most commonly used in automobile industries that assist as a mechanical arm for assembling various parts.
ii. Humanoid Robot: The robots that match the human characteristics are Humanoids. This type of robot is used in humanitarian assistance, public relationship, and healthcare industries.
iii. Autonomous Robot: The robot that acts without human intervention is an Autonomous robot. They are a peculiar type of robot which has various types of sensors to recognize their environment. Examples of autonomous robots are medical assistance robots, home cleaning robots, etc.,
iv. Semi-Autonomous Robot: The robots that are controlled by a human through the wireless network are Semi-Autonomous robots. Examples of semi-autonomous robots are robots used in military operations, fire Fighting, etc.,
v. Augmenting Robot: This type of robot strengthens the human capabilities or puts back the existing ones. Augmenting robot is used in medical devices for replacing prosthetic limbs.

Using robots in various applications reduces human errors and the cost of production. Robots have the competency to choose their travel path, Avoidance of obstacles, fault detection, etc.,[1]. Autonomous Mobile Robots is one of its types that carry out the operation in available environments without human intervention. The autonomous mobile robot is more productive in the various industrial environment. This type of robot relies on its mounted sensor output to carry out its task. The output from this sensor is used to estimate the current position of the robot. Localization is one of the key aspects required by autonomous robots as awareness about its current location is an essential prerequisite for taking future decisions.

Localization helps the robot estimate its current state with noisy observations. The composition of robot localization depends on its internal map together with Multisensor measurement. Sometimes the data from the Multisensor environment contains error values which cause uncertainty in robot location estimation. Figure 1. Shows the taxonomy of robot localization which is broadly classified into four major categories.

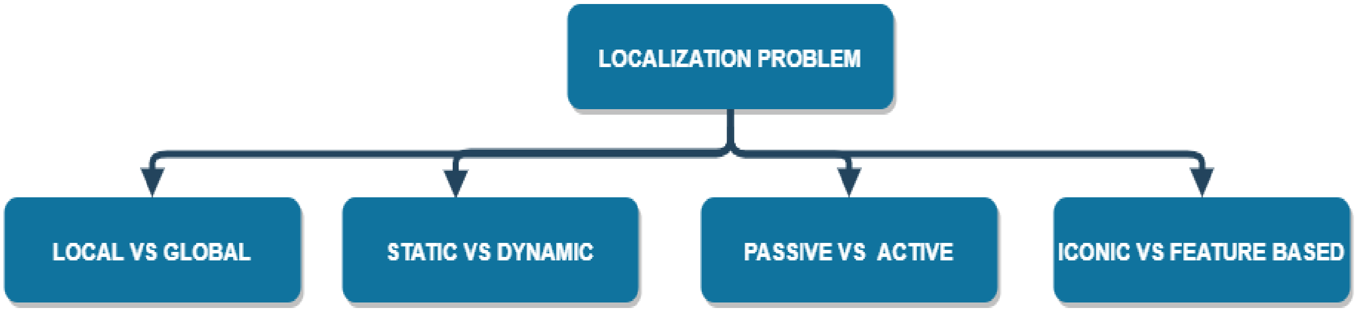

FIGURE 1
TAXONOMY OF LOCALIZATION

Local Vs Global localization: If the initial position of robots is known prior it is called local localization. If there is no prior knowledge about the robot position it is called global localization.

Static vs Dynamic: In the static environment a single variable is taken into account which is the robot's current position. Whereas in a dynamic environment there is a change in the robot position periodically and it involves values obtained from external variables.

Passive vs Active: Passive localization watches whether the robot is operating itself effectively. While the active type concentrates on reducing environmental error and paved the path for successful navigation.

Iconic vs Feature-Based: Iconic localization use source data from the sensor directly, it will match the fused data from the Multisensor measurement with its previous data. However, feature-based localization uses the extracted features from the sensor data [2].

2. Multisensor Data Fusion

Multisensor Data Fusion is defined as integrating the data from multiple sensors to provide a piece of useful information about its environment and helps to make decisions during difficult circumstances [3].

Data fusion techniques are ubiquitous in robot environments based on state estimation in localization. The major challenge that arises from the data fusion is uncertainty in the sensor measurements. Uncertainty is the data collected from sensors that are often erroneous. Fusion techniques should be able to handle such uncertainty and Data inconsistency. Many real-time applications are sensitive to uncertain data. The uncertainty in sensor data is categorized as Discrete and Continuous. Discrete type chooses a single value from many alternates. In Continuous type data item is chosen from a particular time interval [4].

The advantages of Multisensor Data fusion are: (i)Multisensor data fusion reduces energy consumption over the network and decreases the operation cost. (ii)Data collected from multiple sensors are more accurate and reasonable compared to single sensor data [5]. (iii)Sensor fusion helps us to make the right decision during a critical situation. Data fusion may take place in three different layers: (1) Low-level Data Fusion (2) Intermediate level Data fusion (3) High-level data fusion. Low-level data Fusion takes unrefined data as input from the sensors [6].

In intermediate level the features of the sensors are fused. To make accurate final decision the high-level data fusion is used [7].

The remainder of this work is designed as follows Section 2 describes the related background works in the field of robot localization and Multisensor data fusion. Section 3 presents the existing mathematical model for estimating the robot state. Section 4 provides the performance analysis of various state estimation techniques. Section 5 Concludes with future directions.

RELATED WORK

1. Basics of Robot Localization

The noisy data collected from proprioceptive and exteroceptive sensors are used to estimate the robot's current position.

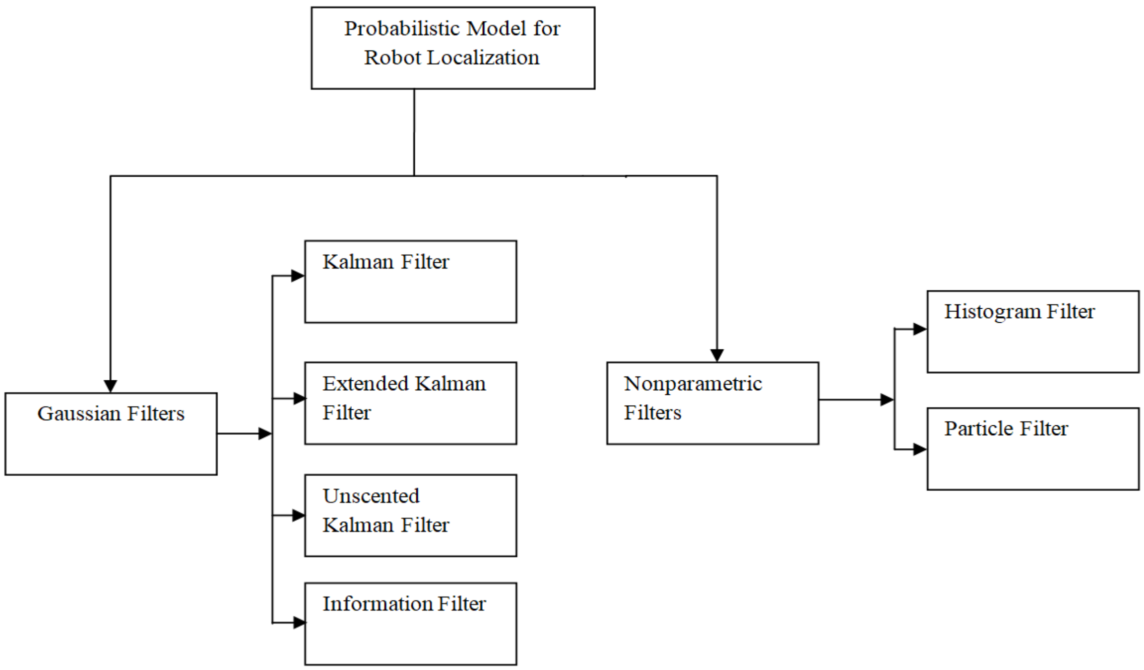

FIGURE 2

FILTERING APPROACHES FOR SENSOR DATA FUSION

Sometimes the sensors mounted on robots are inadequate to determine the position of Autonomous robots. Filtering approaches are used to fuse the data from multiple sensors. Figure 2 shows the available filter-based approaches based on Bayes for robot localization. The robot's current location in x and y coordinates form the pose of a robot. The position of the mobile robot is depicted in Equation 1, state vector A with X, Y coordinates and orientation angle (ϴ).

$$A = [\, X \quad Y \quad \theta] \qquad (1)$$

From Equation 2, The position of robot is determined from time 0 to time t.

$$\text{Ar,0:t=}\{\text{Ar}, 0|\text{Ar}, 1, \dots |\text{Ar}, \text{t}\} \qquad (2)$$

The robot location is determined by the proprioceptive and exteroceptive sensors motion and measurement model from time 1 to t.

$$\text{B1..t} = \{\text{B0}|\text{B1}, \dots |\text{Bt}\} \qquad (3)$$

$$\text{C1..t} = \{\text{C0}|\text{C1}, \dots |\text{Ct}\} \qquad (4)$$

Equation 3 & 4 represents the measurement for Exteroceptive and proprioceptive. Sensors that obtain information about themselves are proprioceptive and sensors that obtain information about the state of the environment is called Exteroceptive sensors.

2. Robot Motion Model

The motion model for robot position takes the noisy data of proprioceptive sensors and describes the probability of position at time t+1 given the pose at time t.

$$\text{P}(\text{Ar}, \text{t} + 1|\text{Ar}, \text{t}, \text{Ct}) = \text{prob}(\text{Ar}, \text{t} + 1 = \text{Ar}|\text{Ar}, \text{t}, \text{Ct}) \ (5)$$

Equation 5 represents the Probability equation for the Robot motion model. Here Ar, t represents the robot pose at time t and Ct is the motion command at time t. The value of Ar, t+1 can be obtained only from probability density function due to noisy data from sensor measurements.

3. Robot Measurement Model

The probability of measuring the robot position at time t for the given measurement Bt (Exteroceptive Measurement) when the position of the robot is Ar, t. It includes the noisy data arriving from Exteroceptive sensors.

$$P(Bt|Ar, t) \qquad (6)$$

Equation 6 is the Probability equation for the Robot measurement model. The value of Bt can be derived from the probability density function due to noisy data from sensor measurements.

4. Multi sensor Data Fusion for Robot Localization

Following steps to be taken for handling localization problems in robots: (i) Gaining Knowledge about initial position of robot followed by robot state estimation and finally choosing the appropriate approach for state estimation. Uncertainty in the sensor data may lead the robot to a confused state. The importance of Probabilistic and simultaneous localization and mapping (SLAM) approaches in state estimation is elaborated in [8]. The SLAM approach helps the robot to construct the environment map. It uses data from the internal part of the sensor such as speed, load, etc, as well as from the external factors like measuring the distance, the intensity of light which helps the robot to know about its environment. The robot's current position and environment map are measured with a probabilistic approach.

The authors in [9] proposed simultaneous localization and mapping techniques. The complexity of finding the robot's current pose is carried out with the Kalman filter estimation method.

Robots in the industrial environment can be able to self-position and move inside their environment without human interference. Self-localization plays a vital role in path planning for autonomous robots. Simtwo simulation the environment is used to simulate the different types of robots. The author suggested for extended Kalman filter because the model used is nonlinear. Unlike Kalman filter, transition equations are differentiable in extended Kalman filter. With the proposed algorithm robots can run through slippery and irregular floors [10].

Greenberg et.al, proposed a best practice for fusing the data from multiple sources to improve the accuracy of robot positioning. The coordinates for robot position are predicted using multiple beacon node strategy. Beacon nodes contain the position information. The uncertainty level in the data is captured by sensitivity metric [11].

Robots used for services indoor can't depend on GPS for their positioning. The model suggested by the author in [12] utilized secondary radar for reference for robot localization. The extended Kalman filter (EKF) approach is used to fuse measurements of wall detection sensors and radar values. In the case of object presence between wall and robot, the estimation technique fails to recognize it. The performance of EKF during this unprecedented situation can be improvised by the Mahalanobis distance formula for detecting those outliers.

PROBABILISTIC MODELS FOR ROBOT LOCALIZATION

1. Kalman Filter

An Autonomous robot system is impelled by a set of inputs from external factors or the sensors mounted on the system. The knowledge about that system relies on its input and calculated output. The considerations from this output carry errors and uncertainties termed sensor noise. Based on input and its observations it is necessary to obtain the state estimation. This is obtained through the use of filters.[13]

Kalman filter is one such kind of filter named after its inventor Rudolf E. Kalman in the year 1960. This algorithmic rule uses the line of measurements over some time and calculates the unknown variable. The Kalman filter basics involve a two-step process (i)Predict (ii)Measurement and update. Figure 3 Shows the iterative steps in the Kalman filter.

The predict step is based on previous measurements and the new state will be predicted with uncertainties. Kalman filter is a repetitive process. One must predict the state with its covariance matrix, every time we receive a new reading from the sensor. The predicted value is now compared with the sensor value and the measurement should be updated.

1.1. Kalman Filter Overview

If you want to locate the position of the autonomous robot, the periodic measurement from the appropriate sensors will be collected, and mix the predicted values with the actual measurement. The Kalman filter is useful for identifying how much prediction and measurement should be imparted for new state identification.

The steps in Figure 4 Elaborates the steps in the Kalman filter process. The information that we gathered are now placed into a matrix format for mathematical computations.

FIGURE 3
ITERATIVE STEPS IN KALMAN FILTER

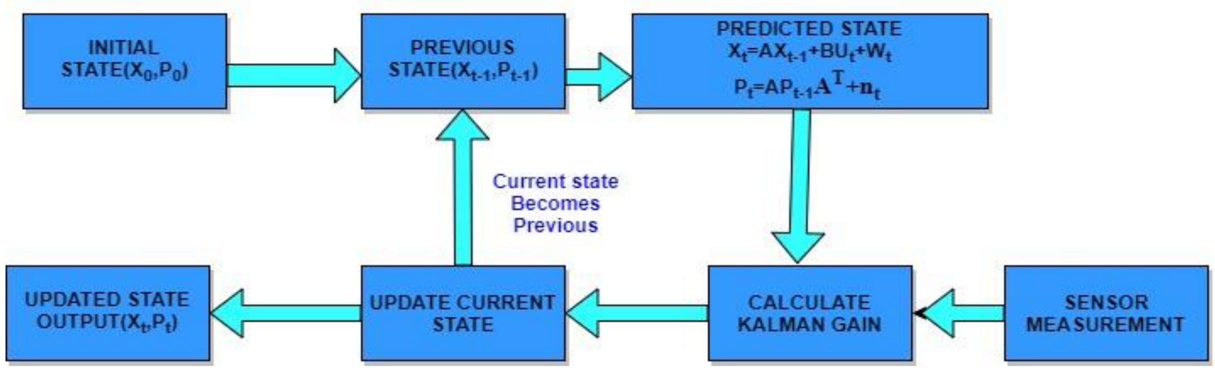

FIGURE 4
OVERVIEW OF KALMAN FILTER

1.2. Formulation

Step 1: The initial state contains X_0 -State matrix (position and velocity of the object) and P_0-Process covariance matrix (To keep track of the errors in the estimate).

Step 2: As we iterate through the process the current state becomes the previous state.

Step 3: We are going to predict the new state with a physical model and previous state estimations.

The Kalman filter problem is formulated with the following two equations:

$$X_t=AX_{t-1}+BU_t+W_t \quad (7)$$

$$P_t=AP_{t-1}A^T+n_t \quad (8)$$

Equation 7 predicts the state vector of a system Xt at time t. It holds the position and velocity of an object in vector form. ‘A’ and ‘B’ are matrices used to convert the input to a new state matrix. The parameter Ut is the vector called as control variable matrix that controls the position and velocity of our object. ‘w’ is the predicted state noise matrix. Equation 8 calculates the process covariance matrix. The matrix ‘A’ and its transpose is used to put them in a correct format. Finally process noise covariance matrix ‘n’ is added to the function.

Step 4: The predicted value is added to the actual measurement. The actual measurement is calculated with Equation 9.

$$Y_t=C_tX_t+Z_t \quad (9)$$

There is a certain number of variations in the measurement which may be controllable or not controllable. So, the matrix ‘C’ is used to convert the measurement into the right format that gives us a vector. Eventually, we have to add measurement noise or error to the equation.

Step 5: The Kalman gain is the important factor of the Kalman filter which modulates the value between estimate and measurement. It will decide how much of the estimate will be imparted on measurement and predicted state. If the current state prediction goes wrong the new weight will be added to the measurement for further predictions (Equation 10).

$$K=\frac{\text{ERROR IN ESTIMATE}}{\text{ERROR IN ESTIMATE+ERROR IN MEASUREMENT}} \quad (10)$$

Step 6: The final step is processes error estimation. Based on the whole process of Kalman gain and filter the error process is estimated. The new state is updated and the whole process is iterative.

Initially, the system receives the measurement from the deployed sensors. If it is the initial measurement the state and covariance matrices will get updated. If not, the new state will be predicted with the measured value. Depends on the uncertainty in predicted and measured value the best one will be taken into consideration.

The Kalman filter improves the estimation of measured variables with the fused sensor data. Fusion through Kalman substantially improves the estimation by reducing the sensor noise.

The limitation of the Kalman filter is, it always works with Linear systems with a gaussian distribution.

2. Extended Kalman Filter (EKF)

In most of the real time, robotic applications the system tries to take the measurement in a certain direction that involves angles that leads to sine, cosine functions which cannot be solved by the Kalman filter. Extended Kalman Filter is a nonlinear translation of the Kalman filter. It is used to calculate the state estimate of dynamic systems. When the system is nonlinear, the state estimates are never gaussian. EKF linearizes the non-linear function and does exactly follow the Kalman filter steps [14].

The extended Kalman filter uses the Taylor series to linearize the nonlinear equations. In this procedure, jacobian matrix is produced which helps for linear mapping.

2.1. Formulation

The jacobian matrix is a non-square matrix m*n. It gives the matrix of first-order partial derivatives. For a vector valued function f(x) in Equation 11

$$f(x) = \begin{matrix} f1(x) \\ f2(x) \\ fm(x) \end{matrix} \qquad (11)$$

The jacobian matrix for f(x) is outlined in Equation 12.

$$f(x) = \begin{matrix} \frac{\partial f1}{\partial x1} & \frac{\partial f1}{\partial x2} \cdots & \frac{\partial f1}{\partial xn} \\ \frac{\partial f2}{\partial x1} & \frac{\partial f2}{\partial x2} \cdots & \frac{\partial f2}{\partial xn} \\ \vdots & & \\ \frac{\partial fm}{\partial x1} & \frac{\partial fm}{\partial x2} \cdots & \frac{\partial fm}{\partial xn} \end{matrix} \qquad (12)$$

The Function f(x) which has M components the jacobian computes a matrix with all the partial derivatives of individual dimensions of the vector valued function f(x). A general non-motion model function for EKF is given in Equation 13.

$$X_t = f\,(X_{t-1}, U_t) + W_t. \qquad (13)$$

Where X is the state model at time t.

X_{t-1} denotes Previous state.

U_t is the control variable & Wt. is gaussian noise.

The nonlinear measurement model is given by equation 14. It handles the measurement arriving at specified time intervals.

$$Z_t = H(X_t) + n_t \qquad (14)$$

The Equation 13 motion model must be linearized with Taylor series expansion.

$$f\,(X_{t-1}, U_t) \approx f\,(\mu t-1, U_t) + \frac{\partial g(\mu t-1, Ut)}{\partial Xt-1}\,(X_{t-1} - \mu t - 1) \quad (15)$$

The sensor model shown in Equation 14 is linearized with the following equation.

$$h\,(X_t) \approx h\,(\bar{\mu t}) + \frac{\partial h(\bar{\mu t})}{\partial Xt}\,(X_{t-1} - \bar{\mu t}) \qquad (16)$$

Where $\frac{\partial g(\mu t-1, Ut)}{\partial Xt-1}$ and $\frac{\partial h(\bar{\mu t})}{\partial Xt}$ in the Equation 15 &16 is a Jacobian matrix.

The Extended Kalman filter has some limitation that includes bad approximation of nonlinear functions. In addition to that reckoning partial derivatives are time consuming process. The approximation in extended Kalman filter may leads to under performance of the state estimation.

3. Unscented Kalman Filter

To enhance the performance of state estimation methods further,an unscented Kalman filter method is introduced. Extended Kalman filter uses single point approximation for converting nonlinear function into linear function, whereas unscented Kalman filter takes a cluster of points for the conversion. The points are assigned with weight and transformed through Gaussian functions [15].

3.1. Formulation

In predict step, the sigma points are calculated with their weight. The mean and covariance matrix are calculated from sigma points. The process and measurement model for unscented Kalman filter in Equation 17 and Equation 18.

$$X_{k+1}=f(X_{k-1}, V_{k-1}) \quad (17)$$
$$Z_k=h(X_k)+W_k \quad (18)$$

If the mean($\bar{x}$) and covariance(P)of the state X is known then the cluster of points that possess the sample mean and covariance can be called as sigma points. The next step is to apply the non-linear function in Z=h(X) to each sigma point. The following steps define the generation of sigma points.

$$x^i_k= \hat{x}_k+ \tilde{x}^i \qquad \text{for } i=1,2\ldots 2k_x$$
$$\bar{x}^i_k = [row_i(\sqrt{k_x P_n})]^T \qquad \text{for } i=1,2\ldots k_x$$
$$\bar{x}^i_k = -[row_i(\sqrt{k_x P_n})]^T \qquad \text{for } i=k_x+1,\ldots 2k_x$$

Where $row_i(A)$ denotes the i^{th} row vector of the matrix A and $\sqrt{k_x P_n}$ is a matrix square root of $(k_x P_n)$ such that

$$\sqrt{k_x P_n}^T \sqrt{k_x P_n} = k_x P_n \quad (19)$$

The above equation does not rely on a jacobian matrix for further process. The recursion of the unscented Kalman filter is the same as Extended Kalman filter except the sigma points to estimate the state. It is better than an extended Kalman filter.Figure 5 depicts the flowchart for choosing the appropriate approach in state estimation methods.

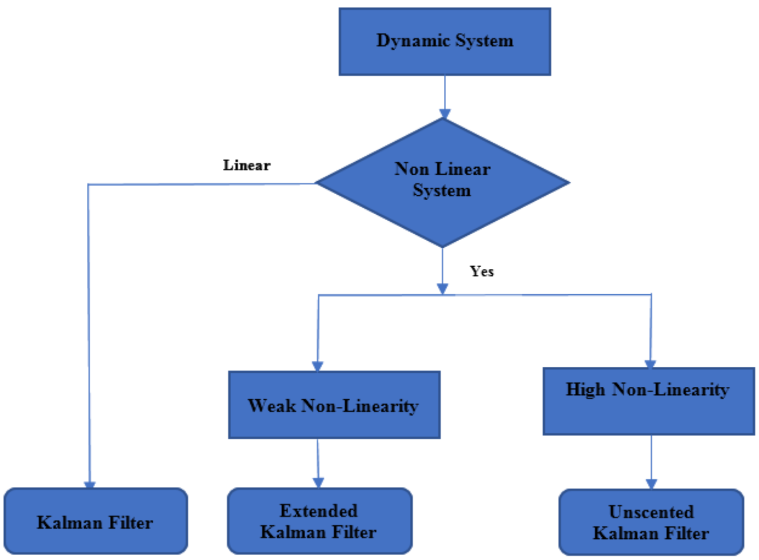

FIGURE 5
FLOW CHART FOR PROBABILISTIC MODEL SELECTION

COMPARATIVE STUDY AND PERFORMANCE EVALUATION

Performance Evaluations are used to determine the best structure for the given problem. It allows us to evaluate which method solves the problem efficiently. We performed the estimation prediction for the position of the robots. The state of the robot can be determined by the following vector

$$S = [X, Y, \Theta] \quad (20)$$

Where X, Y denotes the coordinates of the plane and Θ denotes Yaw angle (the angle between lines pointing in the direction where the robot is moving and its X-axis). The measurements from different types of sensors ascended on the robot aren't accurate. By taking all the simulated sensor observations through Extended and unscented Kalman filter curves out the noisy measurements and gives the better state estimation for autonomous robots. The initialization for EKF and UKF is shown in Table 1. The test path for simulation is shown in Figure 6. The simulated robot moves on X and Y coordinates while the Θ represents the angle of rotation. Measurements from sensors are not always accurate. Due to noisy measurements, we can never be certain about robot location.

We can estimate the current location of Robot using EKF and UKF If we know,

i. The Estimate of the previous step.
ii. The Time interval between two steps.
iii. The Velocity of the robot at the previous step.
iv. The Random noise estimation.

To test the performance of EKF and UKF a list of observations is simulated at successive timesteps.

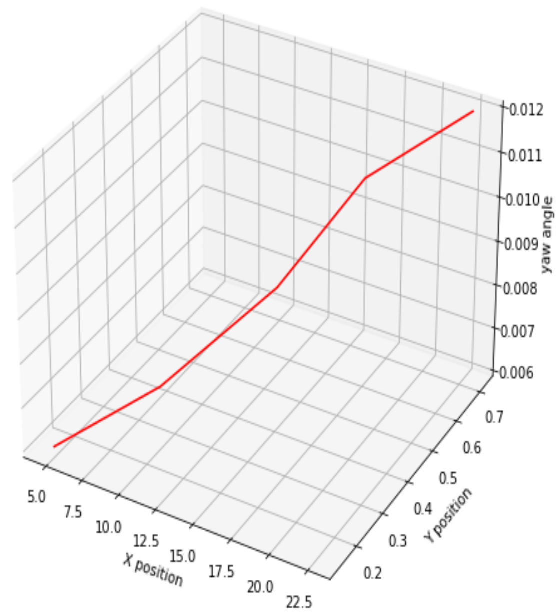

FIGURE 6
SIMULATED TEST TRAJECTORY FOR ROBOT

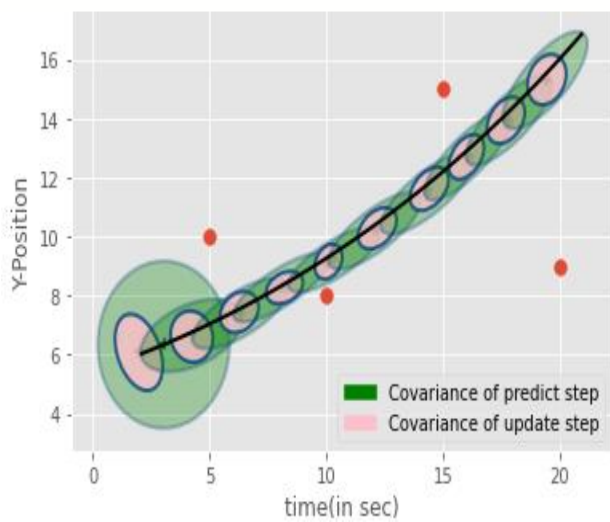

FIGURE 7
LOCALIZATION USING EKF

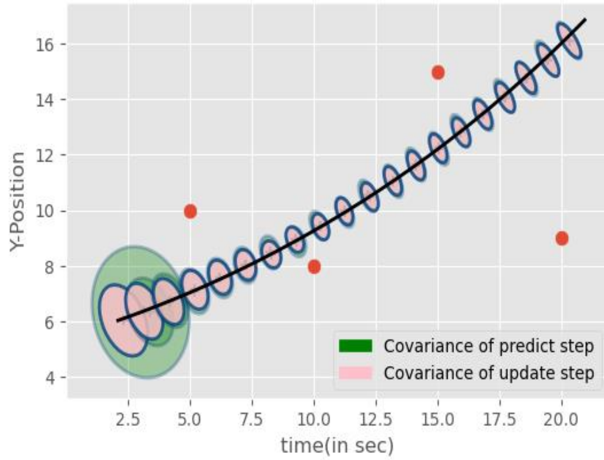

FIGURE 8
LOCALIZATION USING UKF

TABLE 1
ERROR MEASURE OF EKF AND UKF

RMSE			
X	**Y**	**YAW**	**ALGORITHM**
0.006	-0.0059	-0.0011	UNSCENTED KALMAN FILTER
-0.0059	0.0105	0.0105	
-0.0011	0.0015	0.0006	
0.02	0.003	-0.002	EXTENDED KALMAN FILTER
0.003	0.021	0.003	
-0.002	0.003	0.002	

Random inputs are generated from python code and the approximate and actual output of the process is generated. The assumption for landmarks has been made and it is denoted as a red circle in Figure 7 & Figure 8. The robot path is showed with a black line. Kalman filter types fuse noisy sensor measurement to create an optimal estimate of the state of the robotic system.[16]

With the aforementioned equations, the matrix for covariance is calculated at each step. The variance value is taken from the diagonal of a matrix and the covariance value from its off-diagonal. The covariance matrix is a square matrix that has many rows and columns equal to some states in the initialization vector (Equation 16) Since we have three states as per our assumption the size of the matrix would be 3X3.

Analyzing the divergence of values from measured value is error estimation. The most commonly used error estimation method Root mean square error (RMSE) is used for estimating the accuracy. From Table 1, it is noticed that the value of RMSE for Unscented Kalman is least compared to Extended.

Kalman filter. The covariance ellipses for the predict step in the Extended and Unscented Kalman filter are shown in green color and update step in pink color (Refer Figure 7&Figure 8). Covariance ellipses are bounded. With the minimal error values, the unscented Kalman filter accomplishes better accuracy compared to extended Kalman filter.

CONCLUSION

The location of a robot can be determined by the data collected from the sensor deployed in its environment. This type of sensor may carry incorrect and uncertain information. Due to this noisy data, erratic confusion may rise in the final decision. The robot can able to estimate its position with the state estimation algorithm and carry out the assigned task. The most common estimation algorithm belongs to the family of Kalman filters. The pros and cons of each method are discussed briefly in this work. The commonality possessed by Kalman, Extended Kalman, and Unscented Kalman is they operate in two-step processes predict and update. Linear functions are handled by conventional Kalman filter and UKF handles nonlinear functions. In view of robot localization this paper carried out the performance evaluation of two Kalman family algorithms for state estimation. For handling some nonlinear problems in the real world Extended Kalman filter shows poor progress compared to the unscented Kalman filter. This concurs that the UKF will give a better estimation accuracy. In further research, enhanced state estimation methods are carried out with an optimization algorithm to decrease the mean square error in state estimation.

REFERENCES

[1] Li, J., Cheng, L., Wu, H., Xiong, L., & Wang, D, "An overview of the simultaneous localization and mapping on mobile robot," *In Proceedings of International Conference on Modelling, Identification and Control*, 2012, pp. 358-364.

[2] Castanedo, F, "A review of data fusion techniques," *The scientific world journal,* Vol. 19, Issue 704504, 2013, pp.1-19.

[3] Al Khatib, E.I., Jaradat, M.A., Abdel-Hafez, M., & Roigari, M, "Multiple sensor fusion for mobile robot localization and navigation using the Extended Kalman Filter," *In 10th international symposium on mechatronics and its applications (ISMA)*, 2015, pp. 1-5.

[4] Le, T., & Jing, Z, "A data fusion algorithm based on neural network research in building environment of wireless sensor network," *International Journal of Future Generation Communication and Networking,* Vol. 8, Issue 4, 2015, pp. 295-306.

[5] Doumbia, M., & Cheng, X, "State Estimation and Localization Based on Sensor Fusion for Autonomous Robots in Indoor Environment," *Computers,* vol. 9, Issue. 4, 2020.

[6] Jusoh, S., & Almajali, S, "A systematic review on fusion techniques and approaches used in application," *IEEE Access,* Vol. 8, 2020, pp. 14424-14439.

[7] Luo, R.C., & Su, K.L, "A review of high-level multisensor fusion: approaches and applications," *In Proceedings. 1999 IEEE/SICE/RSJ. International Conference on Multisensor Fusion and Integration for Intelligent Systems. MFI'99 (Cat. No. 99TH8480),* 1999, 25-31.

[8] Shit, RC, "Precise localization for achieving next-generation autonomous navigation: State-of-the-art, taxonomy and future prospects," *Computer Communications,* Vol. 160, 2020, pp. 351-374.

[9] Huang, S., & Dissanayake, G, "Robot localization: An Introduction," *Wiley Encyclopedia of Electrical and Electronics Engineering,* Vol. 19, Issue 99, 2016, pp.1-10.

[10] Moreira, A.P., Costa, P., & Lima, J. "New approach for beacons based mobile robot localization using Kalman filters," *Procedia Manufacturing,* Vol. 51, Issue 4, 2020, pp. 512-519.

[11] Greenberg, J.N., & Tan, X. "Sensitivity-based data fusion for optical localization of a mobile robot," *Mechatronics,* Vol. 73, Issue 102488, 2021.

[12] Dobrev, Y., Gulden, P., & Vossiek, M. "An indoor positioning system based on wireless range and angle measurements assisted by multi-modal sensor fusion for service robot applications," *IEEE Access,* Vol. 6, 2018, pp. 69036-69052.

[13] Li, Q., Li, R., Ji, K., & Dai, W, "Kalman filter and its application," *In 8th International Conference on Intelligent Networks and Intelligent Systems (ICINIS),* 2015, pp. 74-77.

[14] Mochnac, J., Marchevsky, S., & Kocan, P, Bayesian filtering techniques: Kalman and extended Kalman filter basics. *In 19th International Conference Radioelektronika,* 2009, pp. 119-122.

[15] Shen, J., Liu, Y., Wang, S., & Sun, Z, "Evaluation of unscented Kalman filter and extended Kalman filter for radar tracking data filtering", *In European Modelling Symposium,* 2014, pp. 190-194.

[16] Labbe, R.R, "Kalman and Bayesian Filters in Python", *eBook,* 2018.