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# Particle Filter Based Mobile Robot Localization

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**Abstract:**

Localization of a mobile robot requires a map of the environment and requires locating the pose within the map. This investigation uses particle filter algorithm for localizing the mobile robot with fixed features. The position and orientation of the mobile robot can be obtained from onboard sensors. The information from the sensors has errors and uncertainty from the environment that may accumulate over time. The implementation of the sensor fusion technique and particle filter has been used to minimize the errors and uncertainty to determine the pose of the robot. Results are demonstrated using simulation.

**Keywords:** Mobile robot, pose, localization, features, particle filter.

## I.INTRODUCTION

Mobile robots are autonomous vehicles that navigate through the environment. A robot without knowledge about the environment is lost. Localization plays a key role in identifying the position of the mobile robot in the environment. Several works have been carried out in recent years. Localization can be classified based upon the type of sensors it uses. Relative localization uses odometer, gyroscopes type internal sensor to get the pose of the robot [12]. Measurements obtained from wheel Odometry has errors that may accumulate over time. Absolute localization uses Global positioning system (GPS), range finders to identify the features in the environment [8] and accumulation of error has been reduced [15].Fusion of these two methods can reduce the localization errors by employing the Kalman Filters.

Kalman filters are linear estimators and it works well for Gaussian data. But mobile robots are non linear in nature and Extended Kalman Filter (EKF) has been generally used [4]. EKF assumes the uncertainties to be Gaussian and it linearizes the non linear function. This non linearization is severe as the uncertainty increases [2, 3].The existing literature includes usage of inexpensive internal sensors like incremental encoders and external sensor like ultrasonic range finder. Here range finder limits the speed of the robot for safety reasons. [16] Proposed odometer, compass and tilt sensor based localization. Since uncertainty grown to be large, it used camera based pose estimation but again existence of unique features not always guaranteed. [10] Used GPS and vehicle sensors where available of GPS signal play a major role. Error grows when the signals are not available.

Data association problem has been another factor that might cause errors to deviate from actual results [3, 9]. Unscented Kalman Filter (UKF) has been introduced to overcome this problem [5]. However, the resulting random distribution when transformed through non linear system was no longer Gaussian and the results were obtained only upon the longer run [1].

A survey has been done on the Kalman filter for robot vision. It speaks about uncertainty in robot localization, navigation, following, tracking, motion control, estimation and prediction[4]. [14] used the Omni directional vision sensors lacks matching the robot pose prediction eliminated by the angular constraints.

Hence, a better estimation is required to estimate the pose of the robot. Particle filter [6, 13] which works on the non linear, multimodal distribution data i.e. non Gaussian data can be used in mobile robot localization.

This paper uses particle filter for mobile robot localization. Here, the pose of the robot has been estimated from a set of samples that are randomly drawn from a set of distribution known as particles. It accustoms wheel encoder as internal sensor and laser range finder as the external sensor to get pose estimate. Particle filter which is a Bayes filter undergoes three stages of working namely sampling, weighting and resampling to obtain the best pose estimate. The rest of the paper has been organized as follows: section II describes about system modeling, section III describes the particle filter algorithm, section IV talks about the results and section V about the conclusion.

## II.SYSTEM MODELING

This section describes about system modeling which has the implementation of the system state, motion model and the observation model. The state of the system can be initialized as

$$p = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} \quad (1)$$

Where x, y are the initial position coordinates and $\theta$ is the initial orientation of the system.

The position of the robot can be estimated from the initial state of the robot using the motion model. The motion model uses the wheel Odometry information and it is shown in figure (1). It helps to predict the next state with the current one using the relation:

$$p' = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} + \begin{bmatrix} \frac{\Delta w_l + \Delta w_r}{2} . \cos(\theta + \frac{(\Delta w_r - \Delta w_l)}{2b}) \\ \frac{\Delta w_l + \Delta w_r}{2} . \sin\left(\theta + \frac{(\Delta w_r - \Delta w_l)}{2b}\right) \\ \frac{(\Delta w_r - \Delta w_l)}{b} \end{bmatrix} \quad (2)$$

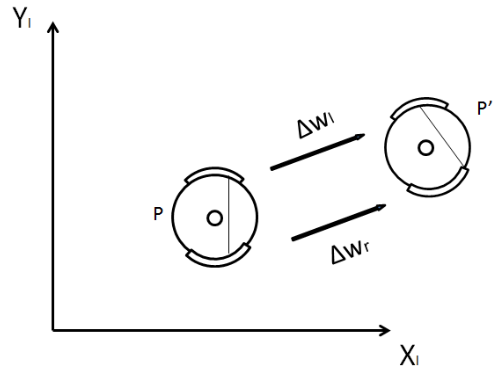


**Fig.1. Odometer motion model**

Where $\Delta w_l, \Delta w_r$ are the distance travelled by the left and right wheel respectively and b is the distance between the two wheels.

The measurement model gives only the information about the position of the robot in the local reference frame. The pose of the robot with respect to the global reference frame is essential for utilizing the observation model. The laser range finder gives raw sensor data to the observation model. This raw sensor data is converted to corresponding distance values as

$$x_L = r * \sin(\Phi) \quad (3)$$

$$y_L = r * \cos(\Phi) \quad (4)$$

Where r is the distance between the robot and the feature, $\Phi$ is the angle between the consecutive laser beams and $x_L$, $y_L$ are the corresponding distance in the local reference frame. After converting equation (3) and (4) the global coordinate is as follows:

$$X_I = r * sin(\theta - \Phi) \quad (5)$$

$$Y_I = r * cos(\theta - \Phi) \quad (6)$$

Where $\theta$ is the angle in the global coordinate frame and $X_I$, $Y_I$ are the corresponding distance in the global coordinate.

The observation model extracts information from the features. Figure (2) shows the features that were predefined in the environment. The features are assumed to be identified and extracted when observation model receives information. Each feature of the map with its location state can be expressed as:

$$x_t = \langle s_t^m, l_{1,t}^m, l_{2,t}^m, l_{3,t}^m, l_{4,t}^m \rangle \quad (7)$$

where $s_t^m$ is the location of mobile robot, t indicates the time step, and $l_{n,t}^m$ is the feature n.

## III.PARTICLE FILTER ALGORITHM

The particle filter algorithm [7] for mobile robot localization has been used in this section. It has been used to estimate the pose of the robot that is multimodal and non linear. It uses samples that are drawn from the set distribution known as particles. It considers the samples that have high weight and sum of all weights assigned is equal to one. The implementation of particle filter follows: Initially the samples are assumed to be uniformly distributed. $p$ is used denote the pose of the robot. As the robot starts exploring the environment from an unknown position, it receives measurements from the wheel Odometry about the internal state of the robot. Then information about the environment is obtained through the observation model. It has been used to draw next generation of particles. This is called sampling. The set of samples obtained from the observation model is applied to motion model. If the predicted location state is closed to the observed state the weight of the particle should be assigned with the difference of the predicted state and the observed state. This process is called weighting. The cumulative of sum weights must be 1 when it is computed. Resampling has been done after weighting process. Here the particles with higher weights are only considered. It resets the whole set of samples that are obtained from the previous set by 1/N and it must be proportional to the samples that are drawn initially. Hence the particles with high weight are duplicated maintaining the sum of weights unchanged whereas the particles with low weights will be eliminated. It is repetitive process until particles with highest weight that contains the pose information is achieved.

## IV.RESULTS

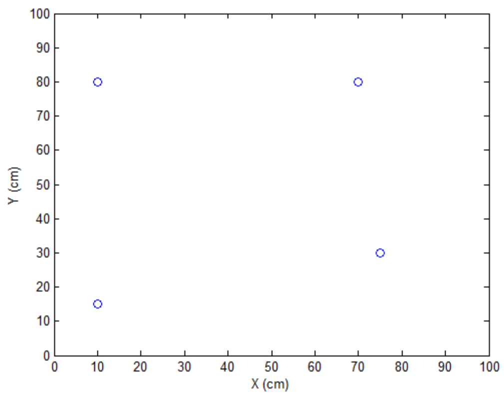


**Fig. 2 Position of features**

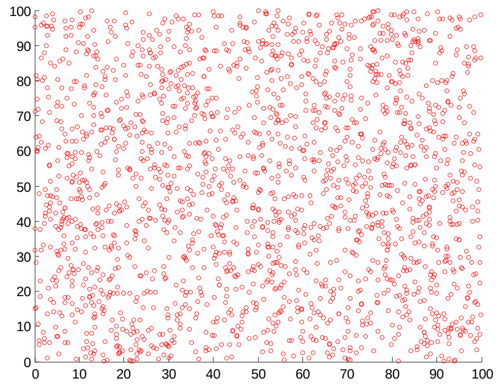


**Fig. 3 Random distribution of particles**

Four features were placed in the environment 100 ×100 in the range [10.0, 15.0], [75.0, 30.0], [70.0, 80.0] and [10.0, 80.0]. The measurement noise of 0.15 radians was given to measure the orientation and distance.

The algorithm was executed for 100 iterations. The particles were randomly distributed in the localizing environment. Fig (3) shows randomly distributed particles possess the position and orientation information. Fig (4) shows the reduced search area after few iterations.

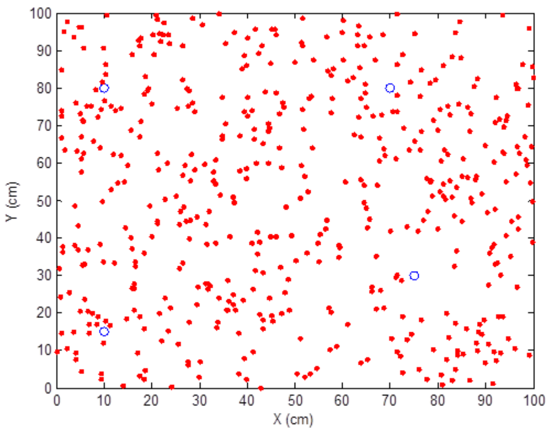


**Fig .4 Distributions of particles after few iterations**

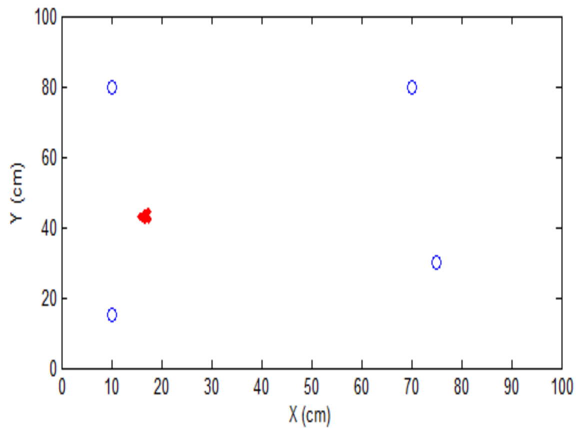


**Fig. 5 Position of the robot**

Fig (5) gives the pose of the robot obtained at [19.26,43.38, 8.24] $^{T}$. Fig (6) gives the distance error and angle error obtained between the observed information of the robot and the predicted information of the particle.

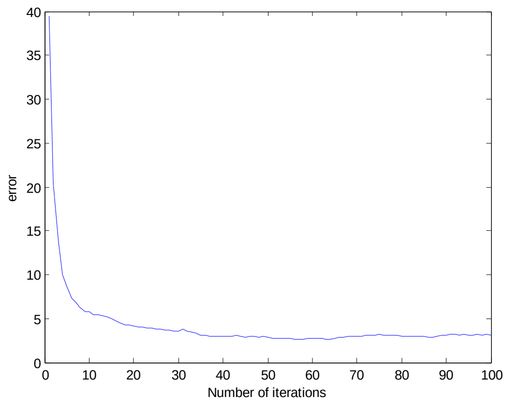


**Fig. 6 Error plot between the sensor position coordinates and predicted coordinates with respect to the world coordinates**

## V.CONCLUSION

This paper uses particle filter for mobile robot localization with laser range finder. The pose of the robot is identified with fixed features. The algorithm implemented used to estimate the pose of the robot by fusing information from the wheel Odometry and laser range finder. Simulation shows the effectiveness of the algorithm in identifying the pose of the mobile robot. Further work can extend by localizing the robot in the unknown environment.

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