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# Mobile robot localization failure recovery

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# MOBILE ROBOT LOCALIZATION FAILURE RECOVERY

by

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# Abstract

Mobile robot localization is one of the most important problems in robotics. Localization is the process of a robot finding out its location given a map of its environment. A number of successful localization solutions have been proposed, among them the well-known and popular Monte Carlo localization method, which is based on particle filters. This thesis proposes a localization approach based on particle filters, using a different way of initializing and resampling of the particles, that reduces the cost of localization. Ultrasonic and light sensors are used in order to perform the experiments. Monte Carlo Localization may fail to localize the robot properly because of the premature convergence of the particles. Using more number of particles increases the computational cost of localization process. Experimental results show that, applying the proposed method robot can successfully localize itself using less number of particles; therefore the cost of localization is decreased.

# Dedication

I would like to dedicate this thesis to my mother and the memory of my father.

# Acknowledgements

I would like to express my gratitude to all those who gave me the possibility to complete this thesis. I am grateful to each of my thesis committee members, whose individual and collaborative efforts and guidance have made this endeavour an unforgettable experience, characterized by academic and professional growth and self-discovery. I wish to thank my advisor, Dr. Dan Wu for his constant support during my thesis work and through completion of my degree requirements and research. Without his support, this thesis could not have been completed. I also would like to thank members of my master committee, Dr. Scott Goodwin, School of Computer Science, Dr. Chunhong Chen, Department of Electrical and Computer Engineering, for being in my committee, and their constructive criticism, helpful advices, and guidance, and to Dr. Jianguo Lu, the chair of the committee.

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# Chapter 1

# Introduction

Localization is the most fundamental problem to provide a mobile robot with autonomous capabilities. Almost all tasks of mobile robots require a robot to have accurate knowledge about its location such as in Robotic Soccer. Mobile robot localization [4] is the problem of determining the position of a mobile robot relative to a given map of the environment and using the sensor data. It is often called position estimation or position tracking [13]. Let $l = (x,\ y,\ \theta)$ denote a location, the robot pose is usually given by three variables, robot's two location coordinates in the plane $(x,\ y)$ and robot's orientation $\theta$. In probabilistic robotics, the notion of belief $bel(L_t)$ is used to reflect the robot's internal knowledge about the state of the environment. The state cannot be measured directly. It must be inferred from the measurement data and control data.

Monte Carlo Localization which is based on Particle filters and represents the belief $bel(x_t)$ of the mobile robot by particles is one of the localization algorithms and has already become one of the most popular localization algorithms in robotics. It is easy to implement, and tends to work well across a broad range of localization problems. Most of the existing approaches can not recover from localization failure and kidnapped robot problems. Therefore we need a method to localize the robot with higher probability and with ability to recover robot from kidnapping problem.

The number of samples to be used is important, since using more number of particles will increase the cost of localization.

The proposed method is an improved approach to localize the mobile robot. It recovers the robot from localization failures with high probability. It has some differences from the regular MCL algorithm, modified initialization step and modified resampling step that helps to reduce some steps of localization and the cost of localization, and re-generating particles in the case of localization failure that helps to prevent the robot from failure in kidnapped robot problem situation. Applying the proposed method, it is expected that robot localizes itself with a high probability with lower cost. In terms of realization proposed method is much easier to implement, since particles are not generated from the very beginning and the cost of localization and computational costs are therefore decreased. Localization is done faster and more accurate with the use of less number of particles.

This thesis is only concerned on the localization problems in indoor environments, particularly in small-scale room with robot equipped with low-cost sensors. The most important aspect of the proposed method is to help the robot to recover from localization failure.

## 1.1 Outline

This remainder of the thesis is organized as follows.

Chapter 2 consists background knowledge. This chapter is focused on the materials that the proposed approach is based on. First, we will introduce the uncertainty in robotics and provide a comprehensive overview of probabilistic robotics. Then description of basic probabilistic concepts are given. Monte Carlo localization which is one of the methods of localization and is the fundament of the proposed method is given in more details and finally there is a brief review of the related works in the area of mobile robot localization. In chapter 3 the proposed method is presented in details. First the statement of the problem and the general description of our method, and then the comparison of the proposed method with the existing methods which is followed by the discussion of the experimental results in chapter 4. Experiments are performed in different environments to verify the performance of the proposed approach. The detailed information of the implementation and the experimental results are discussed. Finally, we conclude this research work with discussion of possible future research directions and open problems in chapter 5.

# Chapter 2

# Background Knowledge

This chapter provides the background knowledge which the proposed method is based on. First, we present basic idea of probabilistic robotics, followed by the definition of mobile robot localization and localization algorithm. Then, Monte Carlo localization (MCL) algorithm is explained since it is one of the most important probabilistic algorithms for mobile robot localization and also the foundation of the proposed method followed by implementations of MCL. Then, we describe kidnapped robot problem which is a problem that may occur during the localization of the mobile robot and will result in localization failure. The summary of the related work to date is given at the end.

## 2.1 Probabilistic Robotics

Unlike the previous approaches relying on a single best guess of what might be the case; probabilistic algorithms describe the robot and the environment using random variable. In particular, there are two basic models involved in probabilistic robotics: perception, the way sensor is processed, and action, the way robot behaves. By doing so, probabilistic robotics provides a great way to accommodate the uncertainty that comes from most robot practice. As a result, they perform excellent in the face of uncertainty.

In probabilistic robotics, we describe the robot and environments using the notion of state, which can be defined as a collection of all aspects of the robot and its environment that can impact the future [14]. The state variables that tend to change over time will be called dynamic state, such as walking people around the robot. The state that does not change is called static state, such as location of walls in buildings. The state also involves variables related to robot itself, such as its pose, velocity and so on. In this thesis, state is denoted as $x$; the state at time $t$ is denoted as $x_t$. Time defined here is discrete. That is, all states can be described at discrete time steps $t = 0, 1, 2, ....$ The initial state of the robot will be denoted as time $t = 0$. For robot action, the state includes variables for the configuration of the robot's actuators. The location and features of surrounding objects in the environment are also state variables. An object may be a chair, a box or a wall. Features of these objects may be their texture or color. The location of objects in the environment is static in this thesis. Many other variables that may impact a robot's operation can be state variables as well. The list of all possible state variables is endless. Typical state variable used in this thesis is the robot pose that includes robot's location and orientation relative to a global coordinate system. Strictly speaking, mobile robots have six such state variables, three for Cartesian coordinates, and three for angular orientation. But for robots defined in planar environments, the pose is usually given by three variables, two location coordinates in the plane and the heading direction.

There are two fundamental types of interaction between a robot and its environment: sensor measurements and control actions [14].

Sensor measurement is the process in which the robot obtains the information about its environment through sensors. Control actions include the robot motion and the manipulation of objects in the environment. In accordance with two kinds of environment interactions, robot receives two different streams of data: measurement data and control data (also referred to as movement data or motion data).

For measurement data, we use $z_{1:t}$ to denote all measurement data from time 1 to time $t$ and $z_t$ to denote the measurement data at time $t$. For movement data, we use $u_{1:t}$ to denote all movement data from time 1 to time $t$ and $u_t$ to denote movement data at time $t$. For these two kinds of data, localization algorithms based on probabilistic robotics [14] have two separate components to process them. One is the measurement model, and the other is the motion model. The measurement model $p(z_t \mid x_t)$ is the conditional probability of $z_t$ at the state $x_t$ . The motion model comprises the state transition probability $p(x_t \mid u_t, x_{t-1})$, which describes the posterior distribution after incorporating the motion data $u_t$ at $x_{t-1}$.

### 2.1.1 Map Representation

Mobile robot localization problem assumes that robot is given a map in advance. If the map of the environment is not given to the mobile robot then the robot should build the map while trying to localize itself in the environment and that is called SLAM (simultaneous localization and mapping). The map specifies the environment in which measurements are generated. Formally, a map $m$ is a list of objects in the environment with their properties. $M = m_1, m_2, , m_n$.

If the map of the environments is not given to the mobile robot, then the robot can calculate the posterior over maps given the data. $p(m \mid z_{1:t}, x_{1:t})$. Let $m_i$ denote the grid cell with index $i$. An occupancy grid map partitions the space into finitely many grid cells: $m = \sum i$. Each $m_i$ has attached to it a binary occupancy value, which specifies whether a cell is occupied or free. We will write "1" for occupied and "0" for free. The notation $p(m_i = 1)$ or $p(m_i)$ will refer to a probability that a grid cell is occupied.

## 2.2 Mobile Robot Localization and Localization Algorithms

### 2.2.1 The Bayes Filter and Kalman Filter Algorithms

The most general algorithm for the state estimation is Bayes filter [14]. It calculates the posterior probability $\mathrm{bel}(x_t)$ according to the measurement and control data as follows:

$\mathrm{bel}(x_t) = p(x_t \mid z_{0:t},\, u_{0:t})$

where $x_t$ denotes the robot pose $(x,\, y,\, \theta)$ at time $t$, $z_{0:t} = z_0,\, z_1,\, \dots\,,\, z_t$ denotes the sensor readings up to $t$, and $u_{0:t} = u_0,\, u_1,\, \dots\,,\, u_t$ is the control data changing the state of the world. The input of Bayes filter is the belief $\mathrm{bel}(x_{t-1})$ at time $t-1$, along with the most recent control $u_t$, and the most recent measurements $z_t$. The output is the belief $\mathrm{bel}(x_t)$ at time $t$. The measurements of sensors and the control information are corrupted with noise. In order to deal with these uncertainties, Bayes filter is conducted in two phases: prediction phase (line 3 of the algorithm), it processes the movement data $u_t$ , and calculate the state $x_t$ using the prior belief over state $x_{t-1}$ and the movement $u_t$. The second step (line 4 of the algorithm) is called update phase. It processes the measurement data $z_t$, and incorporate it into $\mathrm{bel}(x_t)$. But the result $\mathrm{bel}(x_t)$ may not integrate to 1, so it uses the normalization constant $\eta$ to normalize the result $\mathrm{bel}(x_t)$.

The Kalman filter technique is commonly used in local localization. The robot estimates its pose continuously by counterbalancing the odometric error using the sensor data. Therefore, if the initial pose is accurate and sensor error is small, the Kalman filter can provide efficient, accurate, and continuous localization result.

Mobile robot localization is the problem of determining the pose of a robot in a given map of the environment. Localization algorithms are variant implementations of the Bayes filter. A Bayes filter is an algorithm used for calculating the probabilities

Table 2.1: Bayes Filter Algorithm

| | |
|---|---|
| **1:** | **Algorithm Bayes_filter** ($bel(x_{t-1},\ u_t,\ z_t)$ |
| 2: | for all $x_t$ do |
| 3: | $\overline{bel}(x_t) = \int p(x_t \mid u_t, x_{t-1})\ bel(x_{t-1})dx_{t-1}$ |
| 4: | $bel(x_t) = \eta p(z_t \mid x_t)\ \overline{bel}(x_t)$ |
| 5: | endfor |
| 6: | return $bel(x_t)$ |

of multiple beliefs to allow a robot to infer its position and orientation. Table 2.1 shows Bayes filter algorithm.

Localization algorithms based on probabilistic theory are variants of Bayes filter. In the context of mobile robot localization, Bayes filters is also known as Markov localization [14], [2]. Table 2.2 shows the basic algorithm of Markov localization.

It is derived from the Bayes filter algorithm with map $m$ of the environment also as input (line 1 of the algorithm). The map $m$ is important in the measurement model $p(z_t \mid x_t,\ m)$ (line 4 of the algorithm), and is also used in the motion model $p(x_t \mid u_t,\ x_{t-1},\ m)$ (line 3 of the algorithm). The same as Bayes filter, Markov localization calculates the probabilistic belief bel($x_t$) at time $t$ from time $t-1$ recursively.

Markov localization or Bayes filter is independent of the representation of state space [14], and it can be implemented by using different state representation methods, for example, histogram filter and particle filter. Histogram filter decomposes the state space into finite regions and represents the cumulative posterior for each region by a single probability value [24]. Particle filter [11] approximates the posterior by a finite number of samples which populates the state space, and the samples are drawn

Table 2.2: Markov-localization Algorithm

**Algorithm Markov_localization**($bel(x_{t-1}),\ u_t,\ z_t,\ m$):

for all $x_t$ do

$\overline{bel}(x_t) = \int p(x_t|u_t, x_{t-1}, m)\ bel(x_{t-1})dx$

bel($x_t$)=$\eta\ p(z_t \mid x_t,\ m)\ \ \overline{bel}(x_t)$

endfor

return $bel(x_t)$

randomly from the posterior [23], [1].

## 2.3 Categories of Localization Problems

Localization problem can be classified based on 1) whether the initial pose is known to robot or not, 2) weather or not the robot's effectors are controlled, 3) type of the environment, and 4) the number of robots.

### 2.3.1 Whether the Initial Pose is Known to the Robot

Localization can be divided into two parts, global position estimation [7] and local position tracking [21], [22], [14]. Global position estimation is the ability to determine the robot's position in a previously learned map, given no other information than that the robot is somewhere in the map. Once a robot has been localized in the map, local tracking is the problem of keeping track of that position over time.

### 2.3.2 Weather or Not the Robot's Effectors are Controlled

Passive localization approaches, do not exploit the opportunity to control the robot's effectors during localization. In passive localization, the localization module only works as an observer on the robot. Active localization provides setting the robot's motion direction and determining the pointing direction of the sensors during localization. The control of the robot does not include facilitating localization. The robot might move randomly or do its own jobs. Active localization algorithms control the robot in order to minimize the localization error or the costs that risk a poorly localized robot moving into dangerous places. Active approaches for localization problem usually have much better localization results than passive ones, such as coastal navigation.

### 2.3.3 Type of Environment

Environments can be static or dynamic. In static environment, only the robot moves and all other objects stay at the same location. In dynamic environments, other than robot, the location or configuration of other objects change over time.

### 2.3.4 Number of Mobile Robots

The last class of the localization problem is characterized by the number of robots included: single-robot localization and multi-robot localization. In single robot case, all data only need to be collected on a single robot platform, and no communication issue comes in this problem. The multi-robot localization problem is brought by a group of robots. The issue of multi-robot localization arises from the representation of beliefs and the nature of the communication between them.

The most important characteristics of the mobile robot localization problems are covered in these four categories. In this thesis, we deal with global localization of passive localization for a single mobile robot in static environments.

## 2.4 Monte Carlo Localization Algorithm and its Implementation

### 2.4.1 Monte Carlo Localization

As described in previous section, Kalman filters offer an elegant and efficient algorithm for localization. However, the plain Kalman filters is inapplicable to global localization problems due to the restrictive nature of the belief representation. In contrast to Kalman filtering based techniques; MCL is able to represent multi-modal distributions and therefore can globally localize a robot.

Monte Carlo Localization (MCL) takes a new approach to represent uncertainty in mobile robot localization, instead of describing the state space by a probability density function; represents it by maintaining a set of samples that are randomly drawn from it. Monte Carlo methods are used to update this density representation over time. MCL algorithm is the most popular approach to date, since it is easy to implement, and works well across a broad range of localization problems. MCL is applied to both global and local localization problems. MCL algorithm is shown in Table 2.3 [14].

Table 2.3 shows the basic MCL algorithm, which is obtained by substituting the appropriate probabilistic motion and perceptual models into the algorithm particle filters. The basic MCL algorithm represents the belief $bel(x_t)$ by a set of $M$ particles $X_t = x_t^{[1]}, x_t^{[2]}, ..., x_t^{[M]}$. Lines 4 in the algorithm (Table 2.3) samples from the motion model, using particles from present belief as starting points. The beam measurement model is then applied in line 5 to determine the importance weight of that particle. The initial belief $bel(x_0)$ is obtained by randomly generating $M$ such particles from the prior distribution $p(x_0)$, and assigning the uniform importance factor $M^{-1}$ to each particle. As the robot gets sensor measurements line 5 of the algorithm, MCL assigns importance factors to each particle. Line 8-11 in the MCL algorithm shows the resampling step, and after incorporating the robot motion (line 4). This leads to a new particle set with uniform importance weights, but with an increased number of particles near the three likely places. The new measurement assigns non-uniform importance weights to the particle set. At this point, most of the cumulative probability mass is centered on the second door, which is also the most likely location. Further motion leads to another resampling step, and a step in which a new particle set is generated according to the motion model. The particle sets approximate the correct posterior, as would be calculated by an exact Bayes filter [14].

We have used odometry motion model as the basis for calculating the robot's motion over time. Odometry motion model is commonly obtained by integrating wheel encoders information. In the updating part according to the sensor reading the weight of the particles will be updated. After updating, there is a resampling step and then the summation of the weights of all particles should be equal to one.

### 2.4.2 Implementation of MCL

We will describe the implementation of MCL algorithm, in details below.

(a) Motion Model

Within the framework of MCL, motion model corresponds to the step sampling from the state transition distribution $p(x_t \mid u_t, x_{t-1})$, which generates a hypothetical state $x_t$ based on the particle set $x_{t-1}$ and the control $u_t$. The motion model plays an essential role in the prediction step of MCL.

The robot motion of probabilistic robotics conforms to the fact that the outcome of a control is uncertain, because of the control noise or un-modeled effects. Therefore, the outcome of a control will be represented by a posterior probability. The robot motion, formally kinematics, is the calculating of the effect of control actions on the configuration of a robot. The configuration of a mobile robot is commonly described by three variables, referred as pose $(x, y, \theta)$. The pose without orientation is robot's location $(x, y)$. The probabilistic kinematic model, or motion model, plays the role of the state transition model $p(x_t \mid u_t,\, x_{t-1})$ in mobile robotics. The $x_t$ and $x_{t-1}$ are both robot poses and $u_t$ is a motion command. This model describes the posterior distribution over states of kinematic when the motion command $u_t$ is executed at $x_{t-1}$. Fig. 2.1 shows two examples of kinematic model for a mobile robot controlled in a planar environment with the robot's pose initialed as $x_{t-1}$. The shaded area shows the distribution $p(x_t \mid u_t,\, x_{t-1})$: the darker a pose, the more likely it is for the robot to be at that location.

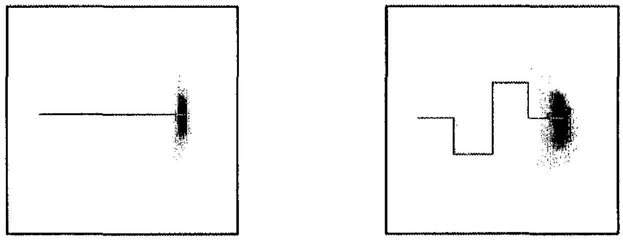


Figure 2.1: Probabilistic generation of robot kinematic; (a) A path of moving forward; (b) A path of more complicated motion command [25].

There are two common probabilistic motion models for mobile robots: velocity motion model and odometry motion model. Velocity motion model assumes robot is controlled through two velocities, a rotational and a translational velocity; and odometry motion model assumes we have access to odometry information, which is commonly obtained by integrating wheel encoder information. Velocity motion model calculates the probability $p(x_t \mid u_t,\, x_{t-1})$ of being at $x_t$ after executing the control $u_t$ at the state $x_{t-1}$. It assumes that the control is carried out for the fixed short time duration $t$. Odometry motion model is used in our proposed method.

The odometry information consists of the distance a robot passed and the angle a robot rotated. Most of the commercial robots provide odometry using kinematic information. NXT has wheel encoders to obtain odomety information. Practical experience suggests that odometry is usually more accurate than velocity. In odometry model, the robot motion in the time interval $(t-1,\, t]$ is approximated by a rotation, followed by a translation and a second rotation shown in Fig. 2.2 [14]. Both the turns and translation suffer noisy, such as drift and slippage.

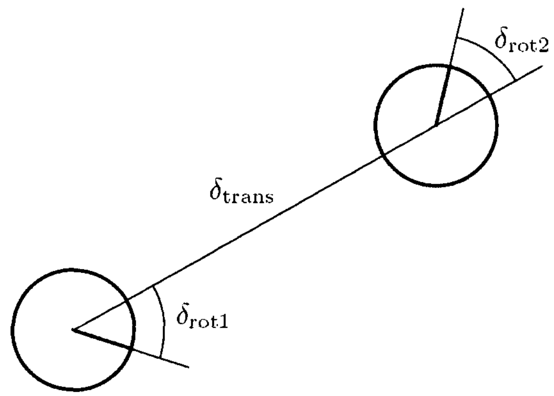



Figure 2.2: Odometry model

In Fig. 2.2 the robot motion in the time interval $(t-1, t]$ is approximated by a rotation $\delta_{rot1}$, followed by a translation $\delta_{trans}$ and a second rotation $\delta_{rot2}$. The turns and translation are noisy.

(b) Measurement Model

Another important model in probabilistic robotics is the measurement model. The probabilistic models of sensor measurements $p(z_t \mid x_t)$ are essential for the measurement update step in MCL. Measurement models describe the formation process by which sensor measurements are generated in physical world. Today's robots use a variety of different sensors, such as tactile sensors, range sensors, or cameras. Probabilistic robotics explicitly models the inherent uncertainty in sensor measurements. NXT has ultrasonic sensor, touch sensor, light sensor and sound sensor. The ultrasonic sensor will return the distance of the NXT to objects. In our experiment, we use the ultrasonic sensor measurements in order to recognize if NXT is close to wall or any object in the environment and light sensor measurements to recognize obstacles. Then, high weight will be assigned to the particles that are close to the sensor reading, and low weight will be given to the rest of particles. The weighted particles are forward to the next step importance sampling.

(c) Resampling

Another important component of MCL is known as resampling or importance sampling. In our experiment, the algorithm low variance sampling is chosen for resampling. The basic idea of low variance sampler includes a sequential stochastic process. Instead of choosing $M$ random numbers and selecting those particles that correspond to these random numbers, this algorithm computes a single random number and selects samples according to this number but still with a probability proportional to the sample weight. The algorithm showed in Table 2.3 selects particles by repeatedly adding the fixed amount $M - 1$ to $r$ and by choosing the particle that corresponds to the resulting number. The while loop at step 8 stops when $i$ is the index of the particle such that the corresponding sum of weights exceeds $U$. Then the particle is selected. The low variance sampler is very efficient. At the end, we count the number of particles with zero weight and if the "num-zero" variable is equal to or greater than half of total number of particles, then a new set of particles is generated.

In regular MCL when the particles can not localize the robot or in situation like kidnapping there is no surviving particles near the location of the robot, there is no chance for to robot to recover from failure. But in the extended works that are based on MCL they inject random particles to the localization process. In this work when we apply the MCL, we calculate the weight of particles; as soon as the weight of all particles are zero then a new set of particles is initialized and randomly distributed all over the environment.

## 2.5 Kidnapped Robot Problem

Kidnapped robot problem [6], [19], [20] is a variant of global localization problem. It happens when a robot that is aware of its location is moved to another location of the environment without being told. The kidnapped robot problem is more difficult than global localization problem. In global localization problem, robot knows that it does not know where it is. In kidnapped robot problem, Robot might believe it knows where it is, while it does not. It is commonly used to test a robot's ability to recover from localization failures.

Most of MCL-based works suffer from the kidnapping problem, since this approach collapses when the current estimate does not fit observations. There are several extensions to MCL that solves this problem by adding random samples at each iteration.

## 2.6 Related Works

Several authors have demonstrated different methods in the area of mobile robot localization. The most efficient ones are based on particle filters where the significant advantage of particle filter is to globally localize the mobile robot. Fox et al. introduces Monte Carlo Localization for mobile robot localization [1]. Later, they have proposed a technique for active localization of mobile robots [2], [3], [10], [9].

In [12] combination of existing methods was used to increase the efficiency of localization, i.e., first global search is made then a local search is performed, in order to reduce the probability of finding a local minimum and improving the stability and accuracy of solutions near the optimum. Extended Kalman filter (EKF) is used to limit the search ares, otherwise the genetic search becomes too costly from the computational point of view. EKF obtains a seed which is used to estimate a neighborhood, where the true value of the state is located, then in this restricted area the most accurate solution is searched. Genetic algorithm only works in restricted areas of the solution space and as the result it is a fast optimization method. Fitness function then focuses the search in a certain neighborhood around the previous estimate, if the new generation contains a solution that produces an output that is close enough or equal to the desired answer then the problem has been solved.

In another related work [5] particle filter algorithm is used at first to generate the cluster of particles. Based on sensor readings, which enables the robot to estimate some positions with higher probability instead of generating particles that are randomly distributed all over the environment, they have initialized particles just in the places that the robot will know it is most probable to be the true position. Genetic algorithm is then employed to work on the clusters that have been generated to get a unique estimate of the real position of the robot.

In [7] a multi-robot active localization technique is proposed based on CEAMCL. Using CEAMCL, samples are clustered into species which will evolve according to a co-evolutionary model derived from the competition of ecological species, and the size of the species will adaptively change according to the state of the robot. In this way, CEAMCL cannot only prevent premature convergence of MCL but also improves its efficiency, so CEAMCL is selected for cooperative localization. In [8] a t-test revealed that it is significantly better to apply the active approach than the passive one for the global localization task. Kummerle et al. [8] have presented an approach to active Monte Carlo localization with a mobile robot using MLS (Multi-level surface) maps. The approach actively selects the orientation of the laser range finder to improve the localization results. To speed up the entire process, a clustering operation was applied on the particles and only evaluate potential orientations based on these clusters. Their new proposed approach is able to increase the efficiency of the localization by minimizing the expected entropy. In contrast to the former approaches [8] focus on reducing the computational demands of the active localization. The goal of this paper is to develop an active localization method which is able to deal with large outdoor environments.

Table 2.3: MCL Algorithm

**Algorithm MCL**$(X_{t-1}, u_t, z_t, m)$

$\overline{X_t} = X_t = \phi$

*for* m = 1 *to* M *do*

  $x_t^{[m]} = sample - motion - model(u_t, x_{t-1}^{[m]})$

  $w_t^{[m]} = measurement - model(z_t, x_t^{[m]}, m)$

  $X_t = X_t + < x_t^{[m]}, w_t^{[m]} >$

endfor

for $m = 1$ to $M$ do

  draw $i$ with probability $\alpha\ w_t^{[i]}$

  add $x_t^{[i]}$ to $X_t$

endfor

return $X_t$

# Chapter 3

# Mobile Robot Localization Failure Recovery

The description of the proposed method can be found in this chapter.

## 3.1 Motivation of Our Method

Most of the existing approaches can not recover from localization failure and kidnapped robot problem. Therefore we need a method to localize the robot with higher probability and with the ability to recover the robot from kidnapping problem . The number of samples to be used is important, since using more number of particles will increase the cost of localization. Since almost all tasks of mobile robots require a robot to have accurate knowledge about its location, we need a method to localize the robot with higher probability and with the ability to be able to recover the mobile robot from kidnapping problem or any type of localization failure with the use of less number of particles and with higher probability.

## 3.2 The Proposed Method

### 3.2.1 Problem Statement

Localization is the most fundamental problem to provide a mobile robot with autonomous capabilities, therefore the result of the localization task should be accurate and reliable to provide the robot an accurate knowledge about its location. Most of the existing approaches can not recover from localization failure, for example kidnapped robot problem which is a variant of localization failure. Therefore we need a method to localize the robot with higher probability and with the ability to recover the robot from kidnapping problem. The number of samples to be used is important, since using more number of particles will increase the cost of localization. Therefore, in the proposed method, we are trying to localize the robot with less number of particles than the other methods in order to reduce the cost of localization and localize the robot with higher probability to recover from the failure.

### 3.2.2 Description of the Proposed Method

The proposed method [15] is an improved approach to localize the robot. It recovers the robot from localization failures with high probability. Proposed method is based on Monte Carlo Localization and has two differences from the regular MCL algorithm, first modified initialization step and second modified resampling step.

It has the ability to re-generate the particles in the case of localization failure. Applying the proposed method, it is expected that robot localize itself with a high probability with lower cost. Two main advantages of the method, first different way of initializing the particles that helps to reduce some steps and the cost of localization. Second a new resampling scheme to solve the kidnapped robot problem and localization failures.

Fig. 3.1 shows the proposed algorithm.

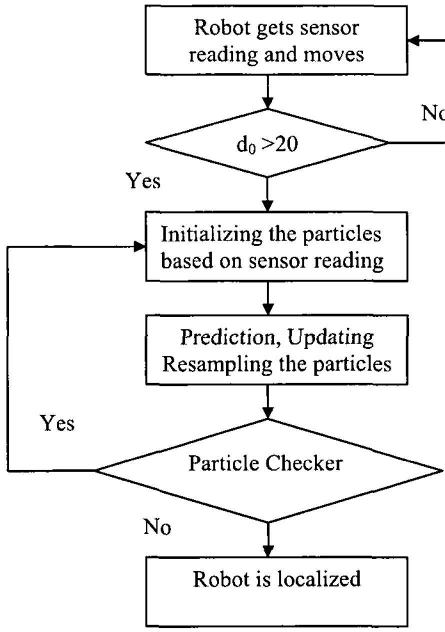



Figure 3.1: Proposed algorithm.

In the algorithm which is presented in Fig. 3.1; in first step, robot moves and gets the value of its sensors. The value of the ultrasonic sensor which presents the distance of the robot to the wall is presented as $d_0$. Whenever the distance of the robot to the wall ($d_0$) is less than 20cm then the particles are initialized; otherwise robot continues moving and getting the sensor data. The distance of the robot to wall is set to 20cm in order for robot to stop and turn since when doing the real environment experiments, robot should have enough space in order to make a turn.

After initializing the particles, they are updating and resampling and their weights changes as the robot moves. Particle-Checker step checks the condition of failure, if the number of the particles with zero weight are greater than half of the total number of particles then a new set of particles is generated.

The experiments are performed in order to evaluate the Error rate for the proposed method and Regular MCL for Kidnapped robot Problem using different number of particles. The error rate is calculated as follows:

$$\text{Error rate} = \frac{\text{Number of times robot cannot localize itself successfully}}{\text{Total number of times}}$$

There is a comparison between Error rates for different experimental environments. In first two cases we calculate Error rate in the simulation environments with obstacle and without obstacle. The last two sets of experiments are performed in the real environment using NXT. In each set of experiments we run the program for MCL and the proposed method 50 times and then draw a graph in order to compare the Error rate for each case.

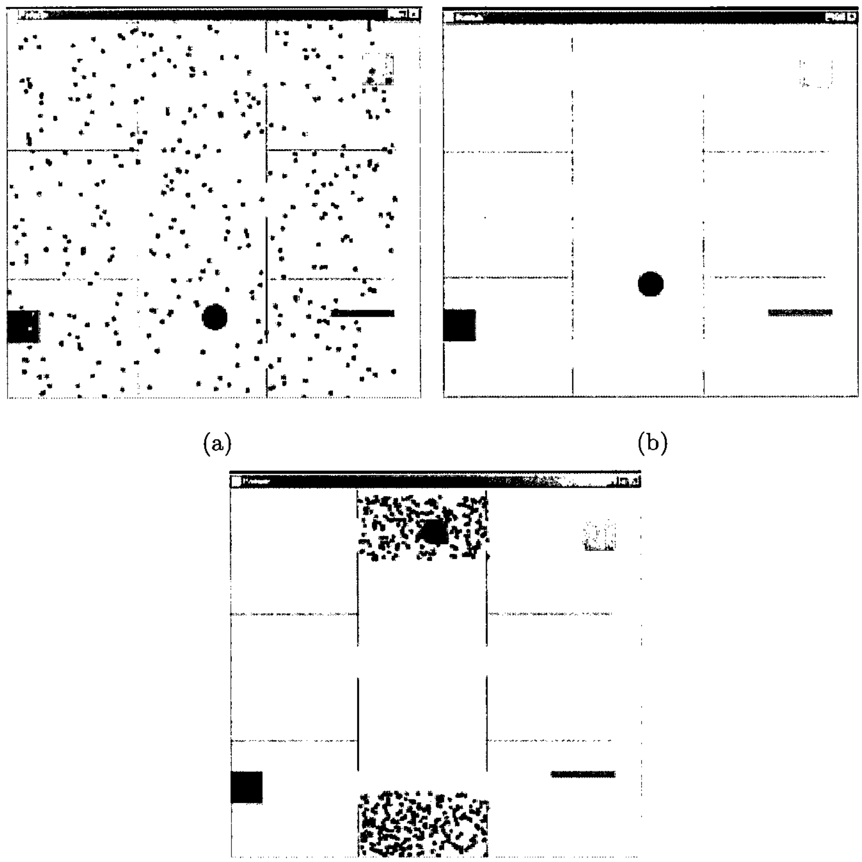
### 3.2.3 Initialization of the Particles

In this part there is a description of the differences of the initialization part in regular MCL and the proposed method. In initialization part of regular MCL, as soon as MCL runs; particles are generated. There is a uniform distribution of the particles all over the environment. As shown in Fig. 3.2 (a) particles all have same weight at the time of generation, bel($L_0$) is uniformly distributed to reflect the global uncertainty of the robot.

In the proposed initialization technique, particles are not generated from the very beginning as in Fig. 3.2 (b), they are generated based on sensor reading. As soon as robot gets a sensor reading; particles are generated based on the most recent sensor reading. The weight of the particles that are close to the location of the sensor reading are higher than the other particles. Therefore particles are generated as some cluster of particles rather than normally distributed all over the environment as shown in Fig. 3.2 (c). Therefore, initial belief of the robot bel($L_0$) is not uniformly distributed.

### 3.2.4 Resampling the Particles

In this part there is a description of the differences of the resampling part of regular MCL and resampling in the proposed method. In the resampling step of regular MCL,



(a) (b) (c)

Figure 3.2: Initialization: (a) Initialization in regular MCL; (b) Beginning of the localization process; (c) Initialization of the particles base on sensor readings.

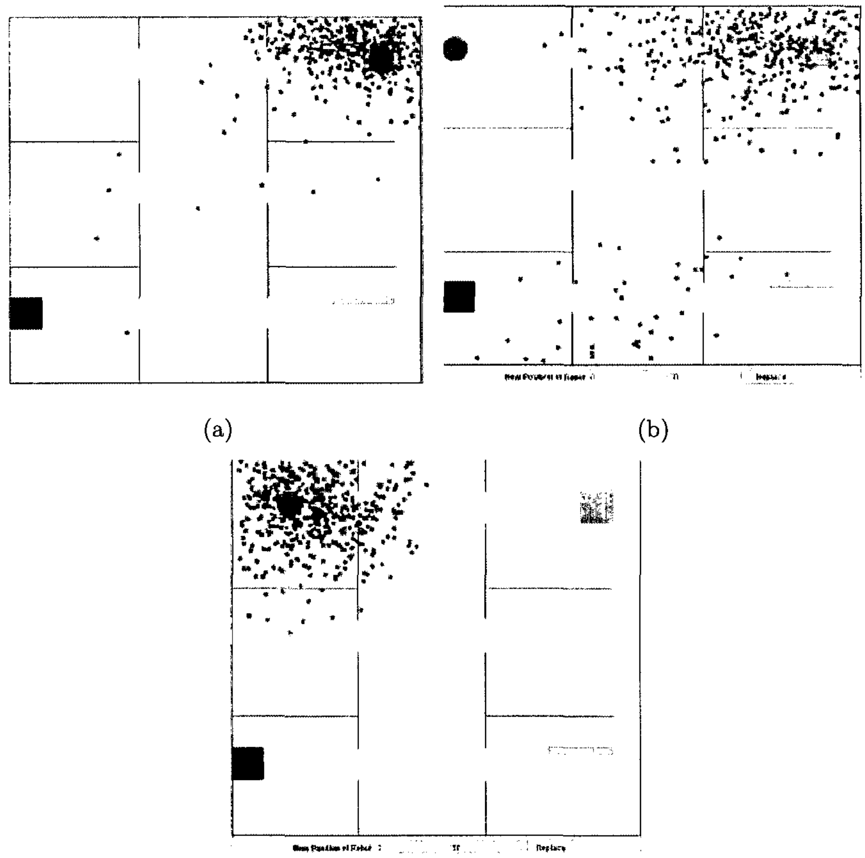
when robot gets a sensor reading in the resampling part, particles are assigned new weights based on new sensor reading. Particles are not re-generated if they do not localize the robot correctly. In the proposed resampling technique, algorithm guesses possible locations of the robot based on the sensor reading.

Using motion model this guess is corrected and particles will be assigned new weights in the resampling step. As the extension of resampling step; if the weight of most of the particles is zero, a new set of particles is generated based on the new sensor reading. In other works done, some random particles are added to re-localize the robot based on regular MCL. In this method, whenever robot knows that it is lost, a new set of particles is generated based on the sensor reading.

### 3.2.5 Kidnapped Robot Problem

In the case of kidnapped robot problem, when robot is taken and placed in another location of the environment; first it can not recognize that its location has been changed and particles are predicted based on the previous information. When the robot gets new sensor readings, since most of the particle's weights become zero, based on new resampling method a new set of particles is generated to help the robot localize itself and to figure out its true location.

The following figures illustrate the kidnapped robot situation. At first, when the robot is taken and placed in another location of the environment it can not recognize of being kidnapped. Particles continue their previous path, but after robot gets new sensor readings and the weight of the particles is updated based on that, after the "Particle-Checker" part which counts the number of the particles having zero weight, if there is more than half of the particles with zero weight then a new set of particles is generated based on the sensor reading. In Fig. 3.3 (a) robot is localized, but as in Fig. 3.3 (b) it is being kidnapped and lost, and using the proposed resampling technique the mobile robot realizes of being kidnapped and it successfully re-localize itself as in Fig. 3.3 (c).



(a) (b)

(c)

Figure 3.3: Failure recovery: (a) Mobile robot is localized; (b) Kidnapped robot problem; (c) Robot is recovered and re-localized.

# Chapter 4

# Implementation and Experimental Results

The implementation of our proposed method and experiment results are described in this chapter. Hardware platform and programming environment are presented at first, followed by experimental results.

## 4.1 Implementation Details

### 4.1.1 Hardware Platform and Programming Environment

In 2006 Lego released MindStorms NXT. It includes a local file system on 256 KB flash RAM. In our experiments we changed the original graphical operating system inside NXT to LeJOS NXJ operating system [28], [29], which is a tiny Java-based operating system and is used for LEGO MINDSTORM NXT. NXT has four sensors, sound sensor, light sensor, touch sensor and ultrasonic sensor.

Sound sensor: is the robot's ears. It allows LEGO MINDSTORMS NXT robot to hear and is able to measure noise levels in both dB (decibels) and dBA (frequencies around 36 kHz where the human ear is most sensitive), as well as recognize sound patterns and identify tone differences.

Touch sensor: is robot's fingers. It reacts to touch and release, enabling NXT to "feel". It can detect single or multiple button presses, and reports back to the NXT

Intelligent.

Light sensor: detects light intensity. The Light sensor assists in helping the robot to "see". Using the NXT Brick, it enables the robot to distinguish between light and dark, as well as determine the light intensity in a room or the light intensity of different colors. It can detect lights invisible to human eye such as infrared light.

Ultrasonic sensor: is robot's eyes, it enables the robot to see and detect objects, also it is used to make the robot to avoid obstacles, and sense and measure distances, and detect movement. It is able to measure distances from 0 to 255 centimeters with a precision of $\pm 3$cm. The Ultrasonic sensor uses the same scientific principle as bats: it measures distance by calculating the time it takes for a sound wave to hit an object and return, just like an echo. Large sized objects with hard surfaces return the best readings. Objects made of soft fabric or those that are curved (like a ball) or the ones that are very thin or small can be difficult for the sensor to detect. The dynamic test revealed two weaknesses of the ultrasonic sensor. The first issue is that it showed some areas where the sensor tends to measure 255cm instead of the actual distance. The second even more important issue is the critical area in between 25cm and 50cm where the sensor has a high probability of returning the wrong value of 48cm.

NXT also contains a break that is robot's brain, features a powerful 32-bit microprocessor and flash memory support for Bluetooth and USB 2.0. It has four sensor ports and three ports in order to connect the motors to the break. It has a LCD with resolution of $100 \times 64$.

The iCommand [30] is used on PC and LeJOS NXT operating system on NXT, instead of uploading the program to NXT and letting the NXT run the program itself, since memory of NXT is very small. If the program is bigger than memory of the NXT, it will not be able to store the program and run it. This limitation of memory is solved by using iCommand. The iCommand runs programs on the computer instead of NXT, and sends commands to NXT through Bluetooth connection. iCommand code runs on PC and iCommand can access to memeory on PC. It controls the NXT

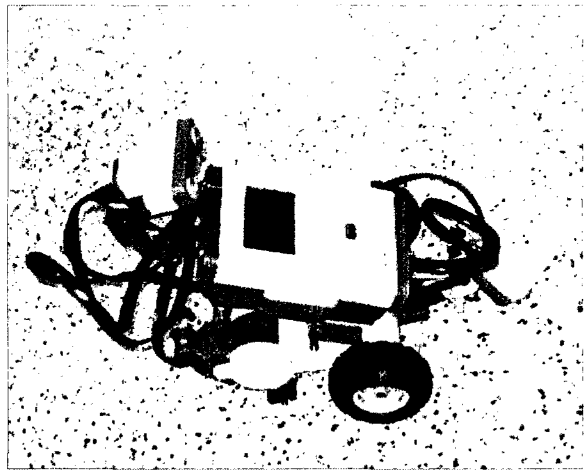


Figure 4.1: LEGO MINDSTORM NXT

brick by sending individual commands wirelessly and can access all devices on PC, such as the Internet and other hardware devices.

Programs are written in Java. In the computer we have to install Eclipse with three packages, iCommand.jar which is a Java package to control the NXT brick over a Bluetooth connection. RXTXcomm.jar [31] which is a native lib providing serial and parallel communication for the Java Development Toolkit(JDK) and Bluecove.jar [32] which is a JSR-82(the official Java Bluetooth API) implementation on Java Standard Edition (J2SE). Fig. 4.1 shows the construction of NXT for doing the experiments. In the experiments light and ultrasonic sensors are used.

The size of the environment is 80cm×80cm and the simulation environment size is 500cm×500cm. Therefore, we make the movement of NXT and the simulation robot simultaneously. The speed of the motors of NXT are set to 60 and $NXT\_distance =$ 10cm. In each step, the distance that NXT moves is calculated as follows:

$$NXT\_X = NXT\_X + NXT\_distance * (Math.cos(NXT\_A))$$

$$NXT\_Y = NXT\_Y + NXT\_distance * (Math.sin(NXT\_A)).$$

## 4.2 Experimental Results

We have performed experiments in two different environments. The environments are of the same shape, the only difference is that in the first one there is no obstacle in the environment and the shape of the environment is symmetry which is the most difficult type of environment for a mobile robot to localize itself. In the second one, there is an obstacle in the environment which makes the environment not to be symmetry anymore. As soon as robot gets to wall, it recognizes and after updating and resmapling parts, there will be more particles next to the wall; since the weight of the particles in that area become more than other particles. If after calling the function "Particle-Checker" which calculates the number of the particles with zero weight, the number of particles with zero wight are more than half of total number of the particles then a new set of the particles is generated.

For each case; we performed experiments for different number of particles, since there is no specific number of particles defined for localization task, we compare the results of the experiments. The number of the particles that we used is in a large range in order to compare different numbers more clear.

One of the issues that has to be taken into consideration while using the proposed method, is the accuracy of the sensors of mobile robot. Robot should have reliable sensors in order to get reliable results or the possible error values should be taken into consideration.

### 4.2.1 Simulation Results

There are a number of experiments that are performed in the simulation environment. For each simulation environment we run regular MCL 50 times for different number of particles and then we run the proposed method 50 times for different number of particles as well in order to compare number of successful localization. In the figures below, the big red circle indicates the mobile robot NXT, and small blue circles indicate the particles. The green square shows the obstacle in the environment. Each particle represents a possible position of NXT. As the robot moves, based on the motion model, particles are predicted to the new location and as soon as the robot gets a sensor reading particles's weight will be updated; particles which are close to the area of sensor reading are assigned higher weight compared to other particles. Then in the resampling step, since particles with higher weight are chosen more; therefore particles which are further from the area of sensor reading are eliminated and the concentration of the particles will be in the places next to the sensor reading area which is the true location of the mobile robot. Therefore, after some steps particles merge to a group to localize the robot and that concentrated group of particles indicates the true location of the mobile robot.

In the previous works done in the field of mobile robot localization, there is no end for the localization process. The robot must recognize and stop when it is localized and a cluster of particles are correctly localize the location of the robot. Therefore, in [27] they have combined MCL and clustering algorithm in order to stop the localization process when it is successfully completed. In our work since our concern is not to implement that part of localization process, we recognize when to stop the localization process manually like the other works done in this area as discussed in [27].

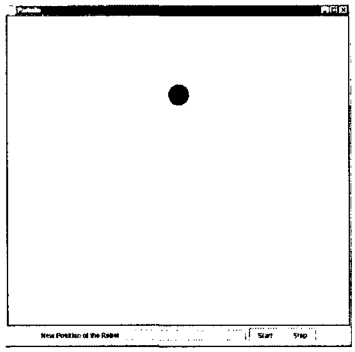
In general, a binomial distribution applies when an experiment is repeated a fixed number of times. Each trial of the experiment has two possible outcomes, namely success and failure. The probability of success is the same for each trial, and the trials are statistically independent. The confidence interval for experimental results is determined via $\hat{P} \pm z_{\alpha/2}\sqrt{\hat{P}(1-\hat{P})/n}$ where $\hat{P}$ is the Error rate and $n$ is the number of experiments. For Error type I, which is the case of study in this work, $\alpha = 0.05$ and thus $z_{\alpha/2} = 1.96$ from the standard normal cumulative probabilities table in [26]. Based on this formula if the number of experiments (n) is increased then the confidence interval range is decreased.

In some situations, there is an estimation on the robot's location with a low probability. For example, if based on the information from its sensors it indicates that it is next to the wall; then all of the particles which are next to the wall will get higher weight. In some other situation, we may have two or more group of particles concentrated in the environment in which robot is trying to localize itself such as in the symmetry environment. But as the robot moves and gets more information about its environment, it can localize itself more accurate until there will be only one group of particles in most cases.

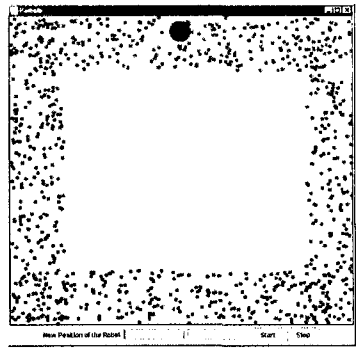
Fig. 4.2, shows the localization process in the environment without any obstacle. Fig. 4.2 (a) shows the beginning of the localization process, where the particles are not generated yet. At the beginning the initial position of the robot is set as a random number. After the mobile robot moves and gets to the border (wall in the real environment) then particles are generate based on the sensor reading as shown in Fig. 4.2 (b). Fig. 4.2 (c) shows the time which robot has localized itself successfully. In the user interface of the program there is three text boxes, as soon as we enter the new pose of the robot which contain the new coordinates and the orientation of mobile robot and press the "Replace" button. The robot moves to the new location and it is being kidnapped. In Fig. 4.2 (d) robot is being kidnapped, but the particles still continue their last path since the robot is not aware of being kidnapped and Fig. 4.2 (e) shows that robot has localized itself again after being kidnapped based on the resampling method.

Fig. 4.3 shows localization process in the simulation environment with an obstacle. Fig. 4.3 (a) shows the beginning of the localization process, where the particles are not generated yet. In Fig. 4.3 (b) particles are generated based on sensor information. Fig. 4.3 (c) shows the time that the robot is localized. In Fig. 4.3 (d) robot is being kidnapped, and Fig. 4.3 (e) shows that robot has recovered from kidnapping problem.

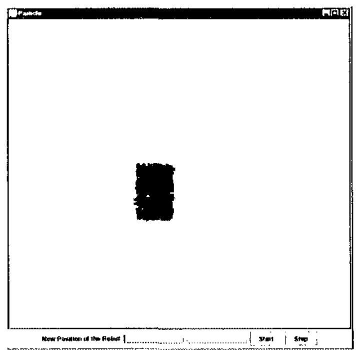
In Tables 4.1, 4.2 and Figs. 4.4 and 4.5 there is a comparison of performance of regular MCL and proposed method for kidnapped robot problem in simulation



(a)



(b)



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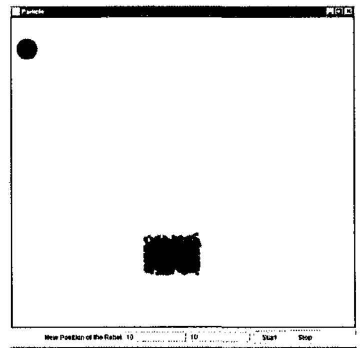
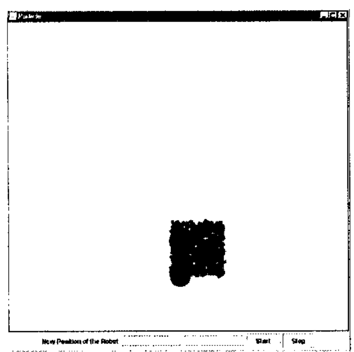
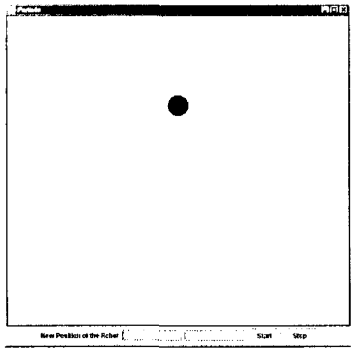
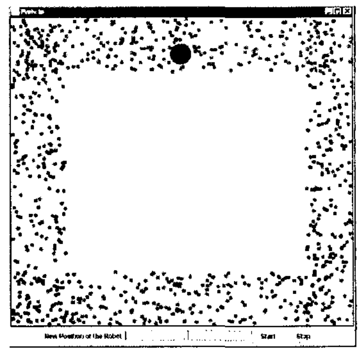


(d)

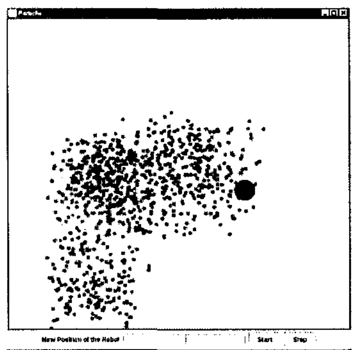
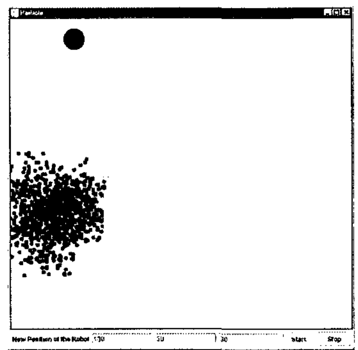


(e)

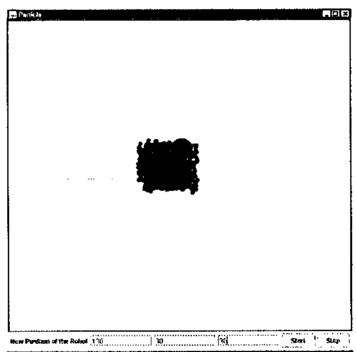
Figure 4.2: Localization in the first simulation environment : (a) Beginning of localization process; (b) Initialization of particles; (c) Mobile robot is localized; (d) Robot is kidnapped; (e) Localization failure recovery.

(a) (b)

(c) (d)



(e)

Figure 4.3: Localization in the Second simulation environment : (a) Beginning of localization process; (b) Initialization of particles; (c) Robot is kidnapped; (e) Localization failure recovery.

Table 4.1: Comparison of performance of the proposed method and traditional MCL, for kidnapping problem in simulation environment without obstacle.

| Number of Particles | Error rate for proposed method (%) | Error rate for MCL (%) |
|---|---|---|
| 500 | 60±14 | 100±0 |
| 1000 | 60±14 | 90±8 |
| 1500 | 52±14 | 100±0 |
| 2000 | 40±14 | 80±11 |
| 2500 | 52±14 | 72±12 |

Table 4.2: Comparison of performance of the proposed method and traditional MCL, for kidnapping problem in simulation environment with obstacle.

| Number of Particles | Error rate for proposed method (%) | Error rate for MCL (%) |
|---|---|---|
| 500 | 40±14 | 80±11 |
| 1000 | 30±13 | 70±13 |
| 1500 | 32±13 | 60±13 |
| 2000 | 40±14 | 62±10 |
| 2500 | 20±11 | 46±14 |

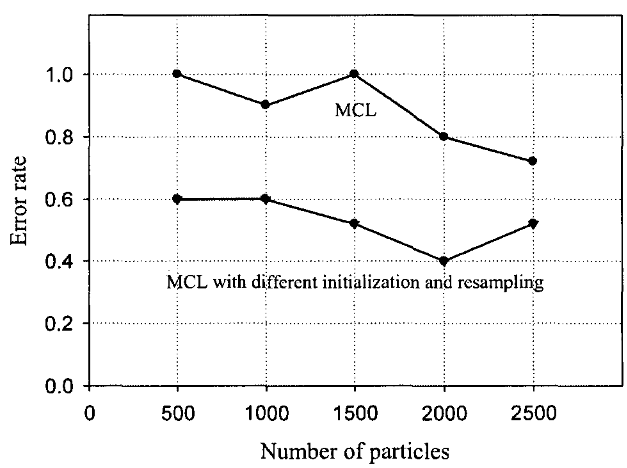



Figure 4.4: Simulation environment without obstacle.

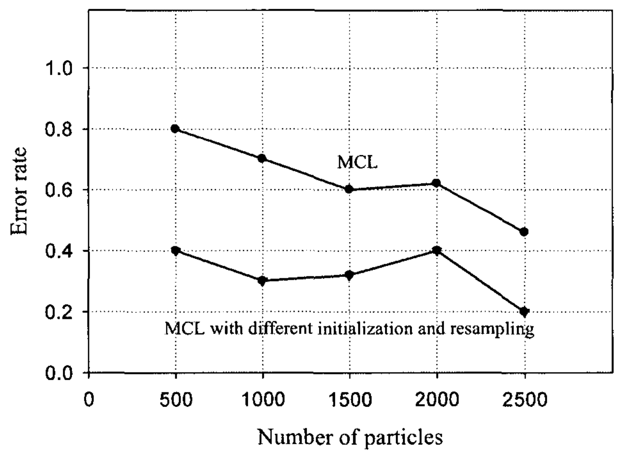



Figure 4.5: Simulation environment with obstacle.

environment with and without an obstacle in the environment. It shows the Error rate, which is measured in percentage of time averaged over 50 independent runs, during which the robot lost track of its position for different number of samples. In this case, Error rate describes the percentage of lost positions. The results of the experiments when there is an obstacle in the environment is better since presence of the obstacle helps the robot to localize itself and removes the symmetry of the environment.

As it is seen in Tables 4.1 Error rate for MCL in simulation environment without obstacle when using 2500 particles is 72% which is even higher than using only 500 number of particles in the proposed method. In Table 4.2 also we can see the higher probability of localization by comparing the Error rates in these two methods in simulation environment with obstacle. The Error rate when using 2500 particles is 46% in regular MCL which is more than Error rate of 40% when using the proposed method. In same table, when using 500 particles for the localization process, the Error rate for the proposed method is 40% and the Error rate for regular MCL is 80%. Using the proposed method we run the program for 50 times and 20 times out of this 50 times the localization process failed. Using regular MCL 40 times out of total runs of 50 were not successful. In same table when using 2500 particles, we see that the Error rate for the proposed method has decreased to 20% and for regular MCL is decreased to 46%, which indicates 10 unsuccessful results for the proposed method using 2500 particles and 24 unsuccessful runs for MCL respectively.

### 4.2.2 Experiments Using Real Robot

We performed two sets of experiments in two different environments in order to make sure that the proposed method works well in any type of environment. For each real environment we run regular MCL 50 times for different number of particles and then we run the proposed method 50 times for different number of particles as well in order to compare the results of the number of successful localization times. In each set of experiments, we use different number of particles for localization, since the number of particles to be used for a specific localization problem is not defined. Therefore, we performed experiments with different number of particles for each environment and then we can compare the results.

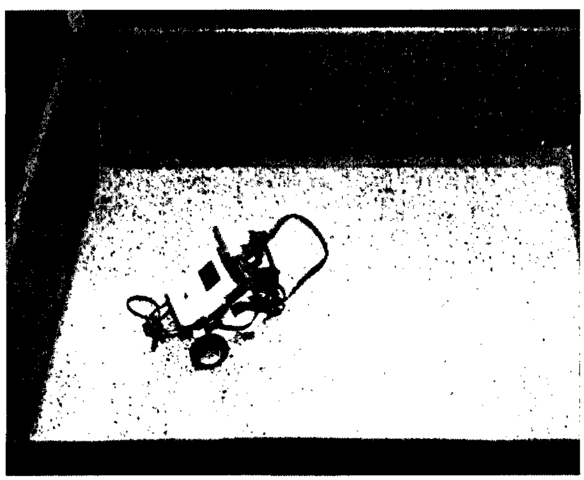


Figure 4.6: Localization environment without obstacle.

Fig. 4.6 shows the first real environment with no obstacle in which robot tries

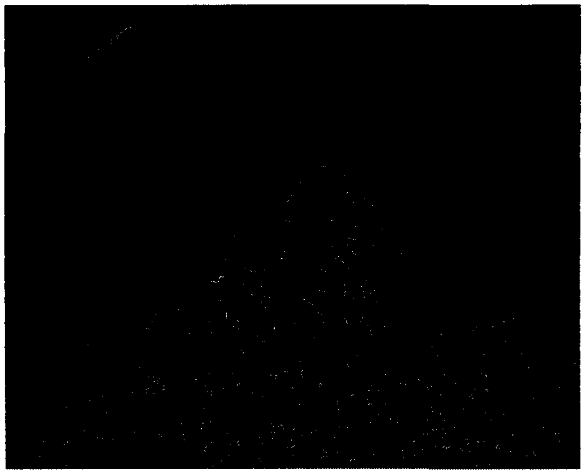


Figure 4.7: NXT calculates its distance to the wall.

to localize itself. In Fig. 4.7, the first time robot gets to the wall and the value of ultrasonic sensor is less than 20, robot turns 90 degrees and particles are generated, but after that each time when the value of ultrasonic sensor is less than 20 it rotates 135 degrees.

Figs. 4.8 and 4.9 show the second environment with one obstacle, which is located in the location (100,300) with size (100,100). When the robot gets to the obstacle, the weight of the particles in that area will be higher. Generally by an obstacle we mean something recognizable by the robot which helps it to localize itself. In most cases they use objects since the robots which are used have vision and they can recognize different objects by taking pictures and that helps them to localize themselves. Since NXT provides light sensor which recognizes different colors from each other, we use color tapes as obstacle, therefore when robot gets to the colored tape it will recognize it by the value of light sensor and the weight of the particles in that area will be higher.

Fig. 4.8 (a), (b) show the beginning part of the localization, where there is no particle generated yet. We put the mobile robot in the experimental environment at the location that corresponds to the location of the big circle in the simulation

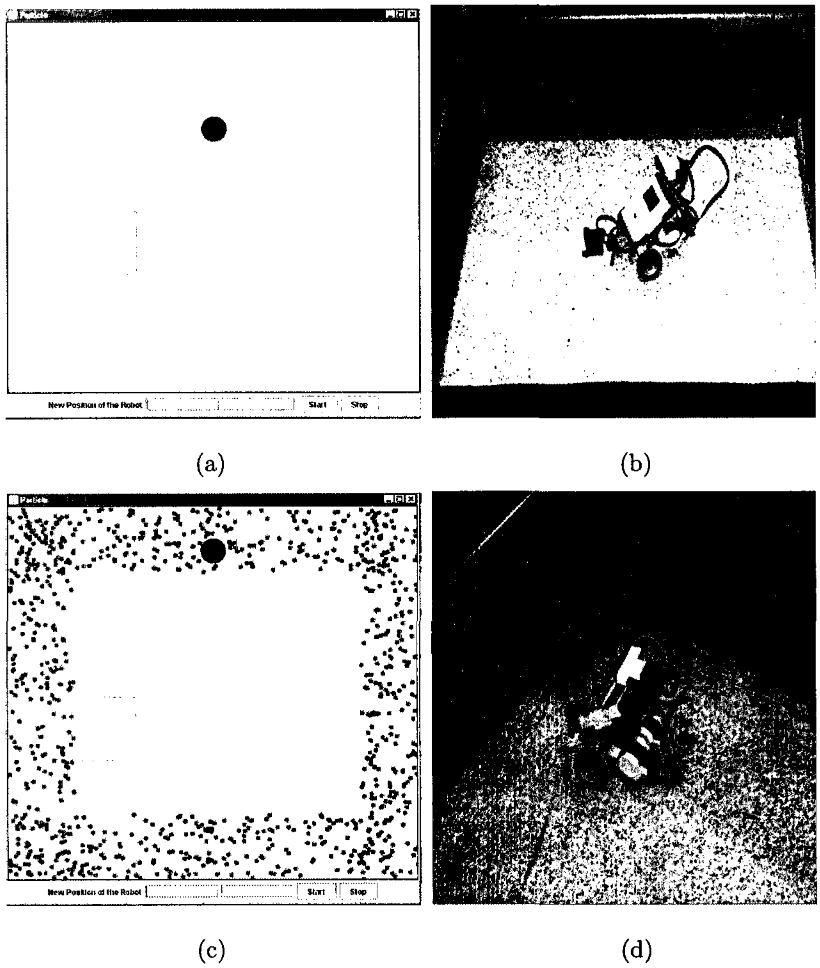



Figure 4.8: Real localization environment with obstacle: (a) Localization environment with obstacle; (b) NXT is located in a random place; (c) Initialization of particles; (d) Initialization of the particles based on sensor data.

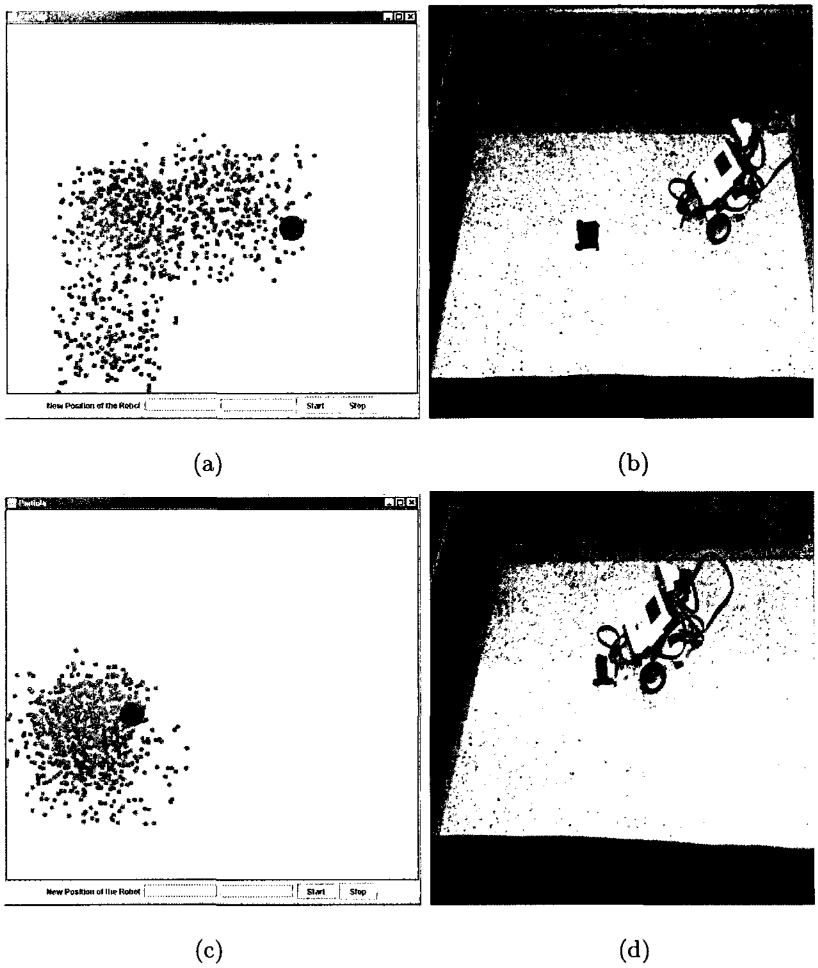



Figure 4.9: Real localization environment with obstacle: (a) Particles trying to localize the robot; (b) Mobile robot trying to localize itself; (c) Particles are localizing the robot; (d)Robot is localized.

Table 4.3: Comparison of performance of the proposed method and traditional MCL, for kidnapping problem in real environment without obstacle.

| Number of Particles | Error rate for proposed method (%) | Error rate for MCL (%) |
|---|---|---|
| 500 | 50±14 | 100±0 |
| 1000 | 40±14 | 100±0 |
| 1500 | 48±14 | 90±8 |
| 2000 | 38±13 | 80±11 |
| 2500 | 40±14 | 72±12 |

Table 4.4: Comparison of performance of the proposed method and traditional MCL, for kidnapping problem in real environment with obstacle.

| Number of Particles | Error rate for proposed method (%) | Error rate for MCL (%) |
|---|---|---|
| 500 | 60±11 | 80±11 |
| 1000 | 60±14 | 72±12 |
| 1500 | 40±14 | 72±12 |
| 2000 | 32±13 | 50±14 |
| 2500 | 32±13 | 40±14 |

environment. Fig. 4.8 (c), (d) show the time in which particles are generated since the robot gets to the wall. As soon as the real robot turns in the simulation environment the big circle which indicates the robot turns as well. Fig. 4.9 (a), (b) show the time that the robot is trying to localize itself. Fig. 4.9 (c), (d) show the time when robot gets to the obstacle and update the weight of the particles based on that. In the real experiments when we enter the new pose of the robot in the simulation environment at the same time we take the real robot and locate it in the corresponding location in the environment.

In Tables 4.3, 4.4 and Figs. 4.10 and 4.11 there is a comparison of performance of regular MCL and proposed method for kidnapped robot problem in real environment using NXT with and without the presence of the obstacle in the environment. They show Error rate, which is measured in percentage of time averaged over 50 independent runs, during which the robot lost track of its position for different number of

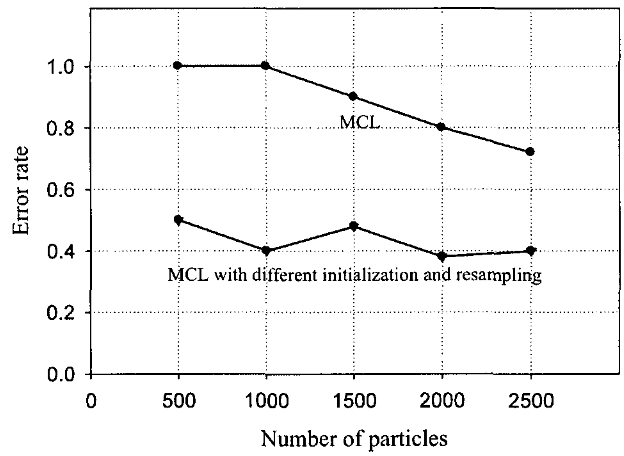



Figure 4.10: Real environment without obstacle.

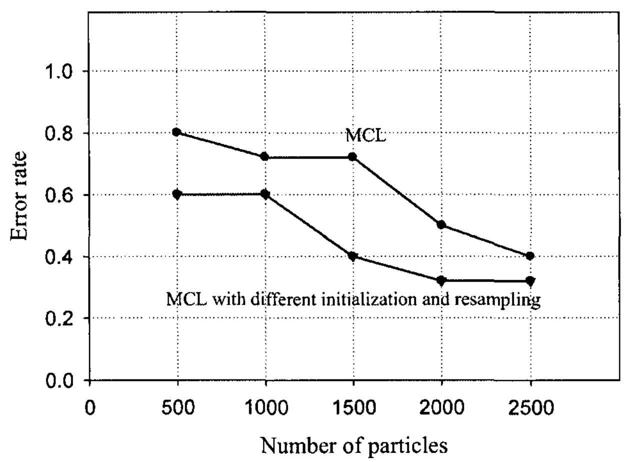



Figure 4.11: Real environment with obstacle.

samples. It shows the ability of this algorithm to handle kidnapped robot problem. The results of the experiments in simulation is better than the result of the experiments performed in the real environment, since in the real environment there is sensor and robot's wheels errors that effect the localization process.

As seen in Tables 4.3 Error rate using 2500 particles is 40% for regular MCL which is equal to the Error rate of using 1500 particles in proposed method. In Table 4.4, for example when using 500 number of particles for the localization process, the Error rate for the proposed method is 60% and Error rate for regular MCL is 80%. The results show that using the proposed method we have run the program for this environment 50 times and 30 times out of this 50 times the localization process failed. Using regular MCL 40 times out of total runs of 50 were not successful. But, for example in same table when using 2500 particles, we see that Error rate for the proposed method has decreased to 32% and for regular MCL is decreased to 40%, which indicate 16 unsuccessful results for the proposed method using 2500 particles and 20 unsuccessful runs for MCL respectively.

### 4.2.3 Discussion and Comparison

We have compared the result of localization for kidnapped robot situation for the regular MCL and the proposed method in four different environments. For each environment we have performed the experiment 50 times for each method and then divide the number of times that the robot could not successfully localize itself by the total number of executing the program for that specific number of particles and then multiply the result by 100 in order to get the Error rate.

There are two timing parameters, i.e., the time that the mobile robot localizes itself ($t_l$), and computational time required for particles ($t_p$). If we have 1000 particles, in each step we have to calculate the new position and assign new weight for each particle, however, if there are only 100 particles then the calculations are only performed for 100 particles. Therefore, using large number of particles the time required for each step is increased and so does the computational cost.

If the number of particles is infinity and robot has infinite amount of time in order to localize itself, then using regular MCL it can localize itself, but our concern is about the possibility of doing this task; i.e., to implement it, and if possible the huge computational cost of large number of particles is the main issue. For example, using a Thinkpad Z60m laptop with an Intel Pentium processor at 1.73 GHz and 512 MB of RAM to perform the experiments, using 500,000 particles, each step of localization takes a long time; since the prediction and update functions calculate new position and weight of each particle respectively in each step and using 1,000,000 particles the program could not run on this computer. Therefore, in reality since using infinite number of particles or very large number of particles is impossible, we require a method to localize the robot with higher probability using the same number of particles that is possible to implement and with lower computational cost. In this thesis the concern is to get better results of localization; with higher probability of success using the same number of particles compared to MCL and less amount of localization time $t_l$.

Regarding $t_l$, the time of localization, using the proposed method it takes shorter amount of time for mobile robot to localize itself in the case of success. This is illustrated in Table 4.5. We have compared the time of localization using 2500 particles in order to give a general idea about the time of localization process. Also using proposed method the time of generation of particles depends on the initial position of mobile robot; how far it is located from the wall or obstacles; since particles are generated based on sensor data. It should be noted that the time that it takes the mobile robot to localize itself depends on different parameters such as the speed of robot. Since we can change the speed of motors through the program, if the speed of robot is increased then it will take less time for the robot to localize itself.

In the comparison that is performed below, $t_0$ is the time that localization process starts, $t_1$ represents the time of initializing the particles. $t_2$ indicates time of

Table 4.5: Timeline of the experiments for the proposed method and MCL.

| Localization process | Timeline | Proposed method (sec) | Regular MCL (sec) |
|---|---|---|---|
| Localization starts | $t_0$ | 0 | 0 |
| Initialization | $t_1$ | 3 | 0 |
| Localization and kidnapping | $t_2$ | 17 | 59 |
| Particles are re-generated | $t_3$ | 22 | 74 |
| Robot is re-localized | $t_4$ | 38 | 149 |

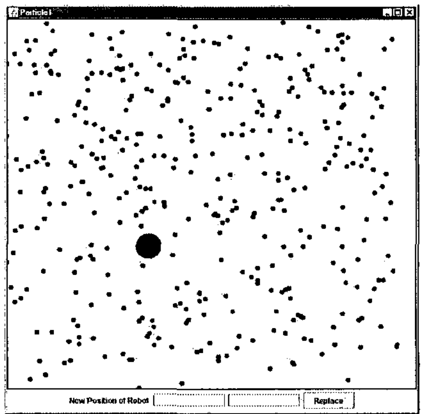
localization and kidnapping the robot, $t_3$ is the time that particles are re-generated and in time $t_4$ robot is re-localized. In the timeline of the regular MCL, particles are generated in time $t_1$ from the beginning of localization process which is equal to $t_0$. $t_2$ is the time that robot has successfully localized itself and being kidnapped. $t_3$ is the time of re-generating the particles randomly all over the environment after detecting that the weight of all particles are zero. At $t_4$ robot is re-localized and it is recovered from the failure. This timeline is obtained from one of the successful runs in order to compare the time that it takes the mobile robot to localize itself; for comparing the time of localization process. Also, it is pointed out that if identical number of particles are used, the proposed method is faster than MCL, as it is shown in Table 4.5.

Tables 4.1, 4.2, 4.3, 4.4 and Figs. 4.4, 4.5, 4.10 and 4.11 show that the proposed algorithm succussed with more probability in mobile robot localization process after comparing the Error rate for each case.

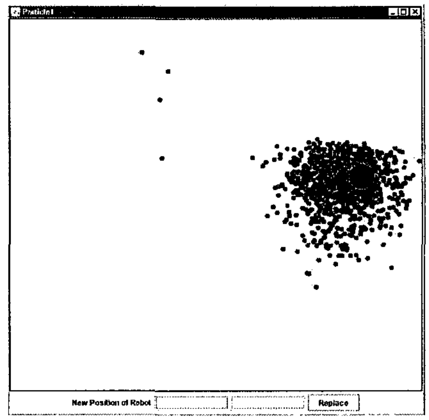
Fig. 4.12 and 4.13 show the result of using regular MCL. Fig. 4.12 shows the environment without any obstacle. In Fig. 4.12 (a) particles are generated randomly all over the environment. Then, after some random movements mobile robot is localized and the particles which are gathered in a group of particles are localizing the robot in Fig. 4.12 (b). In Fig. 4.12 (c) mobile robot is being kidnapped, it is taken and placed in another location of the environment. Respectively Fig. 4.13 shows the localization using MCL algorithm in an environment with obstacle. It shows initialization of the particles, and Fig. 4.13 (a) shows the initialization of the particles, Fig. 4.13 (b) shows the time when the robot is localized, and Fig. 4.13 (c) shows the time when the mobile robot is kidnapped.

As shown in the experimental results, the results are better with higher number of particles. It is obvious that using more number of particles helps the robot to localize itself with higher accuracy since the number of particles that get higher weight are more; therefore, robot loses track of its location with lower probability. We don't want to use large number of particles; therefore, we search for an algorithm to reduce the number of particles during the localization task, in order to reduce the cost of localization. Using more number of particles will result in higher cost of localizing the mobile robot. By using the new way of initialization, since particles are not generated from the beginning all over the environment and there is no estimation of the robot's position in the time of initialization process, it reduces the cost of localization by using less number of particles for a successful localization and it also help to reduce the time of localization.

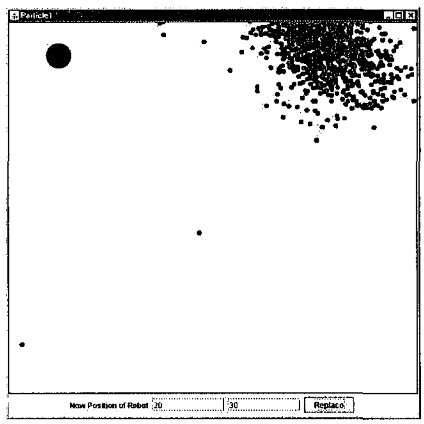
As conclusion, experimental results show that we have reached both lower cost in the localization process and also higher probably of localization failure recovery. The lower cost is reached by using less number of particles and ability to recover from the failure is gained by checking the particles with zero weight and decide weather to re-generate the particle set.




(a)

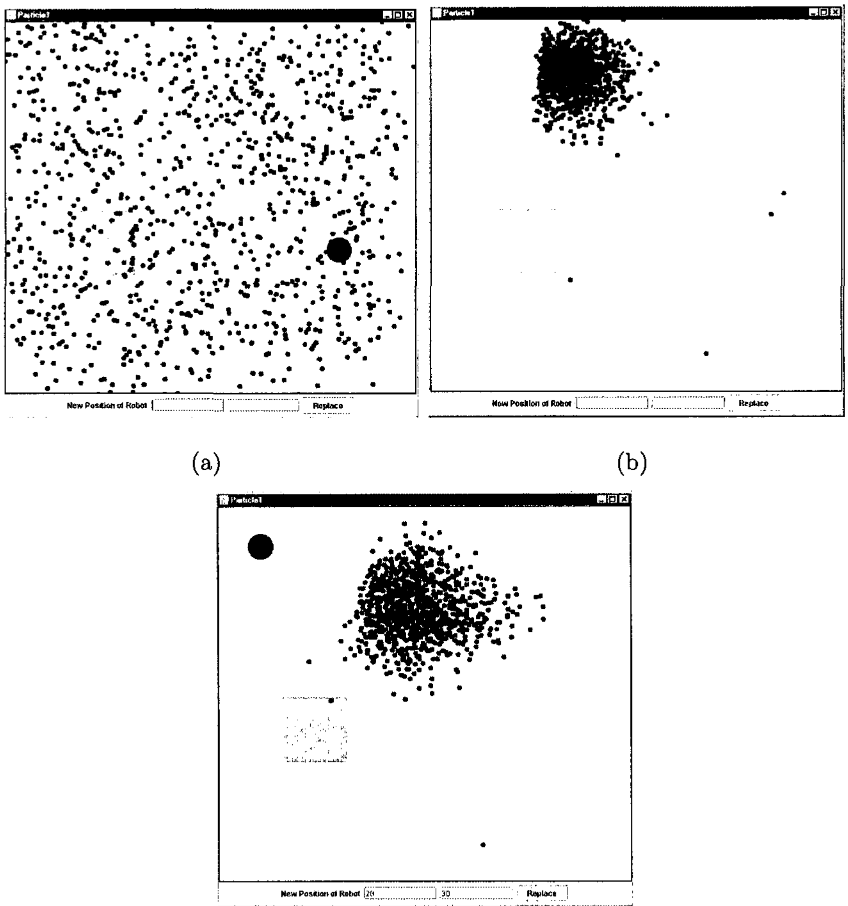



(b)




(c)

Figure 4.12: Localization using MCL in environment without obstacle. (a) Particles are generated randomly; (b) Robot is localized; (c) Robot is being kidnapped.




(a) (b)

(c)

Figure 4.13: Localization using MCL in environment with an obstacle. (a) Initialization of the particles; (b) Mobile robot is localized; (c) Robot is being kidnapped.

# Chapter 5

# Conclusion and Future Work

This chapter concludes this research work with discussion of possible future research directions and open problems.

## 5.1 Conclusion

Most of the existing approaches can not recover from localization failure and kidnapped robot problem. Therefore we need a method to localize the robot with higher probability and with the ability to recover the robot from kidnapping problem . The number of samples to be used is important, since using more number of particles will increase the cost of localization.

The proposed method is an improved approach to localize the robot. It recovers the robot from localization failures with high probability. Proposed method is based on Monte Carlo Localization and has two differences from the regular MCL algorithm, first modified initialization step and second modified resampling step. It has the ability to re-generate the particles in the case of localization failure. Applying the proposed method, it is expected that robot localizes itself with a high probability with lower cost. Two main advantages of the method, first different way of initializing the particles that helps to reduce some steps and the cost of localization. Second a new resampling scheme to solve the kidnapped robot problem and localization failures.

This method can be applied to most type of environments, in order to localize the mobile robots. In regular MCL, the number of samples to be used is generally kept very high in order to cover all the space and converge to the right position. The cost of localization is low; since particles are not generated from the very. Using more number of particles will result in higher cost of localizing the mobile robot. By using the new way of initialization, since particles are not generated from the beginning all over the environment in the time of initialization process, it reduces the cost of localization by using less number of particles for a successful localization and it also helps to reduce the time of localization. As conclusion, experimental results show that we have reached both lower cost in the localization process and also higher probably of localization failure recovery. The lower cost is reached by using less number of particles, and ability to recover from the failure is gained by checking the particles with zero weight and decide weather to re-generate the particle set.

## 5.2 Future Work

The localization described in our approach is being implemented using one mobile robot. Therefore, one objective for future research is to do the localization task using multi-robot and the proposed method.

In dynamic environments, other than robot, the location or configuration of other objects such as people and movable furniture changes over time. Most real environments are dynamic; localization in dynamic environments is more difficult than in static ones. Another possible extension of this work is to use this method to efficiently localize mobile robot in dynamic environments.

# References


[1] D. Fox, W. Burgard, F. Dellaert, and S. Thrun, "Monte Carlo Localization: Efficient Position Estimation for Mobile Robots," *Proc. of the Sixteenth National Conference on Artificial Intelligence (AAAI-99).*, 1999.

[2] D. Fox, Wolfram Burgard, and S. Thrun, "Active Markov Localization for Mobile Robots," *Preprint submitted to Elsevier Preprint.*, March. 1998.

[3] W. Burgard, D. Fox, and S. Thrun, "Active Mobile Robot Localization," *15th International Joint Conference on Artificial Intelligence.*, 1997.

[4] J. Kleinberg, "The localization problem for mobile robots," *In Proc. of the 35th IEEE Symposium on Foundations of Computer Science.*, 1994.

[5] L. Moreno, J. M. Armingol, S. Garrido,A. DE LA Escalera, and M. A. Salichs, "A Genetic Algorithm for Mobile Robot Localization Using Ultrasonic Sensors" *Journal of Intelligent and Robotic Systems*, vol. 34, pp. 135-154, July, 2001.

[6] R.Luo and B. Hong, "An Adaptive Algorithm For Localization In Highly Symmetric Environments," *International Journal of Innovative Computing, Information and Control.*, vol. 1, no. 2, pp. 1349–4198, June 2005.

[7] L.Ronghua, M. Huaqing, L. Maohai, and H. Qingcheng, "A Method for Active Global Localization in Multi-robot System," *International Journal of Advanced Robotic Systems.* vol. 5, no. 3., pp. 269–278, 2001.

[8] R. Kummerle, R. Triebel, P.Pfaff, and W. Burgard, "Monte Carlo Localization in Outdoor Terrains using Multi-Level Surface Maps," *Autonome Mobile Systeme, Springer Berlin Heidelberg.*, vol. 55, pp. 29-35, Oct. 2007.

[9] P. Jensfelt, and S. Kristensen, "Active Global Localization for a Mobile Robot Using Multiple Hypothesis Tracking," *IEEE Transactions On Robotics And Automation.*, vol. 17, no. 5., Oct. 2001.

[10] F. Giuffrida , P. Morasso, G .Vercellit , R.Zaccaria, "Active Localization Techniques for Mobile Robots in the Real World," *IEEE Proc. IROS 96.*, Dec. 1996.

[11] M. Adams, S. Zhang, and L. Xie, "Particle filter based outdoor robot localization using natural features extracted from laser scanners." *In Proc. of the IEEE Int. Conf. on Robotics and Automation ICRA.*, 2004.

[12] A. M. Whitbrook, U. Aickelin, J. M. Garibaldi, "Genetic-Algorithm Seeding Of Idiotypic Networks For Mobile-Robot Navigation," *IEEE Trans. on Circ. and Syst. II, Analog Digit. Signal Process.*, vol. 46, no. 12, pp. 1487-1496, Dec. 1999.

[13] W. Burgard, D. Fox, and D. Hennig, "Fast grid-based position tracking for mobile robots." *In Proc. of the 21th German Conference on Artificial Intelligence, Germany. Springer Verlag.*, 1997.

[14] S. Thurn, W. Burgard, and D. Fox, "Probabilistic Robotics", *MIT Press, Cambridge, MA*, 2005.

[15] S. Seifzadeh, D. Wu, Y. Wang, "Cost-effective Active Localization Technique for Mobile Robots", *International Conference on Robotics and Biomimetics (ROBIO)*, Dec. 2009.

[16] J.S. Gutmann, D. Fox, "An experimental comparison of localization methods continued", *in: Proc. of the 2002 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems, IROS02*, pp. 454-459, 2002.

[17] D. Fox, "Adapting the sample size in particle filters through KLDsampling", *International Journal of Robotics Research*, 2003.

[18] S. Lenser, M. Veloso,"Sensor resetting localization for poorly modeled mobile robots", *in: Proceedings of ICRA 2000*, pp. 1225-1232, 2000.

[19] J. Borenstein, B. Everett, and L. Feng, "Navigating Mobile Robots: Systems and Techniques", *A. K. Peters, Ltd.*, Wellesley, MA, 1996.

[20] D. Fox, "Markov Localization: A Probabilistic Framework for Mobile Robot Localization and Navigation", *PhD thesis, University of Bonn*, Germany, 1998.

[21] Z. Duan, Z. Cai, and J. Yu, "Robust Position Tracking for Mobile Robots with Adaptive Evolutionary Particle Filter", *Third Int. Conf. on Natural Computation (ICNC)*, 2007.

[22] W. Burgard, A. Den, D. Fox, and A. B. Cremers, "Integrating Global Position Estimation and Position Tracking for Mobile Robots: The Dynamic Markov Localization Approach", *Proceedings of the 1998 IEEE LRSJ Intl. Conf. on Intellig. Robots and Syst.*, Victoria, B.C., Canada, Oct. 1998.

[23] S. Thrun, D. Fox, W. Burgard, and F. Dellaert, "Robust Monte Carlo Localization for Mobile Robots", *Artificial Intellig.*, vol. 128, pp. 99–141, 2000.

[24] W.Burgard, D.Fox, D.Hennig, and T.Schmidt, "Estimation the absolute position of a mobile robot using position probability grids", *In: Proc. AAAI-96*, Oregon, USA, 1996.

[25] S. Thrun, "Probabilistic robotics", *Communications of the ACM*, vol. 45, no. 3, pp. 52–57, 2002.

[26] R. L. Mason, R. F. Gunst, J. L. Hess., "Statistical design and analysis of experiments: with applications to engineering and science", *John Wiley abd Sons*, Hoboken, NJ, 2003.

[27] J. Chen, "Bring Consciousness to Mobile Robot Being Localized", *Master's thesis, University of Windsor*, Canada, 2009.

[28] http://www.docstoc.com/docs/22433745/leJOS-NXJ-LEGO-NXT

[29] http://lejos.sourceforge.net

[30] http://mac.softpedia.com/get/Math-Scientific/iCommand.shtml

[31] http://rxtx.qbang.org/wiki/index.php/Download

[32] http://sourceforge.net/projects/bluecove

[33] http://www.eclipse.org/downloads

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