# A New Approach to Improve the Success Ratio and Localization Duration of a Particle Filter Based Localization for Mobile Robots


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## Abstract

**In real world applications, it is important that mobile robots know their location to achieve goals correctly. The localization of the robot is difficult by using raw sensor data because of the noisy measurements from these sensors. To overcome this difficulty probabilistic localization algorithm approaches can be used. The Particle filter is one of the Bayesian-based methods. In this study, two new features incorporated into the particle filter approach. These features are: decreasing the size of sample space using compass data and a new sensor model. The proposed approach is applied in the localization problem of a mobile robot. Performance of the proposed algorithm is compared with the performance of traditional particle filter approach by changing several parameters of the system. These analyses emphasized that the proposed approach improved the localization performance of the system. The results are promising for the future studies on this subject.**


## 1. Introduction

Mobile robots have been used for a large variety of tasks in different environments. To operate correctly, a robot must know its exact position and orientation. The process of computing the position of robots in a known environment using sensor readings, odometer measures and map information is defined as the localization problem [1].

In real world applications, the major problem is the accurate localization of robots because of the lack of perfect sensors. In most cases, it becomes nearly impossible to find the exact position due to noisy measurements. To overcome this problem the fundamental concept proposed in the literature is probabilistic approaches.

Kalman filter approach was first implemented by Mautarlier and Chatila [2] to localization problems and used many times [3]. The disadvantage of the Kalman filter is the use of a unimodal Gaussian distribution and linear system model. To overcome unimodal distribution limitation, multi-hypothesis tracking approach, which uses a mixture of Gaussians, is proposed [4]. In this case, the assumed system model is still linear. The other method, recursive Bayesian filter, is a robust way for estimating the state of robots and different implementations of these methods exist. Moravec [5] and Elfes [6] introduced occupancy grid maps to represent the environment. Graph-based topological methods [7] and metric-based grid approaches are efficient discrete Bayesian methods. Topological methods are easy-to-implement with the use of landmarks, but they have a disadvantage of coarse representation. Whereas, grid-based Markov localization [8] uses fine-grained grid structure, which causes computational and space complexity. An alternative and efficient way of Bayesian methods is the Particle filter approach. Particle filter-based Monte-Carlo localization method is developed by Fox [9]. Later various Particle filter algorithms are proposed [10], [11]. In this paper, two new features incorporated into the particle filter approach. These features are: decreasing the size of sample space using compass data and a new sensor model. This new approach is applied in the localization problem of a mobile robot. The results of the experiments show that the proposed approach improved the performance of the traditional particle filter method.

The structure of the paper is as follows: The Bayesian-based localization is covered in Section 2, the new approach for particle filter based localization is given in Section 3, the applications of the algorithm are given in Section 4, and the detailed analysis of the proposed method is covered in Section 5. Conclusions and the future work are presented in Section 6.

## 2. Bayesian-Based Localization

Recursive Bayesian filters consist of sequentially repeated two steps, prediction step and update step. When a new odometer measure comes, the prediction step is done using earlier motion and sensor data. If a new sensor reading is returned, the update step is executed.

The Particle filter which is a special case of the recursive Bayesian-based filters represents the distribution by a set $M$ of $N$ random samples. Each sample contains a state vector $x$ and a weighting factor $w$, $M = [x_j \quad w_j], j = 1 \dots N$.

The prediction step incorporates the robot motions into the sample set. Here, an incremental motion model is used to calculate new states. The motion model uses angle and distance information between two successive states. Each state is described by the position and orientation of the robot. Position and orientation of the robot are determined by using encoder and compass readings, respectively. Error in each reading is represented by a Gaussian distribution [1].

The update step uses sensor model to calculate the weights of the samples. The weights indicate the importance of samples. The significant point here, how the probability of robot's sensor measurements is determined. Fox et al. [8] has proposed a sensor model to compute the total sensor probability based on the distance to the closest obstacle along the direction of the sensor. This traditional sensor model has been described by approximately a Gaussian distribution with mean the distance to the obstacle. If more than one sensor is used, the total sensor probability for each sample is calculated as the multiplication of individual probabilities.

The last step of the algorithm is called resampling where the samples are redistributed according to their weights. In this algorithm, when a sensor measurement is received, the weight of particle is computed to give the probability of the robot to be in a state. Then, the resampling algorithm is executed to obtain a new sample set from the old set via the particle weights. The key idea of the approach is that the samples with higher weights survive with higher probability than the others.

## 3. A new approach for particle filter localization

The proposed method introduces new features in two steps of the algorithm. These are: inclusion of compass data into localization and using a new normalized sensor model. In the following subsections, these features are explained in details.

### 3.1. Effect of the Compass

Initially, the belief of robot's location is distributed uniformly. This uniform distribution is obtained by using Halton sequence [12] which gives equally spaced samples in position and orientation dimension.

The nature of the particle filter requires a large number of samples. For this reason, the computation and memory cost grows. In this study, information received from the compass is used to reduce the size of the sample space. Thus, the memory requirement and computation time are reduced.

The use of the compass gives information about the robot's orientation. Let $\theta_c$ be the orientation of the robot read by the compass, and $X_s = [x_s, y_s, \theta_s]$ be the state of the sample. The bounds of $x_s$ and $y_s$ are determined by the environment, and $\theta_s$ alters between 0 and $2\pi$. The orientation-space reduction factor, $\delta_\theta$, is used to reduce the configuration space of the orientation. The reduced orientation range, $\theta_p$, is defined by using $\delta_\theta$.

$$\theta_c - \delta_\theta < \theta_p < \theta_c + \delta_\theta \tag{1}$$

The ratio of the probability of the reduced configuration space to the probability of the whole configuration space (reduction constant) is defined as:

$$\frac{P\left(X(x_s, y_s, \theta_p)\right)}{P\left(X(x_s, y_s, \theta_s)\right)} = \frac{\delta_\theta}{\pi} \tag{2}$$

In this study, $\delta_\theta = \frac{\pi}{2}$ is used. The number of the samples is related to the reduction constant. The dimension of the new set is equal to the dimension of the original set times the reduction constant. Smaller number of samples means smaller computation cost. However, for successful robot localization, there should be a lower bound for the number of samples. A detailed analysis of the compass effect is given in Section 5.

### 3.2. Normalized Sensor Model

The sensor model is used to calculate the weight of the samples. In the traditional sensor model, the total sensor probability is calculated by multiplying individual sensor probabilities [1]. Let $P_1(y_1|x)$, $P_2(y_2|x)$,....,*and* $P_n(y_n|x)$ be the individual sensor probabilities for $n$ sensors. In this model, total sensor probability is defined as in equation (3).

$$P_{TSM} = \prod_{i=1}^{n} P_i(y_i|x) \tag{3}$$

In case of accurate measurements, the following relation holds.

$$\frac{P_{TSM}}{(P_{mean})^n} \approx 1 \tag{4}$$

Where $P_{mean}$ is defined as the arithmetic mean of all individual sensor probabilities. However, at a given point $x$, if the calculated probability of a sensor deviates much from the calculated probabilities of other sensors this condition is named as adverse probability condition. This condition occurs under the following situations

$$\begin{gathered} P(y_i|x) \gg \{P(y_j|x) \mid j = 1 \cdots n \,\&\, j \neq i\} \\ \text{or} \\ P(y_i|x) \ll \{P(y_j|x) \mid j = 1 \cdots n \,\&\, j \neq i\} \end{gathered} \tag{5}$$

Then the ratio given in equation (4) becomes

$$\frac{P_{TSM}}{(P_{mean})^n} \ll 1 \tag{6}$$

As this ratio becomes smaller than one, the samples supposed to survive are affected and their probability may decrease below the threshold. Due to this, the success of the localization decreases. In order to overcome this problem, the normalized sensor model is proposed. In this approach, the effect of the adverse probability is normalized by using the geometric mean of the sensor probabilities. The normalized total probability is given by the following equation.

$$P_{NSM} = \left(\prod_{i=1}^{n} P(y_i|x)\right)^{1/n} \tag{7}$$

This normalization reduces the negative effects of the sensors with very low and/or high probabilities. So, the ratio given below stays nearly one, although an adverse probability case occurs.

$$\frac{P_{NSM}}{(P_{mean})^n} \cong 1 \tag{8}$$

The ratio is nearly one, so the samples will survive, unless most of the individual probabilities are adverse. These survived samples may belong to true or false location. The samples belonging to the false location will be eliminated in the next steps of the process. The effect of the normalized sensor model is analyzed in the Section 5.

## 4. Application of the Proposed Method

In this section, the proposed Particle filter approach is applied to localize a Pioneer P3-DX robot in a laboratory environment. The P3-DX has a balanced drive system which includes two-wheel differential drive, caster wheel, and high-resolution motion encoders. It has also wireless Ethernet networking system and Pentium-based onboard computer system [13]. The sensors on the robot are: 16 sonar, a SICK LMS200 laser range finder, a PTZ Camera, and a compass.

In this study, the laser range finder is used for the applications. This sensor emits 180 laser beams with a 10 resolution. The proposed sensor model uses the range values returned by some of these beams. Each beam is considered as an individual sensor.

The applications were realized in the Eskişehir Osmangazi University Electric-Electronic Engineering Department Artificial Intelligence and Robotics Laboratory. The width and height of the experiment environment are 7300mm and 8500mm, respectively. The map of the experimental environment and the path followed by the robot at localization process are shown in Fig. 1. The numbers in the figure represent the localization step. In this part, the robot followed the path and during its travel data from compass, 16 sonar, 180 laser range finder data, the position coordinates, and orientation angle are recorded into a txt file at every 1000 msec. In the next part, the txt file is used as the input of the proposed localization method.

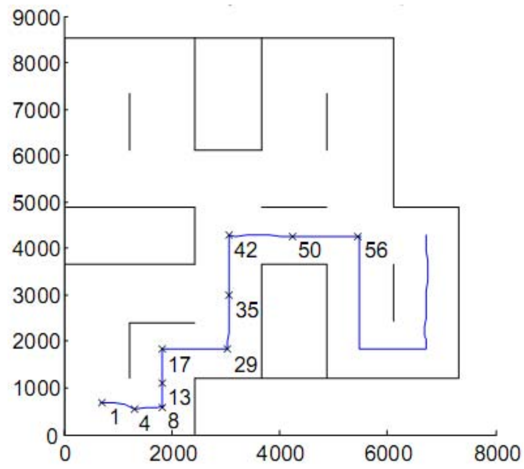


**Fig. 1.** The path followed by the robot at localization

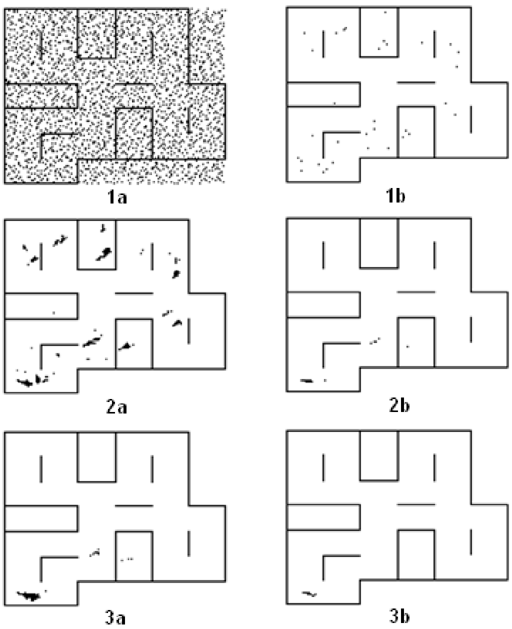


**Fig. 2.** The example of localization process

The localization process results are shown in Fig. 2. In this figure, the results of the prediction and update steps are shown in parts (a); the results of the resampling step are shown in parts (b). The initial belief of the robot location is shown Fig. 2-1a. As seen from this figure, the robot believes that it can be anywhere in the environment. The proposed procedure updates the probability of each sample by using laser beams and chooses the locations which have greater probability than a specified threshold. Fig. 2-1b shows the samples after one cycle. This procedure is recursively applied until the standard deviation of the sample locations is below a given value. In this example, the procedure localized the robot at the third step. Results of each step are given in Fig. 2-2a through 2-3b. As seen from Fig. 2-3b the location of the robot is determined.

## 5. Detailed Analysis of the Proposed Approach

To have a detailed analysis of the proposed approach, first some definitions are given:

NOS (Number of Samples): Density of the samples in Unit Sample Space (USS).

Step Cost: Duration required to process whole samples by utilizing laser beam values.

NOLS (Number of Localization Step): Number of steps that true localization is achieved.

LSR (Localization Success Ratio): Ratio of the number of successive localizations and total number of experiments.

In this study, the USS for the position and orientation are chosen as $1m^2$ and 180°, respectively.

First, the effects of NOS and number of beams on the Step Cost are investigated. The NOS values are 10, 20, 40, and 80 per USS. The numbers of beams are between 1 and 18. The results are given in Fig. 3. As seen in the figure, the Step Cost grows exponentially as the NOS and number of laser beams increase. In this figure and the following figures, the numbers on the right column represent the number of beams. For real time applications, the Step Cost should be minimized without affecting the NOLS and LSR values negatively. The proposed approach is analyzed in this respect.

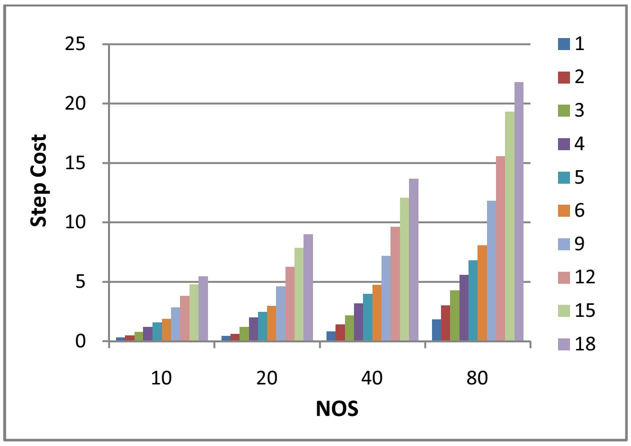


**Fig. 3.** Step Cost vs. NOS and Number of Beams

### 5.1. Performance Factors

The performance of the proposed approach is investigated in terms of the NOLS and the LSR. It is expected that localization performance will improve and the robot will be localized quickly, if more information is injected into the system. The information obtained about the environment is related to the number of laser beams used in the method. It is expected that, NOLS would decrease as the number of the laser beams increases. The experimental results are shown in Fig.4. The results confirm the expectations. However, the performance of the method is better when the number of lasers is odd. The reason of this is that one of the beams having the same angle with robot orientation is selected in the odd number of the laser beam case.

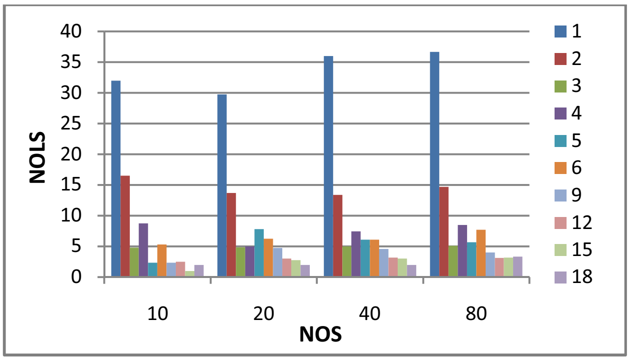


**Fig. 4.** NOLS vs. NOS and Number of Beams

The second factor for the system performance is the LSR. Since the distributed samples are random due to the nature of the probabilistic-based localization systems, successive localization is not guaranteed. Results of the experiments are shown in Fig.5. As seen from the figure, the LSR increases as the NOS increases which is an expected result.

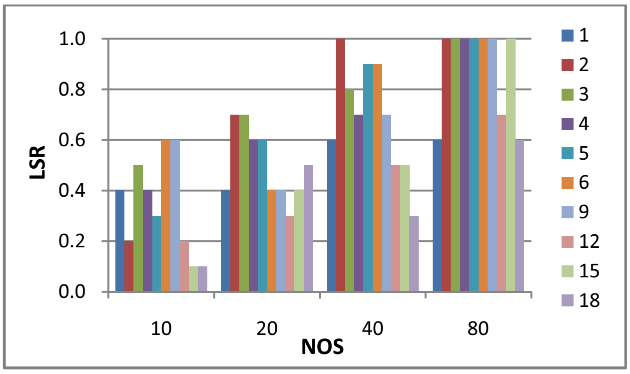


**Fig. 5.** LSR vs. NOS and Number of Beams

### 5.2. Compass Effect

In order to investigate the effect of the compass, experiments are conducted with and without using the compass information. In Fig. 6 the NOLS values are compared for 80 NOS and different number of beams. Except the first value, using the compass information improves the performance of the system.

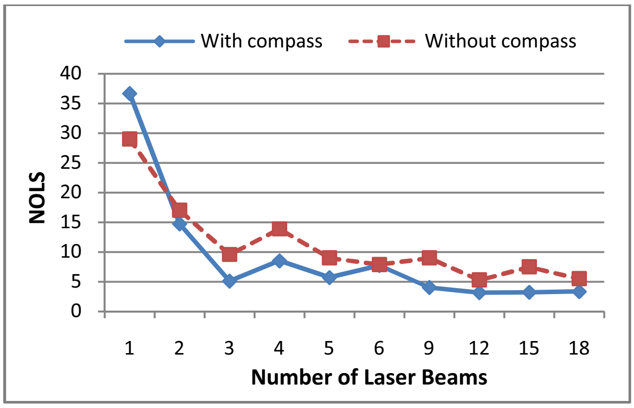


**Fig. 6.** NOLS with and without compass

The LSR is also improved when the compass information is integrated into the system. Results of the experiments are given in Fig. 7. The LSR with the compass is always greater than that of the corresponding value without the compass. Additionally, when the compass is used LSR is 100% for most of the cases.

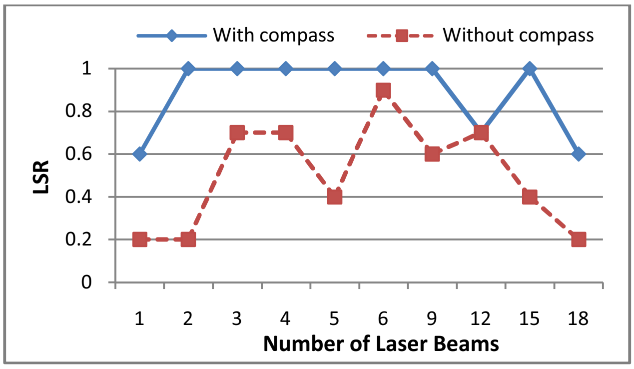


**Fig. 7.** LSR with and without compass

By using additional compass information, range of the configuration space for orientation is reduced. Therefore, the number of samples is reduced by the reduction factor and at the same time, the samples are concentrated around the true orientation. This increases the success probability of the algorithm and also decreases the number of steps.

### 5.3. Effect of the Normalized Sensor Model

The total sensor probability is calculated by multiplying the individual sensor probabilities [8]. But, if one of these sensors gives an adverse probability; the total sensor probability is negatively affected from this adverse probability and the LSR turns out to be very low. In order to improve the LSR, a normalized sensor probability approach is proposed. Fig. 8 shows the LSR for both sensor models. The LSR with normalized sensor model is always greater than that of the corresponding value with traditional sensor model.

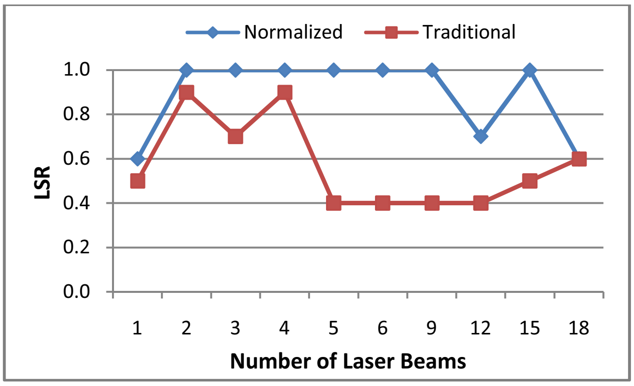


**Fig. 8.** LSR with and without normalized sensor model

Although the LSR is improved when the normalized sensor model is used, the NOLS gets worse. In case of the traditional sensor model, localization is achieved in smaller steps; however, this localization may not occur at the correct location because of negative effects of adverse probability. Comparative results are given in Fig. 9.

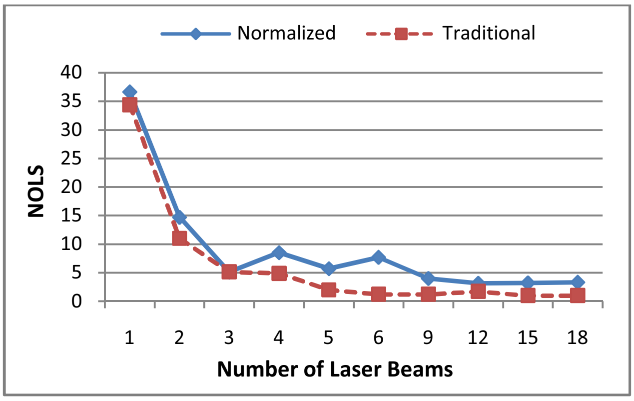


**Fig. 11.** NOLS with and without normalized sensor model

## 6. Conclusions

In this study, two features are integrated into the traditional Particle filter algorithm. One of the features is using the compass information. By using this information, range of the orientation configuration space is reduced into an interval around the actual orientation of the robot. The second feature used is a normalized sensor model. In the traditional sensor model, the adverse probability causes to localize into an incorrect location. To prevent this effect a new normalized sensor model is proposed. In this model, the effect of the adverse probability is normalized by using the geometric mean of the sensor probabilities.

To show the effects of the proposed approach, two performance factors namely the NOLS and the LSR are introduced. These factors are investigated in terms of the NOS and number of beams. It is shown that, both factors are improved by the proposed method.

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