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The Evaluation of Provided Methods in SLAM Problem and a Method Development in Order to Use in Multi Robot

Jenabzadeh MohammadReza
Department of Electrical Engineering And Computer, Yazd Branch, Islamic Azad University
Yazd, Iran

Bakhshi Meisam
Deprtment of Mechatronic, Yazd Branch, Islamic Azad University
Yazd, Iran

Lesansedgh Mohammadmehran
Department of Electrical Engineering And Computer, Yazd Branch, Islamic Azad University
Yazd, Iran

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Abstract

Simultaneously Localization and Mapping (SLAM) in mobile robots is an issue which is of utmost importance to Robotic Science researchers. The goal is to determine the position of intelligent mobile robots and their navigation to provide the overview map of the environment when no knowledge of it exists. So far, various methods have been presented in group robots to solve the SLAM problem. After about six years of research on mobile robots in Yazd Robotic Association and of applying available algorithms on rescue real robots, we will review major approaches on a robot and will introduce a new method that has been applied on two platforms of manual and autonomous robots in IranOpen 2011 competitions. We provide a method based on ROA-BlackWelized Particles filter (RBPF) algorithm and Forgetting curve in Multi robots which, compared to the limitations of collecting environmental data in the past two years, has provided satisfactory results. In the end, we simulate the consequence method in order to provide the robot’s overview and local maps from the environment in PlayerStage software.

Keywords: **SLAM, Rao-Blackwellized particle filter (RBPF)**,**grid map, localization, mobile Robots, leitnerbox, PlayerStage**

1 Introduction

In order for a robot to move correctly in an environment and pass through the barriers, different methods are available including position tracking and controlling. Performing other intelligent systems such as providing a map may not be possible without possessing the position of the robot. Given that a robot owns a world model system for itself, various intelligent components can be situated on a robot. Among these numerous components, one can refer to move to a position in the shortest possible route, avoiding clashing to barriers, coming back, and mapping the environment. In general, the main component and factor in the intelligence of mobile robots is the robot's position tracking system with which its other activities are projected.

Generally, the objective of dissolving the SLAM problem in a mobile robot is to attain the important goal of the simultaneous position tracking and mapping. As it has previously been discussed, too much endeavor has been devoted regarding the SLAM problem. What seems novel, however, is its simultaneous dissolving in several mobile robots, or a set of robots, which will be discussed in this article.

In this case, we will discuss the SLAM issue in some mobile robots and also present our own algorithm while introducing the RaoBlackwelized Particle filter (RBPF) method, and will provide its application results in simulations and virtual environments.

So far, several algorithms have been provided for position tracking mobile robots which are as follows:

- EKF (Extended kalman filter)
- MCL (Mont Carlo Localization)
- Rbpf (RaoBlackwelize Particle filter)

Environment mapping is also one of the results of position tracking and compounding sensor information with the optimum estimations from the environment which has hitherward been presented by different algorithms using Kalman Filter and Particle Filter.

2 Introducing the SLAM Problem for some Mobile Robots

The position tracking and mapping problem is a simultaneous study of the hypothesis stating that if an automatic mobile device starts moving from an indefinite position in an unknown environment, then a map will be incrementally provided from the environment so that this map can be used to calculate the exact position of the device, at the same time.

Concerning some robots, the development issue was the same in a way consisted of the evaluation and annexation of the robot's producing maps and also providing online local and general maps, so that each robot could be informed of the position of the other robots while individually navigating and collaborating with them.

In order to solve the problem, first we must introduce the dominant methods on a robot in simultaneous position tracking, navigating, and producing maps, and then present and develop them for some robots.

3 Position tracking some robots in comparison with a mobile Robot

Position tracking the intelligent robots has been one of the fundamental difficulties in getting perception of an unknown environment by robots, to which other intelligent components are also related. To dissolve the problem, we consider a two-dimension coordinates [x,y] and also the robot angle. We are able to relatively find the robot position from the local map. Accordingly, the main issues on position tracking robots are categorized into three classes:

- Position Tracking
- global Localization
- Kidnapped Robot problem

The first issue includes Odometry error and can be designed and solved by Odometry error correcting algorithm, Gaussian estimation and Kalman filter [34], and we are trying to find the exact position of the robot by solving this issue. The second issue includes the fact that we have no perception of the robot's starting point and environment and that we must get a relative perception of the route by estimation algorithms [8]. A group of the algorithms which have been presented as yet are included in the following main groups:

- Multi-hypothesis Kalman filters
- Markov localization (ML)
- Monte-Carlo localization (MCL)

Certainly, in this field, the Gaussian distribution, Beyz estimation and sensor information compound are used to correct the estimation. A relatively novel method, however, has been presented here which includes the weight vectors (particles). The final issue, which is considered as the most important issue in position tracking robots as well, includes Kidnapped Robot Problem, the setting in which this setting the robot falls into an infinite loop, a situation from which no position tracking algorithm is able to release the robot. Here the robot must be manually transferred from the error position to another position; in this sense, however, there would be no Odometry feedback. While revealing this error, the resistance of the position tracking algorithm against severe errors in Odometry, as well as the robot's ability to release itself from its error position, is examined. The fundamental solutions of the Kidnapped problem have been stated in [1]: in [2], landmarks are randomly established everywhere, excluding some of the samples, making the assumption that some of the samples would be so close to the correct position as to involve the correct position tracking algorithm in a few rerun times and get the desired respond quickly. In [3], an analogous method to image based MCL is followed as well. The method followed in [4] is to some extant different from the other methods; as some certain landmarks are established in special positions except some random position samples. In [5], there also exists a similar method in which image samples used in position tracking are placed around the reference image.

Tracking the position of some robots is also among the most important issues presented in position tracking mobile robots and refers to the cooperation of several robots in position tracking and navigation [6]. Yet, much endeavor has not been devoted to this field and the three main position tracking problems are considered in position tracking of some robots. One of the references in this matter is [7] in which the method development of MCL algorithm for some robots is discussed. According to this method, a robot finds its colleague robot by a camera installed on it and gets to know its position relative to itself and reference coordinates. Indeed, through this method, the robots' positions, with regard to each other, are determined and examined again. Hence, according to [7], tracking the position of some robots with respect to one robot is done better and in a shorter time period. In another case regarding [9], the (kalman filter) KF algorithm has been used in which the discrete processing of Centralize KF (CKF) on mobile robot is used to position tracking robots, so that each robot is also aware of the position and estimation related to the others. The other method, according to [10], is as followed: in the environment of several robots, we divide mobile robots into two groups; A and B i.e. one group is fixed and the other group will move, then the second group will be fixed and the first one moves. In fact, in this method, the fixed robot group plays the landmarks role in each step. The advantage of this method is that the environment map and estimation for robot position tracking and navigation is not required and the navigation is done as cooperation between two groups. Another method like this one is presented in [4] in which other robots, with respect to the considered robot while being visible for it, are accounted as landmark, and position tracking each robot is done in this way. The other method [10] is using local maximization function to solve the position tracking problem in which the weight function of a robot establishing possibility in a position develops so far that becomes able to estimate the position of the neighbor robot. In the method that will be stated here, we will also use the RBPF algorithm based on MCL and use to compounding maps increasing Online weight possibility function- that will be presented- and also using method [4] and Leitnerbox method and will provide a solution for SLAM problem.

4 Creating map by means of some robots as compared with one mobile robot

Creating map by a robot has finally led to a perception of the physical environment in which the robot moves. This created map is further used in the next steps to estimate the automatic robot position and to correct that. So, the mapping problem is important from two viewpoints:

- Presenting the environmental map
- Algorithmic methods

Where the first viewpoint leads to designing the Object map and Grid map methods and the second one leads to presenting mapping algorithms for intelligent robots from an unknown environment in which it is moving and their most important algorithms are as following:

- Kalman filters
- Expectation maximization (EM) algorithm
- Simultaneous localization and mapping (SLAM)
- And some compounding methods from these methods

As it has previously been mentioned, there are too many statements about the SLAM problem. But the most important subject is that SLAM is a problem not a method . Some methods are presented to solve this problem which are contrary to methods such as KF in which landmarks and optimum estimations accompanied by sensor noise are used, some advanced methods are applied in which the method of breaking down a problem into smaller problems with larger amounts of landmarks each is their specific weight function, (particles) is used. This method is known as Raoblackwelizeparticle filter (RBPF). The Particle Filter (PF) is based on Mont Carlo which has less time complexity compared to fast SLAM and EKF; its time complexity is about O(log n) (n= number of particles) [11].

The mapping problem in the case of some robots is approximately similar to the same problem about one mobile robot except for the fact that in some robots, a set of sensor data is used which simultaneously operates on several systems and has a high speed in recognizing the environment and providing a whole map from there. For example, using the development of maximum likelihood (ML), MCL methods in [12], a method is presented at the same time regarding how to navigate, to track and map the position of some robots.

5 Particle Filter method

One way to reduce the computational cost of the problem is to reduce the number of samples we analyze. Particle filtering essentially combines the particles at a particular position into a single particle, giving that particle a weight to reflect the number of particles that were combined to form it. This eliminates the need to perform redundant computations without skewing the probability distribution. Particle filtering accomplishes this by sampling the system to create N particles, then comparing the samples with each other to generate an important weight. After normalizing the weights, it resamples N particles from the system using these weights. This process greatly reduces the number of particles that must be sampled, making the system much less computationally intensive.

The algorithm includes an optimum estimation method using Mont Carlo [30] and Particle Filter for the equations of state 1 and consists of a sample of Marco chains of Mont Carlo method [13].

$$P(x_T \mid Y_{1:T}) = \alpha_T P(Y_T \mid X_T) \int_{\Omega_{T-1}} P(x_T \mid x_{T-1}) P(X_{T-1} \mid Y_{1:T-1}) dX_{T-1} \quad (1)$$

In order to find the optimum estimation of Mont Carlo using equation (2) will suffice,

$$P(x_{1:T} \mid Y_{1:T}) = \alpha_T P(Y_T \mid X_T) P(X_T \mid X_{1:T-1}) P(X_{1:T-1} \mid Y_{1:T-1}) \quad (2)$$

So in order to draw the N equal sample we will have:

$$E(x_{1:T} \mid Y_{1:T}) = \frac{1}{N} \sum_{1}^{N} x_{1:T}^{(i)} \quad (3)$$

The most important issue is recognizing samples using equation (2).
In RBPF method, more number of samples from N sample is needed, so that, as we will mention later, sometimes RBPF algorithm doesn't use a certain method [13]. And in some methods, using the State- space infrastructure model is required so that one can estimate the position of the uncertain objects of that environment [11]. The estimation of these margins is certainly done with RBPF algorithm. The hypothesis of this algorithm is presented in [11]. Here, we just confine the algorithmic expression of this hypothesis. The position tracking and map creating will indeed be discussed based on this algorithm [13].
Algorithm1: Rao-Blacwellized Particle Filters
1: S0:t.1, {hw(j), l(j) 0:t.1i|1 ≤ j ≤ N} {Input sample set}
2: at.1 {Current odometry data}
3: st {Current perception data}
4: S0:t = Φ{Output sample set}
5: F {Function F}
6: N, N {Number of samples}
7: st1:tk = F(st)
8: for i = 1 to N do
9: sample l0:t.1 , S0:t.1 according to w(j), 1 ≤ j ≤ N
10: sample lt , p(lt|lt.1, at.1)
11: m = m(lt1:tk , st1:tk)
12: w(i) = p(st|lt,m)
13: S0:t = S0:t , {hw(i), {l0:t.1, lt}i}
14: end for
15: F(st) = F(st) , st
16: normalize w(j), 1 ≤ j ≤ N, s.t.
Pj=1
w(j) = 1
17: return S0:t

According to this algorithm, based on Mont Carlo and using segmentation, environment acts as Square – rectangular. We divide the total environment into heterogeneous weighted squares and using Leitnerbox method (Figure1, 2), we divide some robots into two main groups of A and B without the need of the uncertain landmarks of the environment, The initial

estimation of the place is presentable. Hence Odometry information can be used directly and the only problem here will apparently be Position tracking in the case of each robot which is also soluble with mentioned methods in section 2. Although what is apparent is that the initial estimation, which is based on sensor information, doesn't satisfy our considered subject as much. So, a method to estimate the robot motion track is needed independently, so that based on it, we can try solving the SLAM problem in some robots. For this purpose, we use Estimation of Relative Poses (ERP) algorithm that is stated in [14]. Accordingly, we will attribute a vector to each local component, and will use a central simulator system according to performance algorithm based on Leitnerbox method to present the cooperation between robot I and robot j. Figure 3 shows the way of the perception of two robots of the other's position according to the state and local vector. It is worth mentioning that the position information through digital compass sensor, shaft encoders, and environmental information will be sent to the central processor of the robots through laser scanner sensor.
Using the dominant method on the mentioned box, and while determining the motion track of each of the two robots using EPR algorithm as online and step by step, we proceed to the local integration of maps from square positions of robot motion track (according the MSLAM algorithm presented in the following).

Fig.1. The way of algorithm operation base on RBPF

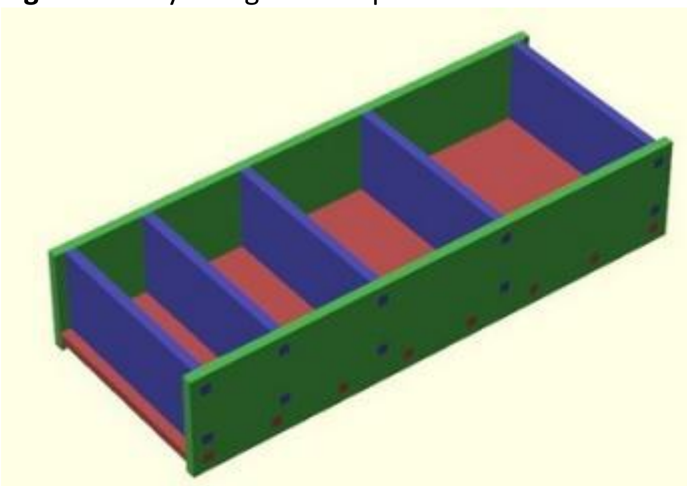

Fig.2. The way of algorithm operation base on RBPF

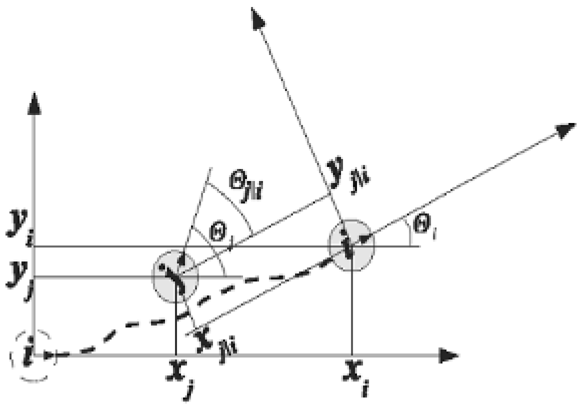

Fig.3. The way of position perception of robots i and j of each other

Algorithm MASLAM (Multi Agent SLAM):

1: i, j {Robot id-s}
2: Si {Samples of local poses of i}
3: Sj {Samples of poses of j in i' map}
4: sj {Current perception data of robot j}
5: F {Function F}
6: Sj|i =? {Samples of relative poses of j w.r.t.i}
7: estimate Si by algorithm RBPF.
8: {(s(t1)i , l(t1)i , i), ..., (s(tk)i , l(tk)i , i)} = F(sj) {Retrieve scans of i}
9: m = bm(l(t1)i , s(t1)i , .., l(tk)i , s(tk)i)
{Compute submap}
10: estimate Sj by algorithm RBPF using m as a map
11: N = |Sj | {Number of samples in Sj}
12:While(Not cycle of rectangle)
13: for i = 1 to N do
14: sample hwj ,lji , Sj {Sample a pose of j}{i is the landmark}
15: sample hwi, lii, Si {Sample a pose of i}{j is the land mark}
16: lj|i = lj. li
17: m = bm(l(t1)j , s(t1)j , .., l(tk)j , s(tk)j)
{Compute submap}
18: end for
19: for i = 1 to N do
20: merg map of Rec i with map of Rec j
21:end for
22: return global map

The calculation algorithm and some robots map using the Leitnerbox method.

The way in which this algorithm performs is based on the clash structure of the Leitnerbox with flash cards.

6 Results from simulating in PlayerStage environment

Simulating is one of the most important initial steps in installing complex systems. Simulation has different levels. Some of the simulation systems just simulate the behavior and mechanism of high levels, while in some cases, the system details are considered as well. In this article, the robots virtual model is created using programming environment C++ and then the output matrix of the robot position and virtual information of scanner laser is inserted into the given algorithms in the same software PlayerStage. Having installed the algorithm, we would find two environment maps. What is important here is the executable ability of this algorithm and solving the multi careers SLAM problem in the shortest period of time. Although at the present time, and compared to the hitherto presented PF and KF methods, this algorithm has less accuracy, in virtual environment and in ten motion steps, it shows some logical results as the following:

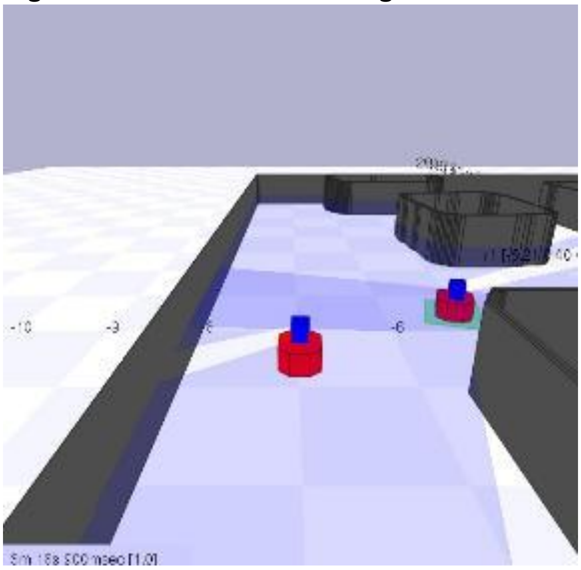

Fig.4. The performance environment of two robots cooperating with each other

Finally, according to the mentioned data in the update phase, the performance environment of the robot and its map as for the position of the existing barriers and drawing spaces are determined. Based on the Odometry issue, the position error of the two robots will indicate that the above mentioned position can be corrected using error emission function. The error, however, cannot be fully removed.

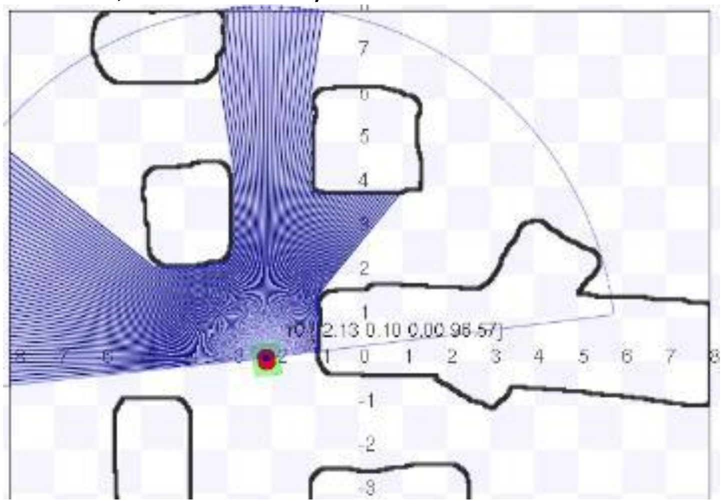

Fig.5. Performance environment according to the saved track from the viewpoint of camera on the top of robot in PlayerStage

7 Conclusion

In the present article, we presented a method to provide the map and to track the position of mobile robots, and showed the output of the mentioned method using the existing methods and also the method presented using virtual environment of PlayerStage. It is worth mentioning that the obtained results are almost true for actual robots excluding some slight errors.

Corresponding Author

Lesansedgh Mohammadmehran
Department of Electrical Engineering And Computer, Yazd Branch, Islamic Azad University Yazd, Iran
mlesansedgh@gmail.com

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