A Fuzzy Touch to R-MCL Localization Algorithm

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Abstract. In this work, a novel method called Fuzzy Reverse Monte Carlo Localization (Fuzzy R-MCL) for global localization of autonomous mobile agents in the robotic soccer domain is proposed to overcome the uncertainty in the sensors, environment and the motion model. R-MCL is a hybrid method based on both Markov Localization(ML) and Monte Carlo Localization(MCL) where the ML module finds the region where the robot should be and MCL predicts the geometrical location with high precision by selecting samples in this region. In this work, a fuzzy approach is embedded in this method, to improve flexibility, accuracy and robustness. In addition to using Fuzzy membership functions in modeling the uncertainty of the grid cells and samples, different heuristics are used to enable the adaptation of the method to different levels of noise and sparsity. The method is very robust and fast and requires less computational power and memory compared to similar approaches and is accurate enough for high level decision making which is vital for robot soccer.

Keywords: Global localization, ML, MCL, Fuzzy logic, Robot soccer.

1 Introduction

The localization problem is the estimation of the position of a robot relative to the environment, using its actions and sensor readings. Unfortunately the sensors and the environment are uncertain, so the results are typically erroneous and inaccurate. From the simplest geometric calculations which do not consider uncertainty at all, to statistical solutions which cope with uncertainty by applying sophisticated models, many solutions have been proposed [1, 2, 3]. Although some of these approaches produce remarkable results, due to the nature of the typical environments they are not satisfactory. Generally, solutions producing precise results suffer from slowness, and high memory usage. Whereas a fast solution in practice typically produces only coarse results. Even when they produce precise local results, some approaches like Kalman filters, fail to find the global position. Consequently, localization still remains as a nontrivial and challenging problem.

In robot soccer, a robot is typically expected to find its own location using the distinguishable unique landmarks in the field, and then use this information

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to find the location of the ball and goal. For such a real-time application with robots limited by on board computational resources, fast solutions with less memory and computational resources are especially demanded. Consequently, localization is a vital problem for robot soccer. This work is a part of the Cerberus Team Robot soccer project [4], and aims to localize the legged robots in the soccer field globally, while solving the above mentioned problems. There are a several limitations and assumptions related to the rules of the Four Legged League of Robocup [5]. In this work, the previously developed hybrid approach called *Reverse Monte Carlo Localization*(R-MCL) [6, 7] combining the ML and MCL methods is extended by using fuzzy sets to improve success in case of high sparsity and noise.

The organization of the paper is as follows: In the second section, a brief survey of localization methods is presented. In the third section detailed information R-MCL algorithm can be found. In the fourth section, the fuzzy extension to R-MCL is presented. The results of the application of proposed approach are given in section five. In the sixth section, conclusions and suggestions for future work are given.

2 Localization Methods

The simplest localization method depending on the range and bearing data is triangulation, which uses geometry to compute a single point that is closest to the current location. But in real world applications a robot can never know where it is exactly because of the uncertainty in its sensors, and the environment. Consequently, several different approaches which estimate the position of robot probabilistically were introduced to integrate this uncertainty into the solutions.

Kalman filter (Kalman-Bucy filter) is a well-known approach for this problem. This filter integrates uncertainty into computations by making the assumption of Gaussian distributions to represent all densities including positions, odometric and sensory measurements. Since only one pose hypothesis can be represented, the method is unable to make global localization, and can not recover from total localization failures [8, 9, 3].

Many works consider Markov localization (ML) [1, 10]. ML is similar to the Kalman filter approach, but it does not make a Gaussian distribution assumption and allows any kind of distribution to be used. Although this feature makes this approach flexible, it adds a computational overhead.

Monte Carlo Localization (MCL) is a version of Markov localization that relies on sample-based representation and the sampling/importance re-sampling algorithm for belief propagation [2, 11]. Odometric and sensory updates are similar to ML. Most of the 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 solve this problem by adding random samples at each iteration. Some of these methods are Sensor Resetting Localization (SRL), Mixture MCL (Mix-MCL), and Adaptive MCL (A-MCL). In SRL, when the likelihood of the current observation is below a threshold, a small fraction of uniformly distributed random samples is added [12]. Mix-MCL additionally weights these samples with current probability density. This method has been developed for extremely accurate sensor information [3]. Adaptive MCL only adds samples when the difference between short-term estimate (slow changing noise level in the environment and the sensors) and the long-term estimate (rapid changes in the likelihood due to a position failure) is above a threshold. [3].The MHL method discussed in [13] aims to avoid caused by using a single Gaussian, by using a mixture of Gaussians enabling the representation of any given probability distribution of the robot pose.

ML-EKF method is a hybrid method aiming to make use of the advantages of both methods, taking into consideration the fact that ML is more robust and EKF is more accurate [3].

Although there have been only a few fuzzy logic based approaches, they appear to be promising [14, 15]. In these approaches, the uncertainty in sensor readings (distance and heading to beacons) is represented by fuzzy sets.

3 R-MCL Method

As mentioned in section 2, ML is robust and converges fast, but is coarse and computationally complex. On the other hand, sample based MCL is not as computationally complex as ML, and gives accurate results. However, it can not converge to a position as fast as ML, especially in the case of an external impact on the position of the robot (such as kidnapping). In addition, the number of samples to be used is generally kept very high to cover all the space and converge to the right position. Several extensions have been made for adaptive sample size usage, but these still do not solve the slow coverage problem. The Reverse Monte Carlo Localization algorithm [6, 7] was developed to benefit from the advantages of these two methods while avoiding their disadvantages. The idea is to converge to several cells by ML or another grid based method, then produce a limited number of samples inside these bulk of grids to find the final position. The average of these samples would give the final position and the standard deviation might give the uncertainty of the final position as in the MCL based methods. In the original MCL, the number of samples is increased to decrease the bias in the result. In R-MCL since we converge by selecting the cells with maximum probability, so the bias is already decreased. The R-MCL algorithm is given in Figure 1.

In this work, some improvements were done on the R-MCL method and in particular the ML module. In the modified ML, not only the distance but also the bearing information is used to find the best grids, so the number of chosen grids decrease and confidence increases. When the samples are drawn, also the best samples are selected using distance and the bearing from these very good cells, and their average is returned as the current pose. Note that samples are taken into consideration only when the position is above a certainty level, in other words the number of chosen cells are below a limit(e. g. 50), and there is at least one very good cell which is below or equal to the minimum error in

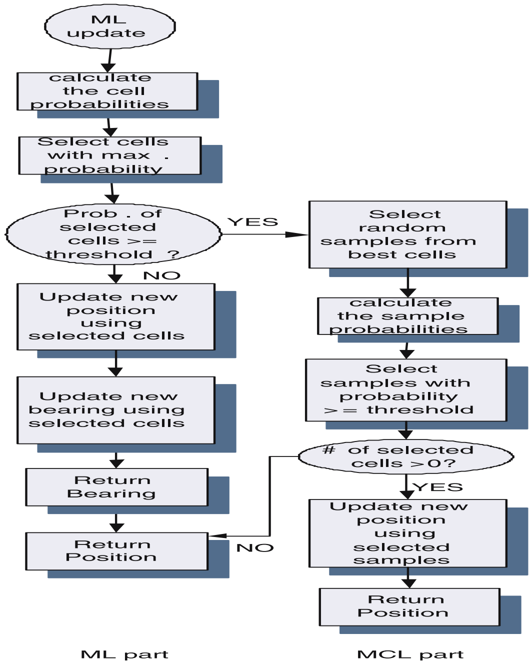

Fig. 1. The R-MCL flowchart

both distance and bearing limitations. Also if there are no samples which satisfy the minimum bearing and distance error condition then the results of ML are used instead. The bearing of the new pose is found by the ML module inside the R-MCL because it is more accurate and robust.

4 Fuzzy R-MCL

In this work, after improving R-MCL, a fuzzy approach was embedded in it, to improve flexibility, accuracy and robustness. Fuzzy membership functions are used in modeling the uncertainty of the grid cells and samples. Here, the uncertainty model μ_1 which is used in both ML and R-MCL is replaced by the fuzzy model μ_2 represented by the fuzzy membership function given in Figure 2(b). The previous model was simple and fast but it was not flexible enough to improve success when sparsity and noise is high. Especially if the cell size is kept high (30 cm) as in [6, 7] compared to 5 cm used in [3] a more flexible model is needed to weight the probability of being in that cell. It is not preferable to give the same weight to every point when the cells sizes are so big, and to the samples inside these cells.

In both of the models given in Figure 2, d_i represents the difference between the observed relative distance from robot to the currently observed landmark, and the calculated distance from the current cell center to the currently observed

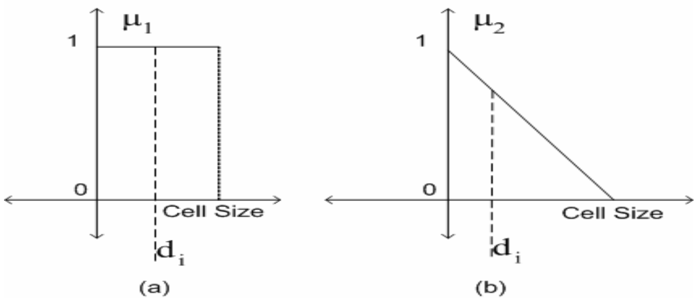

Fig. 2. Fuzzy membership functions used

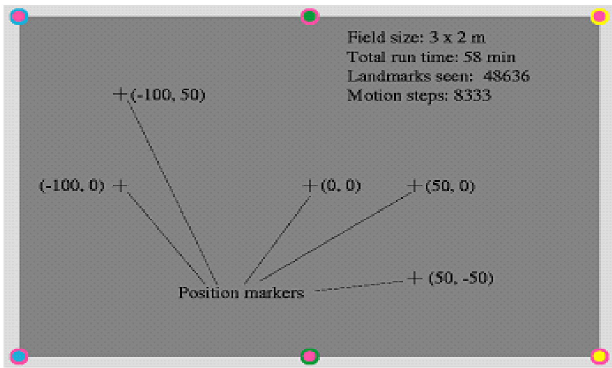

Fig. 3. The test field

landmark. This enables us to weight the samples according to their fitness to the observation and odometry.

5 Tests and Results

In the testing phase, a standard set of test data is used. These data are based on the records of the test runs of Sony's ERS 210 quadruped robots (AIBO) on the Robocup soccer field, used in [3] for comparison of several well-known localization methods in literature. These are produced by running the robot on the field as shown in Figure 3 on an eight like path for almost an hour, stopping the robot on several predefined points called markers, and recording the observations and odometry readings during this run. The tests aim to analyze accuracy and robustness in case of noisy and sparse data, and the ability to handle kidnapping problem. In the noisy data tests, randomly chosen data are replaced by noisy ones. The number of noisy samples is increased to see the robustness and accuracy of observed methods in case of high noise levels. In sparse data tests, samples are deleted from the tests, in a predefined sequence, (beyond the robots awareness). As the frequency increases, the behavior of the selected methods is

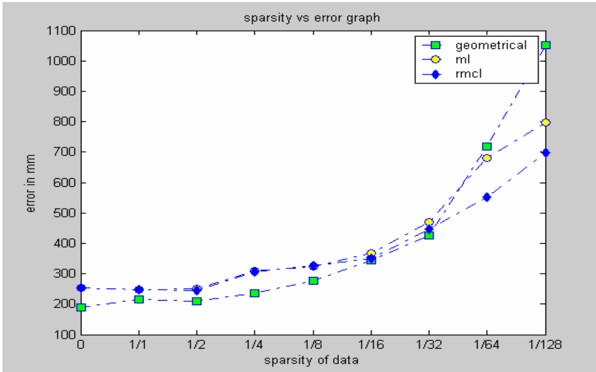

Fig. 4. The results for the sparse data case

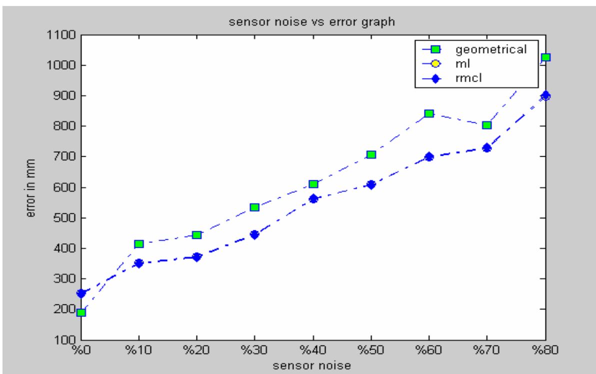

Fig. 5. The results for the noisy data case

observed. Lastly, the kidnapping problem is tested, by changing the position of the robot (beyond the robots awareness), and the time for recovery is recorded.

Several different kinds of membership functions (e. g. trapezoidal) and different sizes (e. g. twice the cell size) were tested and the best model found is the model μ_2 presented in the Figure 2(b). In Figure 4 and Figure 5, the accuracy of Fuzzy-RMCL and other proposed methods are presented, in case of sparse and noisy data, respectively. The results of the previous versions of the proposed methods can be found in [6, 7]. The error rates of the tests are calculated from the expected location of robot, when it reaches a marker, and its exact location. Note that, there are also unavoidable errors in the exact locations of robot due to experimental problems reported by the data providers. When the results of the tests are compared to the similar tests in [3, 13], the R-MCL method shows similar performance in the sparse and noisy data tests. The cell size is chosen as 5 cm in the referenced works, but it is taken as 30 cm in the current work, to increase the speed, and triangulation method which is used in the case of observing two or more landmarks are not used in the implementations. These facts would decrease the error rate very much, but the current case is more realistic and similar to real world case. The parameter set is chosen after detailed tests and comparisons.

Note that in the case of sparse data, Fuzzy R-MCL outperforms ML especially when sparsity is more since it is logical to gain more information to locate the robot by throwing more samples as the sparsity increases. However, as the noise increases it is not logical to throw more samples, but to keep the number of cells as small as possible to cope with noise.

During the tests, it was realized that choosing the cell size very big decreases the effect of odometry, and can cause a *temporary kidnapping* effect when the robot moves from one cell to other, which also decreases the success rate.

6 Conclusions

Localization in a totally unknown area is a very hard task for autonomous mobile robots. This work aims to propose a fast, reliable, computationally and resource efficient solution to the global localization problem. The solution should be successful in environments like the Robocup Games and the challenges which require very high accuracy and speed. For this reason previously a hybrid method called R-MCL method was developed. In this work, a fuzzy approach is embedded in this method, to improve flexibility, accuracy and robustness. In addition to using Fuzzy membership functions in modeling the uncertainty of the grid cells and samples, different heuristics are used to enable the adaptation of the method to different levels of noise and sparsity. The method is very robust and fast and requires less computational power and memory compared to similar approaches and is accurate enough for high level decision making which is vital for robot soccer. There is an ongoing research for improving the success by solving the temporary kidnapping problem due to large cell size.

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