A Reliable Position Estimation Method of the Service Robot by Map Matching

Dongheui Lee    Woojin Chung    Munsang Kim

Abstract – In this paper, a reliable position estimation method of the indoor service robot is proposed. The service robot PSR1 is a wheeled mobile manipulator which navigates in office buildings. Our localization method is a map-matching scheme using scanned range data, without using any artificial landmark. The proposed algorithm can provide solutions for both a global localization problem and a local position tracking. A probabilistic position estimation scheme is designed based on MCL (Monte Carlo localization). Two measure functions are developed for computing positional probabilities. The robot automatically decides whether it uses geometric pattern matching (i.e. walls, pillars) by Hough transform. The proposed scheme shows reliable performance in both polygonal environments and non-polygonal environments even there exist many obstacles. Experimental results demonstrate the validity and feasibility of the proposed localization algorithm for the service robot to navigate in an office building, using the natural environmental characteristics.

I. INTRODUCTION

The Public Service Robot 1 developed by the KIST (called PSR1 below) performs patrol and transportation in indoor office buildings. The indoor environment is dynamic because of walking human beings as well as opening and closing doors. The PSR1 has a holonomic, omni-directional wheel mechanism which causes worse dead reckoning accuracy than the two-wheel differential drive mechanism because of the shopping cart effect. The PSR1 should be able to estimate its precise position in order to carry out its given tasks in the dynamic human working environments.

Sensor-based localization of mobile robots is a prerequisite in a successful navigation. Localization problems can be classified into global position estimation and local position tracking. Local tracking problems can be solved by scan matching algorithms, which estimate the current robot position with respect to its previous location. Gutmann/Schlege [2] compared scan-matching methods such as Iterative Dual Correspondence (IDC) [7], COX [6], and Cross Correlation Function (CCF) [8]. Although Cox and CCF are quite accurate, it can be used only in a polygonal environment. IDC can be used in non-polygonal environments. However, it is less accurate than Cox and ccf. It is difficult to apply approaches in [11] to the dynamic environments because sometimes extracted landmarks are not sufficient enough to estimate a robot’s position, if the sensor readings are partially corrupted. Moreover, the algorithms using landmarks, which require environmental modification in some cases, have to register and extract feature points. Gutmann/Burgard [1] compared Kalman filter using scan matching and Markov localization through experiments. In brief, their conclusion was that Kalman filter using scan matching can be a useful solution for the local tracking problem. However, it is difficult to use for the case of high uncertainty on the odometry or a global localization problem. Markov localization [9] can solve those problems because multiple hypotheses are available. However, the accuracy of Markov localization is relatively low and grid-based Markov localization requires a lot of memory and much computational burden. Since Monte Carlo localization [3] exploits a sample-based representation of probability density function, memory consumption and computational burden are acceptably low.

The probabilistic localization based on Monte Carlo localization using map matching is proposed for the mobile robot navigation in this paper. Applying the Monte Carlo localization using map matching is proposed for the mobile robot navigation in this paper. Applying the Monte Carlo localization enables both local position tracking and global localization. The map matching algorithm enables the implementation in both polygonal and non-polygonal environments by using the natural characteristics of the surroundings selectively. Modification of environment or putting artificial landmarks is excluded. This scheme can be applied in dynamic environments and is able to estimate reliable robot position using grid map.

The rest of this paper is organized as followings. In chapter 2, the map structure of PSR1 is explained. Our localization procedure and detailed algorithms will be presented in chapter 3. Chapter 4 illustrates proposed measure functions of map-matching. Experimental verifications are presented in chapter 5 and some concluding remarks are given in chapter 6.
II. MAP STRUCTURES OF PSR1

An appropriate representation of the environment is essential for localization. Grid map and topological map are the most well known approaches of environmental descriptions. Grid-based map [10, 5] represents environments by evenly-spaced grid cells. Each grid cell indicates the presence of an obstacle in the corresponding region of the environment. Topological map is composed of nodes and arcs. Nodes represent feature points, landmarks, or distinct places. Arcs represent the relationship between nodes. Grid map is easy to build and provides accurate geometrical information. Therefore, recognition of places is unambiguous. Topological map, on the other hand, is useful for planning long distance travel paths and compact to demonstrate environments.

PSR1 possesses three kinds of maps for navigation: grid map, topological map, and information map. Although a topological map provides a convenient interface, users sometimes find that it is hard to recognize the exact geometric position of the nodes. Therefore, information map is constructed in order to provide a familiar interface for humans. A global map consists of local maps (Fig. 2). A local grid map provides environmental representation for localization, on-line updating of obstacles and local path planning. A topological map is prepared to carry out global path planning. If users command PSR1 to move from one room to another room by clicking on those rooms in the window which represents information map, then path planner plans a traveling route on the topological map. Localization provides the robot’s current position using grid map. Localization based on grid map leads it to achieve a more precise robot position because the grid map is an accurate way to demonstrate environments and reduce ambiguity of locations. In addition, real-time mapping enables real-time local path planning and obstacle avoidance. A grid map is convenient to integrate many sensor data, such as Infrared, ultrasonic sensor information and laser sensor information. Thus this is the reason for selecting grid map in this paper.

Topological map is built by using thinning method, an image processing algorithm. The Histogramic In-Motion Mapping method [5] is applied to construct grid map. The grid map is manually built from off-line computation since it is still difficult and dangerous for the robot to explore unknown environments for autonomous map building. For the service robot, the cost of manual map building is acceptable in most cases. Laser scanner, the only sensor used for map building, may assume that the down stairways is an open space in that it can sense only the horizontal layer at the height of the sensor. The grid map of PSR1 is different from other grid maps because it is not a binary map. In conventional grid maps [10, 5], each grid has a certainty value and each grid value is changed to binary, empty (0) or occupied (1), through thresholding. However, a map built with a laser scanner and a map built with sonar sensors may be different because sensors have different characteristics. Therefore, a separated grid code is assigned according to the different sensor. In this map, integration of many sensor data is possible and localization with different sensor readings can be achieved with one map. When updating the probability density function (PDF) of the robot’s position with sensor data, specific sensor data will be compared with the corresponding code in the map.

![Fig. 2 Grid Map](image)

If the robot is located at a certain place in the map, expected sensor readings of the robot can be calculated easily. The expected scan distance is called reference distance. By using a grid map, an accurate reference distance can be obtained. Obtained reference distance is used to compare with scanned distance to calculate the similarity between them, which will be explained in section 4. As the laser range finder covers a range of 180 degrees with resolution of 0.5 degrees, the corresponding reference distance is calculated with regard to the sensor. There are still problems in getting accurate reference distance. Suppose that the robot is in a very big hall or a long corridor and the expected reference distance is calculated as 15m. If the maximum detectable distance of the sensor is 8m, then the reference distance, which is longer than the sensor capability, should be modified to 8m. The problem of expecting unlimited reference distance is called open space problem. The maximum reference distance is set as 8 m to avoid open space problem.

III. PSR1 LOCALIZATION STRATEGIES

A. Algorithms

The following five characteristics can summarize the major requirements of localization of PSR1. (1) The strategy should be able to deal with both local and global localization. (2) The localization strategy should be able to deal with uncertainties like inaccurate odometry, noisy sensors, imprecise maps and dynamic environments. (3) The method should work in natural office environments. In other words, the environment should not be changed for localization. (4) The Localization scheme should provide reliable results even in dynamic environments. (5) The method should allow the integration of various sensor readings, such as wheel encoders, a laser range finder, infrared sensors, sonar sensors, and a gyro sensor. MCL
Probabilistic localization consists of two steps: prediction phase and update phase. Prediction phase forecasts the robot's position and diffuses samples \( (s_i) \) at the current time step with respect to the previous robot states \( (s_{i-1}) \) based on the Markov principle and control input \( (a_{i-1}) \). In the update phase, the samples' probabilities can be obtained according to the sensor data \( (o_i) \) using Bayes theorem. Similarity measure functions calculate \( p(o_i | s_i, m) \), which implies the probability of the sensor reading under conditions of the robot's current state and a given map. The probability is computed by comparing scan data and reference data. The PSR1 map-matching algorithm is developed based on two measure functions: the range image similarity measure function and the angular similarity measure function. Samples are converged into positions with high probabilities by the re-sampling step. The meaning of used parameters is explained by the following. \((d : data, o : observation, a : action, t : time, s : state, m : map)\)

**Step 1: Global Sampling**
Draw uniform samples
\[ s_{i-1} = \{s_{1,i-1}, s_{2,i-1}, ..., s_{N,i-1}\} \] with \( b(s_{i-1}) = 1/N \)
over the whole region of the global map

**Step 2: Prediction Phase**
For all samples \( b(s_i) \leftarrow \int p(s_i | a_{i-1}, s_{i-1}) b(s_{i-1}) ds_{i-1} \)

**Step 3: First Update Phase**
For all samples \( b(s_i) \leftarrow \eta p(o_{i-2} | s_i, m) b(s_i) \)

**Step 4: First Re-sampling**
Draw uniform samples
\[ s_i = \{s_{1,i}, s_{2,i}, ..., s_{N,i}\} \] with \( b(s_i) = 1/N \) based on \( b(s_i) \)

**Step 5: Second Update Phase**
For all samples
\[ b(s_i) \leftarrow \eta_1 p(o_{i-2} | s_i, m) \eta_2 p(o_{i-2} | s_i, m) b(s_i) \]

**Step 6: Second Re-sampling**
Draw uniform samples
\[ s_i = \{s_{1,i}, s_{2,i}, ..., s_{N,i}\} \] with \( b(s_i) = 1/N \) based on \( b(s_i) \)

---

Localization algorithm is shown in figure 3. At the initial stage of global localization, step 1 is carried out. Then steps 2, 3, 4, 5 and 6 are iterated with new sensor readings. \( p(o_i | s_i, m) \) represents the probability, calculated by the i-th measure function, that state \( s_i \) have sensor reading \( o_i \) in the map \( m \). Two similarity measure functions are proposed in chapter 4. Update phase is carried out twice because angular similarity measure function is robust regardless of sensor noise and it leads fast convergence of PDF.

**B. Motion Model**

The odometry errors can be classified into systematic errors and non-systematic errors. The systematic error is caused by kinematical parameter modeling errors such as unequal wheel diameters, the alignment of wheels and so on. Systematic error is obtained by a bi-directional square-path experiment, called University of Michigan Benchmark (UMBMark). Nonsystematic motion uncertainty is presented in the motion model of the localization algorithm.

After mobile calibration, the motion model of PSR1 is obtained by several experiments, comparing the reference position, the odometry position, and the real position. The robot is commanded to move \( a \) several times forward, backward, right, and left. After the robot's motion, when the odometry movement says \( a_1 \) and the actual movement is \( a_2 \), the odometry movement is normalized from \( a_1 \) to \( a \) and the corresponding actual movement is \( (a_2^*a)/a_1 \). Mean and standard deviation of the corresponding actual movement is calculated. \( P(d | l) \), the probability to go \( a' \) when \( l \) is commanded, is obtained as a Gaussian distribution function like equation (1). The correlation between translation and orientation is obtained in the same way. The motion model \( P(d | l) \) is designed as to be a more uncertain model than the estimated motion model of PSR1 so that the corresponding sample space covers all possible robot positions.

\[ P(d | l) = \frac{1}{\sigma \sqrt{2\pi}} \exp(-\frac{(d - \text{mean})^2}{2\sigma^2}) \]  

**IV. SIMILARITY MEASURE FUNCTIONS (SF)**

**A. Range Image Similarity Measure Function**

The range image based similarity measure function (RISF) computes similarity as the range differences between the scanned distance and the computed reference distance for each angle over the sensing range. RISF provides high speed, reliable solutions even if there exist unknown dynamic obstacles or the sensor data is partially corrupted, because it uses the whole scan data instead of extracting a few feature points. The advantage of RISF is the use in non-polygonal environments because this is similar to the point-to-point scan matching method [7].

Fig. 4 represents the validity of RISF. The left sub-figure is the grid map of test environment. The laser scanner reading from the position of \([x, y, 0] = [4000, 2000, 0] \) was used for this experiment. Probability to be at a position for entire domain is calculated with the sensor data by RISF and the calculated \( p(o_i | s_i, m) \) is illustrated in z axis in the right sub-figure. The actual position \([4000, 2000, 0] \) has the highest probability and the probability of near that position drops smoothly. Therefore, samples will be converged into the actual position by RISF.
B. Angular Similarity Measure Function

The angular positional similarity measure function (ASF) is especially developed in order to improve the angular accuracy of the estimated position in polygonal surroundings. A high accuracy of relative positioning is required in some applications, such as object picking from a pre-determined position or docking with a battery charging station. In such cases, relative positioning with respect to reference geometry is required. During the task, not only MCL is used to know robot’s position, but also Markov localization RISF is applied to obtain the precise relative position. A map of the environment is the target geometrical map and Markov localization with the range image based similarity measure function calculates PSR1 position with respect to the target.

The range image based measure function can be applied not only to robot position estimation but also to a relative positioning problem with respect to a pre-determined local geometry. A high accuracy of relative positioning is required in some applications, such as object picking from a pre-determined position or docking with a battery charging station. In such cases, relative positioning with respect to reference geometry is required. During the task, not only MCL is used to know robot’s position, but also Markov localization RISF is applied to obtain the precise relative position. A map of the environment is the target geometrical map and Markov localization with the range image based similarity measure function calculates PSR1 position with respect to the target.

The range image based measure function can be applied not only to robot position estimation but also to a relative positioning problem with respect to a pre-determined local geometry. A high accuracy of relative positioning is required in some applications, such as object picking from a pre-determined position or docking with a battery charging station. In such cases, relative positioning with respect to reference geometry is required. During the task, not only MCL is used to know robot’s position, but also Markov localization RISF is applied to obtain the precise relative position. A map of the environment is the target geometrical map and Markov localization with the range image based similarity measure function calculates PSR1 position with respect to the target.

The range image based measure function can be applied not only to robot position estimation but also to a relative positioning problem with respect to a pre-determined local geometry. A high accuracy of relative positioning is required in some applications, such as object picking from a pre-determined position or docking with a battery charging station. In such cases, relative positioning with respect to reference geometry is required. During the task, not only MCL is used to know robot’s position, but also Markov localization RISF is applied to obtain the precise relative position. A map of the environment is the target geometrical map and Markov localization with the range image based similarity measure function calculates PSR1 position with respect to the target.

The range image based measure function can be applied not only to robot position estimation but also to a relative positioning problem with respect to a pre-determined local geometry. A high accuracy of relative positioning is required in some applications, such as object picking from a pre-determined position or docking with a battery charging station. In such cases, relative positioning with respect to reference geometry is required. During the task, not only MCL is used to know robot’s position, but also Markov localization RISF is applied to obtain the precise relative position. A map of the environment is the target geometrical map and Markov localization with the range image based similarity measure function calculates PSR1 position with respect to the target.

The range image based measure function can be applied not only to robot position estimation but also to a relative positioning problem with respect to a pre-determined local geometry. A high accuracy of relative positioning is required in some applications, such as object picking from a pre-determined position or docking with a battery charging station. In such cases, relative positioning with respect to reference geometry is required. During the task, not only MCL is used to know robot’s position, but also Markov localization RISF is applied to obtain the precise relative position. A map of the environment is the target geometrical map and Markov localization with the range image based similarity measure function calculates PSR1 position with respect to the target.

The range image based measure function can be applied not only to robot position estimation but also to a relative positioning problem with respect to a pre-determined local geometry. A high accuracy of relative positioning is required in some applications, such as object picking from a pre-determined position or docking with a battery charging station. In such cases, relative positioning with respect to reference geometry is required. During the task, not only MCL is used to know robot’s position, but also Markov localization RISF is applied to obtain the precise relative position. A map of the environment is the target geometrical map and Markov localization with the range image based similarity measure function calculates PSR1 position with respect to the target.
V. EXPERIMENTS

When a traveling path is decided, the robot tracks the planned path performing localization. Path re-planning is required if any obstacle blocks the original path. Therefore, PSR1 has a reactive process of navigation, which is called automove. If an obstacle blocks the path, the robot takes a roundabout way. If an obstacle blocks a goal position of the path, the robot waits until the goal is unoccupied. Localization with automove behavior was performed in L3 building, KIST for the experimental verification of the localization performance in a dynamic indoor environment. At the initial stage, a global localization is carried out first. Since continuous localization is carried out, PSR1 needs to perform a certain pre-defined movement, such as rotation at the origin point, during the beginning of global localization. A uniformly distributed sample set is assumed, and then the robot’s position is computed according to our map matching algorithms. A robot’s position is described with respect to a discrete probability sample set. When a robot starts to move, a sample set is updated using the odometry information. At this stage, a pre-defined motion model determines the robot’s positional belief. Using Bayes theorem, the update phase estimates the probability to be the present state with sensor data. Update phase contains two SF, which compare the similarity between sensor data and computed reference data from the map for each sample. If the robot moves along a lengthy corridor, ASF leads fast sample convergence in local localization. ASF knows a very accurate position in the traverse direction of corridor but an ambiguous position in the direction of corridor. RISF used with ASF helps determine the robot’s position even in the direction of a corridor using the characteristic of doors. Therefore, two similarities play an important role in accurate position estimation.

Figure 7 shows how global localization is performed on the second floor of the L3 building, KIST without knowing its initial position. 1000 samples are spread over all the area measuring roughly 13 meters by 41 meters. Each time our localization algorithm is performed, samples converge into the real place. Initial samples are shown in x-y plane in Fig 7 (a). Localization procedure is carried out according to the proposed scheme in figure 3. The samples after ASF and first re-sampling (step 3, 4) are shown in (b). As mentioned above, ASF leads to very fast convergence of PDF and very accurate in traverse direction of corridor. However, samples posed ambiguously along the direction of corridor. Samples after second re-sampling (step 6) regarding to RISF and ASF are shown in (c). After RISF and ASF are carried out together, samples converged into near doors using door configuration. In short, samples convergence is performed accurately along the direction of corridor also. In experiments, RISF has weighting value 1.0 and ASF has weight value 0.2. Dominant orientations of the samples are either 0° or 180°. At this stage, the real robot position was [8930, 24600, 180°] and the estimated position was [8931, 24600, 179.65°]. Figure (d) represents sample distribution after moving 6.5 meters forwards. The samples after step 6 are illustrated in (e). At this stage, the real robot position was [8910, 18100, 179.3°] and estimated position was [8824, 17632, 178.6°]. After motion of 6.6m forward, samples are drawn in (f), after SF in (g). At this stage, the real robot position was [8920, 11500, 179°] and the estimated position was [8847, 11540, 178.3°]. Samples after moving 2.1 meters in the x direction, 1.6 meters in the y direction, and 90° in the Ө direction are shown in (b), and after MF in (i). At this stage, the real robot position was [11020, 13100, -91°] and the estimated position was [10801, 12890, -90.5°]. Samples are converged into one location. Therefore, only local position estimation problem is concerned after this stage.

Figure 8 addresses localization performance in dynamic environments. There are two obstacles whose information is not included in the grid map. In the right sub-figure, estimated robot position is shown as a circle. Laser scan distance and reference distance of the sample with maximum
probability is displayed to show accuracy of this localization method. (Dotted curve - Scan distance, Solid curve - Reference distance) Although some part of the current scan data is occluded because of those obstacles, the other part is well matched with reference data. Therefore, we can see that localization with obstacles works reliably even sensor measurements are partially corrupted due to obstacles.

Fig. 8 Localization with obstacles

VI. CONCLUSIONS

In this work, we presented the probabilistic localization strategy with explicit similarity measure functions. Experimental results show that our strategy is useful in practical applications. The follows are the advantages of the proposed localization scheme.

- The localization algorithm does not fail even if the sensor readings are partially corrupted.
- Use of artificial landmarks is not required. In other words, the environment is not changed for the service robot.
- This algorithm provides solutions for both local tracking problems and global position estimation problems through MCL.
- The scheme is applicable in both polygonal and non-polygonal environments. ASF provides fast sample convergence and high accuracy in polygonal environments. RISF makes position estimation in non-polygonal surroundings possible.
- Our method can deal with uncertainties like inaccurate dead reckoning information and sensor noise.
- The algorithm is based on a 2 Dimensional range sensor. This range sensor based localization is developed for double effects because 2D scan sensor readings can be used for not only localization but also obstacle detection.

Reference