RELIABLE POSITION ESTIMATION METHOD OF THE MOBILE ROBOT BY LASER SCANNER AND INDOOR GPS SYSTEM

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Abstract: The robust position estimation has been important issue of mobile robot research for past few years. However, because of physical constraint of each sensor, sensor fusion algorithm arise alternative proposal for solving the problem. In this paper, we proposed a sensor fusion algorithm for probabilistic localization of service robot using laser scanner and indoor GPS system. This scheme is a sample based algorithm as an application of Monte Calro Localization. Samples are scattered by referring to odometry data and position data of indoor GPS system. We are able to get more robust localization results by using these processes, even though the floor condition is deteriorated and there are huge obstacles. And it is possible that remove errors which are caused when the robot is blocked by unexpected obstacles for a long time.

Keywords: Sensor Fusion, Probabilistic localization, Service robot, indoor GPS system, Range Image Sensor

1. INTRODUCTION

Recently years, various mobile robot systems are developed for guiding and human interaction. To achieve offering people those service, position estimation of the mobile robot is the core technology, and diverse sensors are used for localization. Most widely used sensors for robot localization are range image sensors such as laser scanner. Additionally, vision, sonar, odometry and radio sensor network has been utilized for the localization.

Localization problem of mobile robots are summarized as how to recognize the position of a robot using sensor data. There are two major kinds of sensors. One is a kind of sensors those are equipped outside of the robot, like indoor GPS system. The other is a set of sensors equipped inside of the robot like odometry encoder, gyro and laser scanner. In these days, those various sensors are employed compositely, and many researchers try to fusion several types of sensor data. Montesano *et al*. researched a method to cooperatively localize pairs of robots fusing bearing-only information provided by cameras and the motion of the vehicles [3]. Diosi and Kleeman had presented SLAM using laser scanner and advanced sonar in [4]. Batalin and Sukhatme described an algorithm for robot navigation using a sensor network embedded in the environment [5].

In the filed of localization with sensor fusion, many systematic methods starting with Kalman filter have been suggested. Among them, the most briskly studied branch is the probabilistic localization with Bayes' filter. Especially, Markov Localization[6] method or Monte Carlo Localization method [7] that reduces computation time and memory consumption is the most successful case.

Fig. 1 shows a guide robot 'Jinny' which was developed by the KIST (Korean Institute of Science and Technology) and performs guiding services for visitors in the National Science Museum and in the KIST.

Fig 1 Guide robot JINNY

In the previous work, the localization for the service robot were executed by using only odometry and range image data[1]. However, when a robot performs the guide services in the large places such as museums of public office buildings, two major problems occur. First, in the situation that many people pass by or keep close around the robot, the range image sensor is polluted extremely. In this case, range image sensor data cannot be adopted as reliable measurements. Second, when the floor condition is cranky, tender or dizzy, the raw information of odometry data become inaccurate resulting in critical faults. In this research, in order to overcome those problems, a probabilistic localization model that combines laser scan data and indoor GPS system data is developed.

As we mentioned above, the previous researches about the localization of service robots were executed by using only odometry and range image data. For that reason, the case that error handling is physically limited. To cope with the problems, we propose a probabilistic localization method that is based on Monte Carlo method. The sample is evaluated by utilizing range image sensor and indoor GPS system. And a scheme for choosing a more proper sensor in different situation is suggested, and we prove its effectiveness experimentally. In chapter 2, we will review the related works. Map-matching method and the composition of indoor GPS system are described. In chapter 3, modified motion model of the mobile robot and novel sensor model is proposed. Experimental results are shown in chapter4 and conclusion and distribution of this paper is depicted in chapter 5.

2. RELATEDE WORKS

2.1 Localization using Laser Scanner

2-D range image sensor is used for probabilistic localization and this method is calculated on the base of recursive Bayes' filter frame. The belief distribution in the Bayes filter method for the localization is represented as equation (1).

$$Bel(x_t) = \eta p(z_t \mid x_t, u_t, z_{t-1}, \ldots\ldots, z_0)\, p(x_t \mid u_{t-1}, z_{t-1}, \ldots.., z_0) \quad \ldots(1)$$

where

$Bel(x_t)$: Probability of Robot exists on the position x_t.

η : Normalization Constant

$p(z_t \mid x_t, u_t, z_{t-1}, \ldots\ldots, z_0)$: Conditional Distribution

$p(x_t \mid u_{t-1}, z_{t-1}, \ldots.., z_0)$: Prior Distribution

$Bel(x_t)$ (= $p(x_t \mid z_t)$), consequently obtained by the above equation, means what is the probability of the robot's position given certain sensor data red. As for a practical application of this assumption, we use Monte Carlo method.

B. Matching Error of Range Image Sensor [1].

When the robot navigates in real environments, error distribution is varying with the shape of environments. Hence, there is a need for a model that could reflect the various error distributions. And the problem is solved by adopting map matching algorithm.

$$\text{MatchingError}(\%) = \frac{\sum_j \text{DelArea}_j}{\sum_j (\text{ReferArea}_j + \text{ScanArea}_j)} \times 100 \quad (2)$$

$$f(\text{Matching Error}) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(\text{Matching Error} - \text{Biased Error})^2}{2\sigma^2}\right] \quad (3)$$

2.2 Compositions of Indoor GPS system

The principle of indoor GPS system consists of TOF(Time of Flight) and trigonometry. Ultrasonic sensors and RF(radio frequency) communication are used. Distances between beacons and the listener of indoor GPS system are derived from the TOFs. As shown in Fig2, three or more beacons are detected at each scanning time. And having absolute coordinate of all beacons, the listener's position can be calculated position by trigonometry [2].

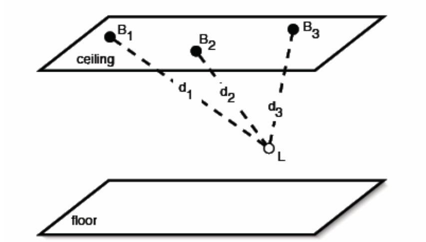


Fig 2 Fundamental principle of indoor GPS system

The indoor GPS system used in this paper is composed of three more beacon modules and one listener module. Commercial devices named 'Cricket' are used for each module. The listener of the indoor GPS system controls beacons to release ultrasonic signals in series by RF signals. At that time, beacons that accept RF signal from listener release ultrasonic and RF signal with the starting time of the ultrasonic. Listener receives again these signals and calculates distance between each beacon and the listener. Knowing the absolute coordination of there or more beacons with the corresponding distance data from the listener, we could obtain the absolute position of host device attached with the listener.

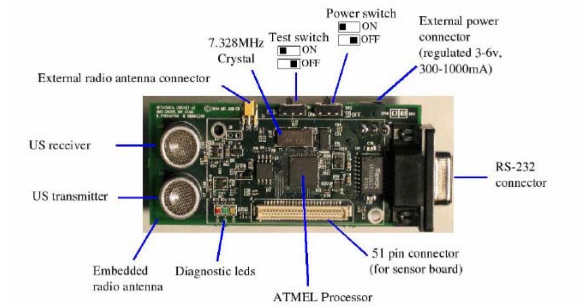


Fig 3 Components of indoor GPS system hardware

If the indoor GPS system data is greatly accurate, we might use the range image simply for avoidance of obstacles and use the indoor GPS system data for localization solely. However, it is possible those ultrasonic signals are polluted by temperature, surface texture of environments and so on which results in that indoor GPS system data may have impulsive errors. To remove the errors properly, we use median filter.

The position data from the indoor GPS system is updated three or four times per one sampling time of localizer. Offsets between the data and the latest updated position from the whole localization process are carried out. Next, data are sorted by ascending order according to offsets and the medium data is chosen. Using median filter, some impulsively fault data (10~20% of whole data) out of normal distribution could be removed.

2.3 Architecture for Position Estimation

Fig 4 demonstrates software architecture of indoor GPS system. The system will be described from bottom end.

TOF data from listener is sent to 'cricketd', a device supervisor, through RSC232 cable. The device supervisor passes the TOF data to 'Cricket Daemon', a processor. And the processor derives the position of host device from the distance data. User can access not only the position data but also statistical data, beacon's ID recently hooked up, and the hardware time stamp that is latest updated through Java application. And these data could be selected by user with call-back system.

Therefore, we made java application as a server for sending data to other program modules by socket communications. We had implemented MFC-based program for controlling our mobile robot. The program is called 'the mobile program'. In this program, navigation functions like localization and path planning is embodied and various functions for control of the robot's behaviors are embodied also as well. The old localization using only laser scanner is executed as a part of this mobile program, and we developed novel localization method by modifying the program. The indoor GPS system data is implemented for the novel localization.

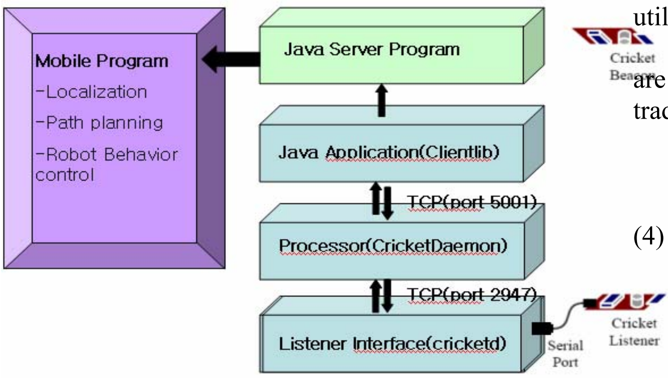


Fig 4 Software architecture

3. PROBABILISTIC MODEL FOR SENSOR FUSION

Monte Carlo localization based on Bayes' filter has two major processes. One is the motion model, the other is sensor model. Motion model is the methodology for how to disperse samples, and sensor model is how to pick up the right position.

3.1 Modified Motion Model

Previous works about localization of the guide robot, the samples are distributed in proportion to augmentation of odometry merely [3]. However this method could fail when odometry is ruined by non-systematic error such as slipping or being catching by the bulgy and the hollow on the floor. Then samples could be scattered at irrelevant position.

In this paper, we suggest a novel method using indoor GPS system for sample distribution to remove the non-systematic errors. When the motion model is performed in the map, samples are scattered by depending on not only error diffusion by the range of short-time movement, but also location data from the indoor GPS system. The number of samples is 300 and 200 respectively. Those are divided from 500 samples equal to the number that was used in previous research.

As a result of this method, the localization is evaluated. If there are no non-systematic errors, samples would be scattered densely attributed to the increase in the accuracy of the localization. Also, even if there are non-systematic errors in the robot's encoder system, the results can be correct because some of samples are scattered around approximate position which are given from the indoor GPS system.

3.2 Distance Error of the indoor GPS system:

Essential problem about developing sensor model is how to define of measurement errors from sensors. In other words, if it is possible to depict preciseness of sensors, then knowing which sensor data to choose is also possible. In this paper, range image sensor and the indoor GPS system is used for localization. The sensor model of range image sensor is already mentioned in related works, (*B. Matching Error of Range Image Sensor).* Measurement error of each sensor is defined as the following descriptions and it is utilized for the design of novel sensor model.

Measurement errors from the indoor GPS system are not influenced by shape of environments. Consequently, traditional distance error model could be used directly.

$$\text{DistanceError}(\%) = \frac{\Delta d_j}{\Delta d_{\max}} \times 100 = \frac{\sqrt{(x^{cr} - x_j)^2 + (y^{cr} - y_j)^2}}{\sqrt{x_{\max}^{\;2} + y_{\max}^{\;2}}} \times 100$$

(4)

where

(x^{cr}, y^{cr}): position data from the indoor GPS system

(x_j, y_j): j –th sample's position data

$$f(\text{DistanceError}) = \frac{1}{\sigma_{dis}\sqrt{2\pi}} \exp - \frac{(x_j - x^{cr})^2 + (y_j - y^{cr})^2}{2\sigma_{dis}^2}]$$

(5)

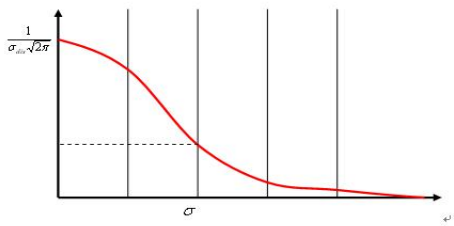


Fig 1 Probability distribution of distance error

And the function of distance error is usually modeled by deviated Gaussian with mean the each sample's position and standard deviation σ_{dis} from distance between listener and beacon during latest 5000ms.

3.3 Weighted Sum of Each Probabilistic Value

Weighted sum method is adopted for fusing 2 position data from two kinds of sensors as shown in equation (6-10). First, calculate the corresponding probability values of each sample from range image sensor and from the indoor GPS system, and normalize them to values between 0 and 1.

$$p_j(Total) = \frac{1}{2}(w^L \times p_j(Laser) + w^{cr} \times p_j(GPS)) \quad (6)$$

Where,

$$p_j(Laser) = \eta_{lm} f_j(\text{Distance Error}) \quad (7)$$

$$p_j(GPS) = \eta_{cr1} f_j(\text{Matching Error}) \quad (8)$$

$$w^L = \frac{1}{361}\sum_{1}^{361} p(z_t^k \mid x_t, m) \quad (9)$$

$$w^{cr} = \eta_{cr2}\frac{1}{\sigma_{dis}} \quad (10)$$

w^L and w^{cr} are the weight for p_j(Laser) and p_j(GPS) respectively. w^L is defined as being proportional to the average of probability value for each distance by beam model, while w^{cr} as being in inverse proportional to the standard deviation of distance between beacon and listener during 5000ms. These values are normalized to ones between 0 and 1. p_j(Total) became maximum when all of w^L ,$w^{cr,}$ p_j(Laser) p_j(GPS) are 1, and if all of parameters approximate to 0,the p_j(Total) has the value close to 0. At this time,if the p_j(Total) is below the threshold induced by experiments, position is not updated.

4. EXPERIMENTAL RESULTS

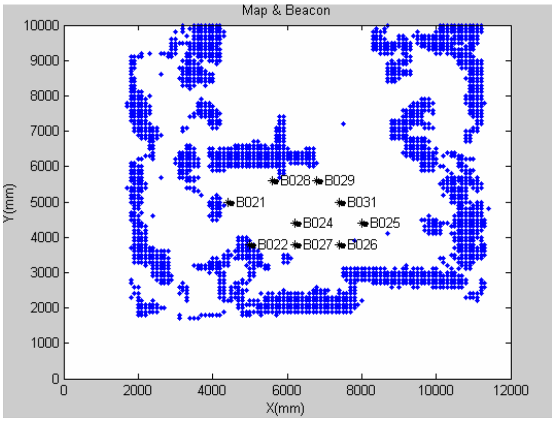


Fig 5 Grid map of the environment and positions of beacons(blue dots are grid map and black stars are the positions of beacons)

Fig 5 describes the grid map of the environment of the robotics laboratory in KIST. That is regular office circumstance. In this figure, blue dots are occupied space by furniture, and black stars are the position of the beacons of the indoor GPS system. The service robot navigates in this environment along the trajectory, as shown in Fig 6. Red stars are the position of the robot using our novel scheme, and green dots are the positions estimated by indoor GPS system. Though these data are almost same, there are some errors in middle of the map. The reason why is the pollution of range image sensor. At first time, the errors are generated because of ascendancy of the range image sensor. Though the according to localization performed few times, the results approach to each other.

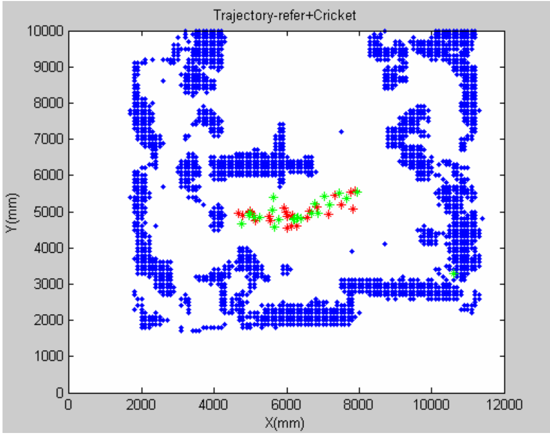


Fig 6 Trajectory of the robot(Red stars are positions of the robot of the robot using our novel scheme and green dots are the position data from indoor GPS system)

For showing superiority our novel scheme, we performed contrast experiments. In both experiment, the trajectory of the robot is same and there are same size obstacles. However, the localizer used only range image sensor in the first experiment. And the weighted sum method is used in second experiment.

Fig 7 and Fig 8 Shows the result of localization using only range image sensor and indoor GPS system. In Fig 7, x axis is the time domain and y axis is the localization status , 620 means the success of the localization, and 627 means failure of that. In the first experiment, when the huge obstacle is the map, the localization is failed. And as we shown in Fig 8, although the removing the obstacle, the bearing of the robot is not accurate. Actually, the robot was crashed in this experiment.

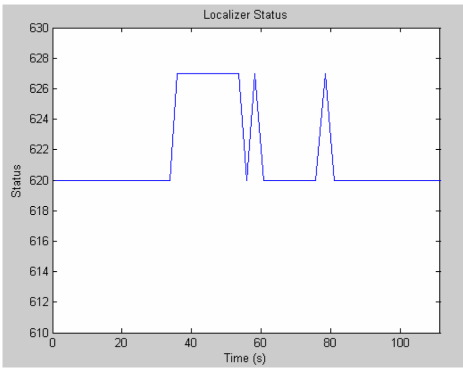
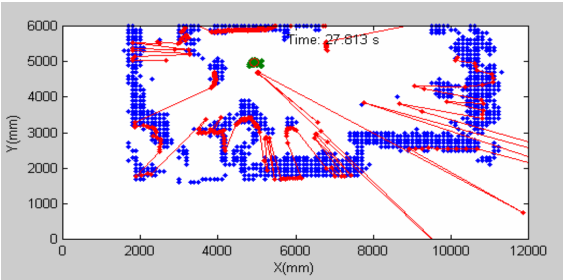
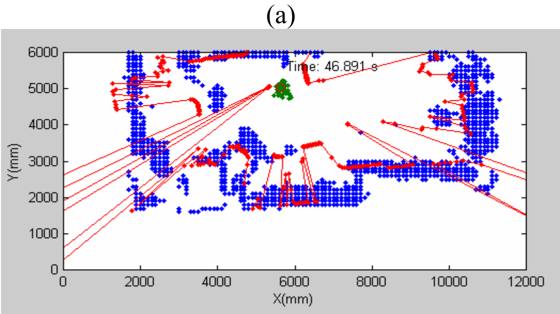


Fig 7 Localizer status when only map matching method is used to estimate position

In the constant, the second experimental results show the robustness. As we shown in the Fig 9 and Fig 10, even though the obstacle in the map, the localization results are success continuously. And after removing the obstacle, the map matching results are retrieval quickly, and the localization is accurate through the experimental. The localization status is not concerned with existence of obstacle or not.



(a)



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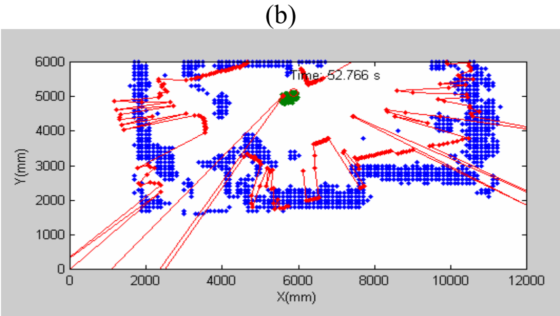

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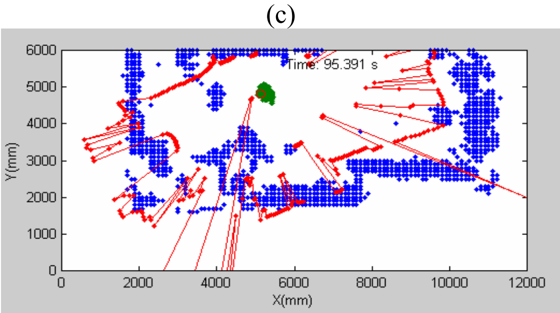


(d)

Fig 8 Laser data of the localization when the novel scheme is not used.

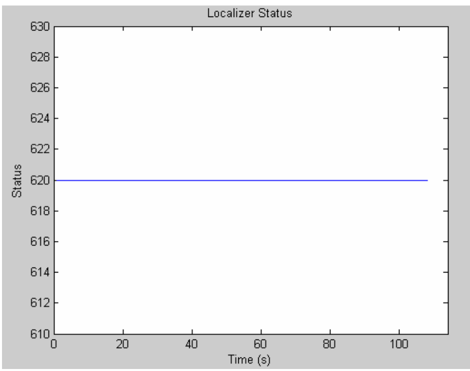
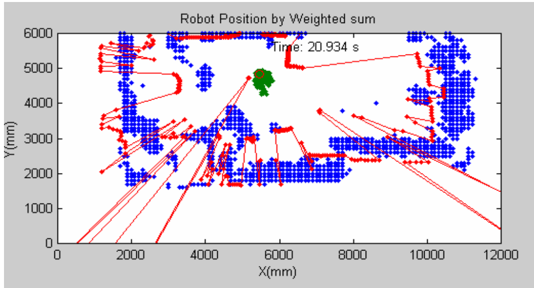
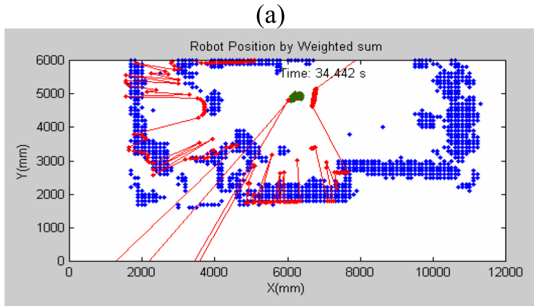


Fig 9 Localizer status when novle scheme is used to estimate position



(a)



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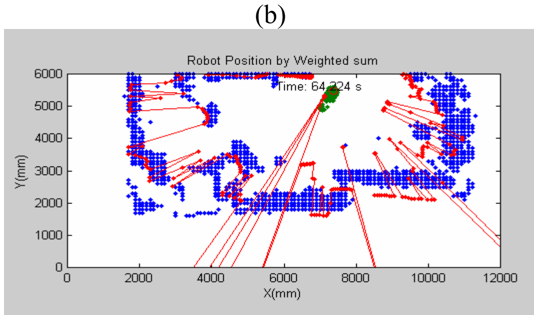

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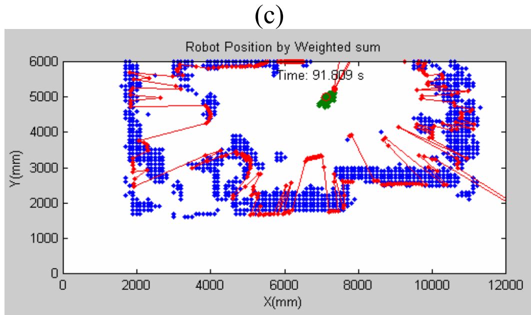

(d)

Fig 10 Laser data of the localization when the novel scheme is used.

5. CONCLUSIONS

In this work, we presented a scheme of localization using indoor GPS system and range image data. The proposed localization method is composed of three processes. First, in the phase of motion model, sample injection that around position data from indoor GPS system is added. Second, in the sensor model phase, probabilistic model using range image sensor and indoor GPS system is developed. Third, each sample is weighted by data from two sensors. The proposed localization method has following advantages.

- Even though there are a great deal of dynamic obstacles, localization is robust and autonomous.

- Under the ill floor condition, localization could be executed accurately.

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