RFID-based Localization System for Mobile robot with Markov Chain Monte Carlo

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***Abstract* ---This paper proposes a robust and precise localization system for mobile robots with the aid of Radio Frequency Identification (RFID) technology and the Markov Chain Monte Carlo (MCMC) optimization algorithm. By integrating the RFID module, RFID tags, a mobile robot and an off-board computer together, the localization system uses MCMC to analyze RFID signal information and get optimized mobile robot's location information. This paper focuses on explaining the development of RFID sensor model and the processes of building the MCMC algorithm. For sensor model development, the effects of orientation between the RFID reader and RFID tag and the velocity of the mobile robot are investigated. For the MCMC method, a sequential Monte Carlo method is adopted to optimize the result. Finally, the initial experiment results indicate that the proposed localization system has low error and could be used to effectively locate mobile robots.**

***Index Terms*---localization, Markov Chain Monte Carlo, mobile robot, RFID**

I. Introduction

Reducing human efforts and avoiding placing humans in risky situations are always priorities in many different sectors like industries, defense, etc. This has increased the demand of research on localizing mobile robots not only in industries and defense but also at home, in service sectors, in hospitals, and other areas. However, research on reliable and efficient localization is still a major issue.

Mobile robots were located with the help of Dead-reckoning by measuring the displacement with respect to the initial coordinates and initial orientation [1]. This method is limited, as errors would accumulate as the moving distance increases. Also, mobile robots were equipped with vision to locate themselves by comparing the obtained image with reference images [2]. This method has a constraint of low accuracy. Global Positioning System (GPS), a prevalent tool of localization, was chosen to locate mobile robots [3]. But it is difficult to use this technology in indoor environment. Eventually, there is necessity to find new methods or technologies for localizing mobile robots in indoor environments.

For localization, Ultra-wideband (UWB) and ultrasonic sensors have been extensively used, but they have limitations too. UWB method increases the cost of localization systems since the UWB transmitter and the energy detection receivers that must be implemented [4]. In the calculation of UWB method, if Time of Arrival (TOA) or Time Difference of Arrival (TDOA) is used, the synchronization of transmitters and receivers has to be considered for TOA, and moreover, precise time reference is also required for TDOA [5]. For the ultrasonic method, environment temperature, and humidity have influence on the speed of sound [6].

In recent years, magnetic landmarks have been used for localization [7]. These landmarks have 6 patterns, and each pattern consists of 4 magnetic landmarks. On the bottom of the mobile robot, four hall sensors were installed, which pass on the sensor information. The mobile robot's position and orientation were corrected based on that information. This localization method has good accuracy, but it is hard to use this method in complex environments, as the number of patterns is limited and landmarks must be very accurately placed.

Recently, the popularity of Radio Frequency Identification (RFID) for localization is being recognized globally, and concurrently, RFID tags are being utilized to locate the mobile robot [8]. The mobile robot was equipped with an RFID reader and vision system. RFID tags' positions and codes were known. When the reader detected the RFID tag, the robot's location on the pre-stored map would be recognized by the navigation planning module, and the next step's direction would be decided. However, there was no accurate localization, as the RFID tags could be detected at a distance of even 1m from the reader. The difference of RFID signal phase was proposed for localization, but this method was only validated by simulation [9]. Moreover, the impact of variety of velocity of mobile robots was not provided by any of the previous systems.

Based on the above information, a RFID-based localization system is suggested in this proposal. The proposed method utilizes the RFID technology to help locate the mobile robot. The received signal strength (RSSI) is taken to estimate the possible distance between mobile robot and target objects. A Markov chain Monte Carlo algorithm is used to obtain optimized location of the mobile robot. This proposed system is aimed to solve the problems mentioned above, such as high cost equipment and big error.

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The rest of this paper is organized as follows. Section 2 introduces some related works. Section 3 gives an overview of the proposed localization system. Section 4 presents the development of sensor model or the first phase- distance estimation. Section 5 explains the algorithm of the proposed system. Section 6 discusses the initial experiments, result, and problems, and section 7 finalizes the conclusion.

II. RELATED WORKS

During last few years, RFID and other wireless sensors for localization of mobile robots have drawn many researchers' attention.

One of the earliest and classic RFID localization systems was built in [10]. In this project, researchers first built a probabilistic sensor model by detecting frequencies of RFID tags in different locations that with respect to RFID tag. Then, based on this sensor model, the geometrical structure of the environment, and the path of the robot, the mobile robot could locate the RFID tags in the environment. Finally, a Monte Carlo algorithm was used to estimate the mobile robot's potential positions and get optimized result. Kodaka et al. proposed to deploy a lattice of RFID tags to estimate the mobile robot's pose [11]. All RFID tags were placed on the floor at an interval of 30 cm. In this case, even in a small room, many RFID tags were needed and it was necessary that they be placed with high accuracy. [12] studied to use the phase difference of passive a RFID signal to locate the mobile robot, but sophisticated software and heavy-duty hardware led to a high cost necessary to process and analyze the signal.

Also, some researchers explored the possibility of using Received Signal Strength Indication (RSSI) in the mobile robot's localization system. [13] studied the relationship between RSSI and the distance between sensor nodes. The paper indicates the RSSI could be used for indoor localization, the reliability of which was evaluated by [14]. [15] analyzed the log-normal relationship between RSSI and distance with dynamic variance, which was part of an attempt to obtain a more accurate result.

In [16], a database of signal strength and location information was built by measuring the signal strength of all RFID tags in each position. The mobile robot could locate itself by matching the current signal strength information with the information in the database. [17] proposed using active RFID tags to identify an object's location. In this project, the coordinates of the object, which has a RFID tag, could be estimated by comparing the RSSI with the reference RFID tags. The locations of the reference RFID tags were known.

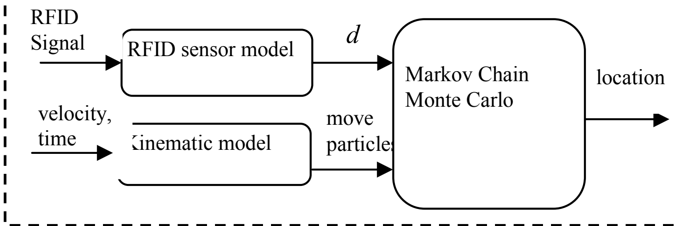

Fig. 1 Structure of the proposed localization system

Based on the RSSI of the target RFID tag and reference RFID tags, each reference would be assigned a weight, and the target RFID tag's coordinate would be calculated by summing the product of references' coordinates and weights. Also, [18] used RSSI measurements and a back-propagation artificial neural network to locate mobile robot itself.

III. OVERVIEW OF THE PROPOSED SYSTEM

A. General structure of the system

In this paper, a RFID based localization system using Markov Chain Monte Carlo (MCMC) method is proposed. In the system, MCMC is a stochastic optimization method, which uses Monte Carlo method to get all potential locations of the mobile robot and utilizes an RFID sensor model for correction. A kinematic model is used to move particles. The controller of the localization system consists of three parts. One part is used to control the movement of the mobile robot. One part is used to control the RFID reader to capture the signal and analyze its strength. The last component is the Markov Chain Monte Carlo algorithm, which can optimize the estimated position of the mobile robot. The structure of the proposed localization system is shown in Fig. 1. Multi-threads will be employed in the C++ control program. One thread is to control the RFID reader so that the multi-tasks can be performed concurrently. For example, the program is able to control RFID and get completed RFID data when it controls the mobile robot's movement. Fig. 2 indicates the data transmission in the system.

A. Hardware setup of the system

As shown in Figure 3, the hardware consists of four parts: the Mobile Robot, the RFID module, RFID tags, and a control laptop.

One set of Amigobot Robots with the size of 33 cm (length) 28 cm (width) and 13 cm (height), is used in this project. The maximum translate speed is 1000 mm/second and the maximum rotational speed is 100 degrees/second. The Amigobot Robot has 8 sonar sensors total and one auxiliary serial port. The auxiliary serial port can provide 5 DC and 12 DC power to additional devices.

A TR-50 RFID module (RFID reader) is installed on the mobile robot. The RFID reader is powered by the auxiliary serial port on the Amigobot Robot via two Dupont Lines and has a reading range of 1.5 meters with the supplied low-gain antenna. Because of the short reading range, the RFID reader is sensitive to RFID signal strength. This equipment's frequency band is between 860 MHz to 960 MHz and the baud rate of the reader is 115200 bps. Besides, ALN-9662 RFID tags, which are with a global operation between 860 -

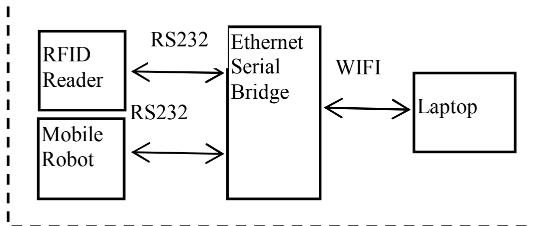

Fig.2. Structure of data transmission in the system

960MHz and have an antenna with dimensions of 70 mm × 17 mm, are employed. These RFID tags can be used in many hash environments. Each RFID tag has a unique code, which can be modified by programming. On the bottom of the mobile robot, there is an Ethernet Serial Bridge-WiBox2100E, which converts an RS-232 serial connection to a TCP/IP connection available through an 802.11 (WIFI) wireless network. Both the RFID module and the mobile robot are connected to the WiBox2100E via customized RS-232 cables. Thus, the laptop-Aspire 5532 can control the Mobile Robot and RFID module via wireless.

IV. RFID SENSOR MODEL

In the experiment, the sensor model is using the RSSI to estimate the distance between the RFID tag and the mobile robot. According to our last project [19], when the height of the RFID tags changes within a small range, it will not significantly affect the accuracy of the result. As a further step, the RFID tag's orientation effect will be investigated in this paper, too. There are several steps that must be done in order to perform this task.

A. Calculate RSSI

Firstly, in order to estimate the distance between the RFID reader and the RFID tag, RSSI should be calculated. According to the Thinkify RFID reader manual, RSSI can be calculated using the follow formula:

$$RSSI = 2 \times high\_rssi + 10 \times log(1 + 10^{(-delt\_rssi/10)}) \quad (1)$$

Where *high_rssi* is the higher value of the two channel magnitudes and *delta_rssi* is the absolute difference between the two channel magnitudes.

B. Analyze the effect of RFID tag orientation

In order to analyze the effect of RFID tag orientation, different orientations were studied. In the real scenario, the orientation of the RFID tag, which is relative to the RFID reader, is varied between 0 degrees and 90 degrees (Fig. 4: α). So, this project studies the orientations within 0 to 90 degrees.

Three kinds of experiments are designed to collect data for analysis. The first kind of experiment collects RFID data when the tag orientation is 90 degrees. The RFID tag is placed on the front of the mobile robot and the height of RFID tag is equal with the antenna of the RFID reader. The RFID reader collects data every 5 cm and 100 sets of data per time. Since the reading range of RFID reader is about 150 cm-200 cm, experiments are designed within (0 cm, 200 cm). Fig. 5 is the result of the relationship when the RFID tag orientation is 90 degrees. Similar experiments are conducted when the tag orientation is 60 degrees and 30 degrees; Fig. 6 and Fig. 7 show the results of experiments when the orientation is 60 degrees and 30 degrees.

In Fig. 8, the blue points indicate the experiments' results for 90 degree tag orientation, the red points represent the experiments' results for 60 degree tag orientation, and the light green points are the results of the 30 degree orientation experiments. Each point is the mean of 100 sets of data. From Fig. 8, significant influence of the orientation on the results

Fig. 3: Hardware setup

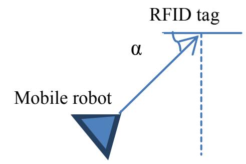

Fig. 4: Investigated Orientation

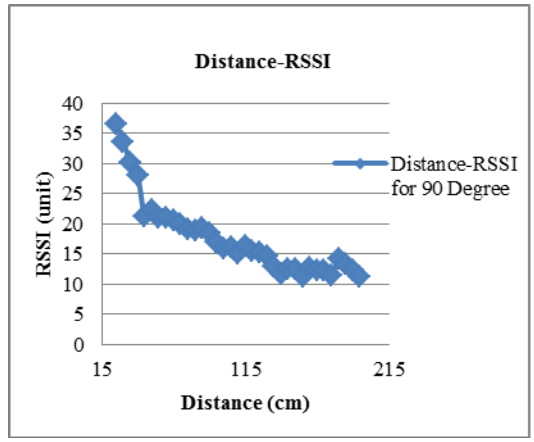

Fig. 5 Distance RSSI relationship (90 degrees)

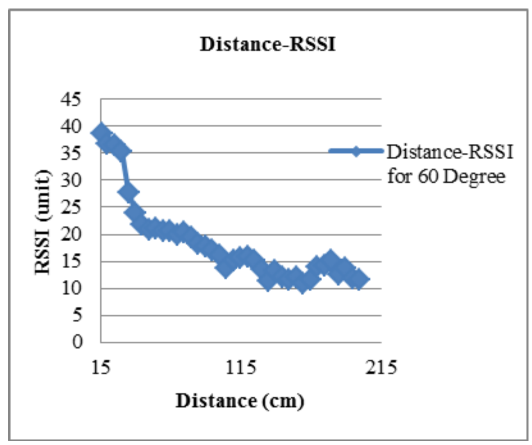

Fig. 6 Distance RSSI relation (60 degrees)

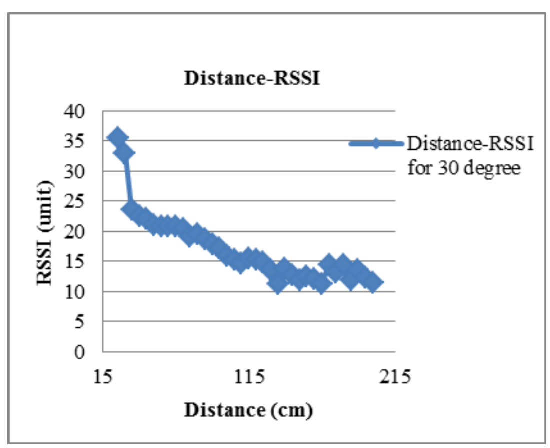

Fig. 7 Distance RSSI relationship (30 degree)

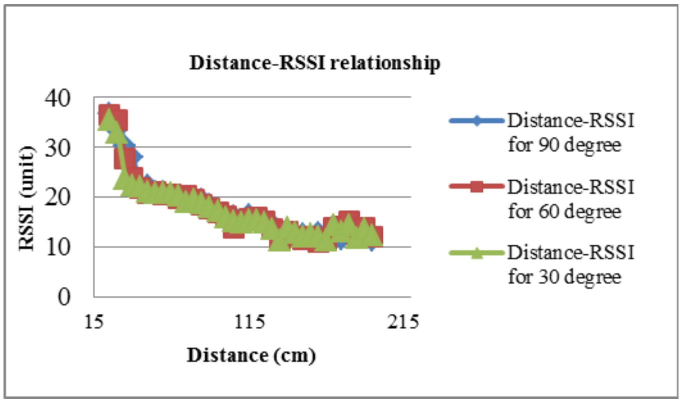

Fig. 8: Analysis result of different orientations' effect could not be determined. So, in this project, the influence of the RFID tag's orientation will not be considered. All the experiments are conducted when the mobile robot is in a static state.

C. RFID sensor model based on the dynamic state of the mobile robot

According to [19], the dynamic state of the mobile robot is a significant factor in estimating the distance between the RFID tag and the mobile robot. In this project, a fixed velocity of the mobile robot is analyzed because the velocity of the mobile robot will not significantly vary when the mobile robot is moving at a low speed. Also, because the encoder localization method of the mobile robot has high accuracy within a short moving distance, the encoder method is used to collect distance data then utilized to build the RFID sensor model.

In order to build the sensor model, 50 experiments are conducted. In each experiment, the mobile robot approaches the target object, which has a RFID tag. The RFID reader performs two readings per centimeter. The results indicate that the RFID reader could always read the RFID tag within 130 cm at the velocity of 100 mm per second, and the RFID reader may fail to read RFID tag when the distance is between 130 cm and 200 cm. Based on these results, the relationship below was found (Fig. 9), and equation (4) is the regression model of the relationship between distance and RSSI.

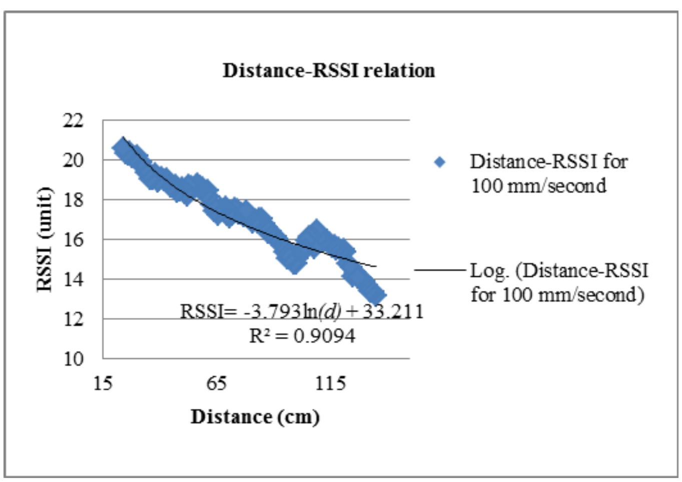

Fig. 9 Distance RSSI relationship for dynamic state (100 mm/second)

$$RSSI = 33.21 - 3.79\ln(d) \tag{2}$$

Where d is the distance between the mobile robot and the RFID tag, and RSSI is the received RFID signal strength. Considering the noise factor, equation (2) evolves into equation (3):

$$RSSI = 33.21 - 3.79\ln(d) + X_\sigma \tag{3}$$

In equation (3), X_σ is the noise signal, which follows a random Gaussian distribution with the mean of zero and standard deviation of σ. Thus, the sensor model is obtained as below:

$$d = e^{\frac{33.21 + X_\sigma - RSSI}{3.79}} \tag{4}$$

Based on this sensor model-equation (4), when a RSSI is measured, a related d can be estimated.

V. METHODOLOGY

This paper presents an effective stochastic method in Markov chain Monte Carlo (MCMC) which has been successfully applied to task allocation for multi-robot systems [20] [21] or build localization systems for mobile robots. The methodology can be described as the following steps:

Step 1: Initial particles

As the first step of the algorithm, a set particle of the mobile robot's state should be initialized according to the real application. N particles are selected ($S_0 = [S_0^1, S_0^2, S_0^3 \cdots \cdots S_0^N]^T$). S is the potential state of the mobile robot and includes the *x, y* coordinates-(x_n^t, y_n^t) and the weight w_n^t. w_n^t indicates the importance weight of coordinates (x_n^t, y_n^t) at time t and they sum up to one. For the potential state particle, n is the number n particles and t is the time. If the start point of a mobile robot is known, initial particles should be centered on the start point and particle weight is following Gaussian distribution; and if the start point is unknown, initial particles are uniformly distributed in all possible area and the particle weight follows uniform distribution. Generally speaking, the larger the N value is, the better the result is. However, large N numbers will add computer computation burden. Therefore, N should be chosen with the consideration of the accuracy requirement.

Step 2: Prediction phase

When mobile robot moves, new samples S^t will be generated after each command- u_t In this project, each particle is randomly sampled from the old samples S^{t-1} by a motion model [22]:

$$\hat{v} = v + sample(\alpha_1|v| + \alpha_2|\omega|) \tag{5}$$

$$\hat{\omega} = \omega + sample(\alpha_3|v| + \alpha_4|\omega|) \tag{6}$$

$$\hat{\gamma} = sample(\alpha_5|v| + \alpha_6|\omega|) \tag{7}$$

$$x^t = x^{t-1} - \frac{\hat{v}}{\hat{\omega}}\sin\theta + \frac{\hat{v}}{\hat{\omega}}\sin(\theta + \hat{\omega}\Delta t) \tag{8}$$

$$y^t = y^{t-1} + \frac{v}{\omega}\cos\theta - \frac{v}{\omega}\cos(\theta + \hat{\omega}\Delta t) \quad (9)$$

$$\theta^t = \theta^{t-1} + \hat{\omega}\Delta t + \hat{\gamma}\Delta t \quad (10)$$

$$P(S_n^t/S_n^{t-1}) = P(S_n^{t-1}) \quad (11)$$

(x^{t-1}, y^{t-1}) is the position of mobile robot's old state and θ^{t-1} is the old orientation. (x^t, y^t) is the new position of mobile robot and θ^t is the updated orientation. u_t- $(v, \omega)^T$ is the control command, which consists of translational velocity- v and rotational velocity- ω. α_1 - α_6 are the added motion noise. $P(S_n^{t-1})$ is the probability of particle S_n at time $t-1$. $P(S_n^t/S_n^{t-1})$ is the probability of particle S_n drawn from time $t-1$ to time t.

Step 3: Sensor reading updates

In this step, sensor reading is incorporated to update the weight of particles. For each particle:

$$P(Z_t/S_n^t) = \frac{1}{\sigma\sqrt{2\pi}} \times e^{-\frac{(d_n^t - d_t)^2}{2\sigma^2}} \quad (12)$$

$$P(S_n^t) = P(S_n^t/S_n^{t-1}) * P(Z_t/S_n^t) \quad (13)$$

d_t is the distance, which is estimated by the RFID sensor model. d_n^t is the distance between particle S_n^t and the related RFID tag. $P(S_n^t)$ is the updated probability.

$$d_n^t = \sqrt{(x_n^t - x_j)^2 + (y_n^t - y_j)^2} \quad (14)$$

Where (x_j, y_j) is the coordinates of the number j RFID tag.

Step 4: Normalize the particles' weight

By normalizing the updated particle probabilities, the importance weight can be sum up to one.

$$w_n^t = \frac{P(S_n^t)}{\sum_{n=1}^{N} P(S_n^t)} \quad (15)$$

Where w_n^t is the weight of particle S_n at time t.

Step 5: Resampling

One problem is that sample population will be depleted as the iteration goes on. Some particles, which have low weights, will be eliminated. In order to maintain enough particles, resampling is a necessary action. Usually, a threshold-a percentage of the number of particles is set to monitor the performance of the sample. If the effective sample size (ESS), is lower than the threshold, the resample action will be conducted. There several resample methods, such as multinomial, residual, stratified, systematic, and so on [23].

Step 6: Iterating

Repeat step 2, 3, 4, 5 until the required iterations are finished.

Step 7: Output the final results

Followed by step 7, output can be calculated by equation (16) and equation (17):

$$\bar{x} = \frac{\sum_{n=1}^{N} P_n^t x_n^t}{\sum_{n=1}^{N} P_n^t} \quad (16)$$

$$\bar{y} = \frac{\sum_{n=1}^{N} P_n^t y_n^t}{\sum_{n=1}^{N} P_n^t}$$

(17)

Finally, the optimized location of the mobile robot is determined to be -$(\bar{x}, \bar{y})$.

VI. Experiments and Testing

As shown in Fig. 10, the testing experiment was set up in the fourth floor hallway of the Industrial and Manufacturing Engineering Department building at Bradley University. All RFID tags were placed on the wall, and locations of all tags were known. In the sensor model development section, the RFID tag was attached on a carton. Since different materials have different abilities to absorb ratio waves, in order to simulate the same environment with the sensor model section, the same material with the carton was put between RFID tags and the wall. Also, some tapes were placed on the ground and coordinates were marked on the tape as references to help measure the mobile robot's real location. All experiments were conducted under low noise environment.

Fig. 10: Testing Environment

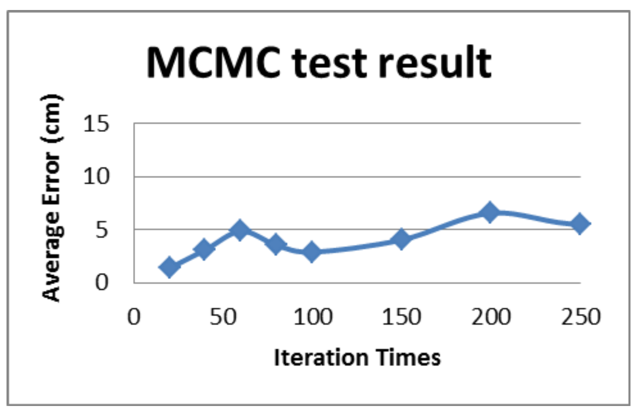

Fig. 11: Position tracking test result of MCMC localization system

Initial data and results are shown in Fig. 11. In the experiments, the start point of mobile robot was known. MCMC localization system was used to track the position of the mobile robot. The results indicate average error is less than 6 cm. Compared with classic RFID localization system [24], which had average error of 25.19 cm, our localization is more accurate. Thus, the proposed localization system still works well.

VII. CONCLUSION AND FUTURE RESEARCH

This paper proposed a localization system for a mobile robot with the aid of RFID technology and an optimized algorithm of MCMC. A sensor model was built based on RFID technology by using RSSI to estimate the distance between RFID tags and the mobile robot. The effect of different orientations between the RFID reader and the RFID tag on RSSI was analyzed, and the result shows that orientation does not have a significant effect in this project. Since the velocity of the mobile robot would affect the RSSI, the sensor model is built under a reasonable speed. Also, the MCMC algorithm was proposed to optimize the localization result. Testing results indicate the proposed system is a feasible method to locate mobile robots with low average error. Future research will focus on global localization and investigating the effect of particle number in different environment.

REFERENCES

[1] Johann Borenstein, "Internal Correction of Dead-reckoning Errors Withthe Smart Encoder Trailer," in Proc. IEEE/RSJ/GI Int. Conf. Intelligent Robots and Systems, Vol. 1, pp. 127-134, Sept. 1994.

[2] De Souza, G.N. and A.C. Kak, 2002. Vision for mobile robot navigation: Asurvey. IEEE Trans. Pattern Anal. Mach. Intell., 24: 237-267.

[3] Georgiev, A.; Allen, P.K. Localization methods for a mobile robot in urban environments. IEEE Transactions on Robotics, Oct. 2004, Vol. 20(5), pp. 851-864.

[4] Yong Liang Guan, Francois Chin, "Indoor Elliptical Localization Based on Asynchronous UWB Range Measurement", IEEE Transactions on Instrumentation and Measurement, Vol. 60, NO. 1, January 2011.

[5] Sek Sze Wei, R.M. Kuppan Chetty, "RFID based Intelligent Navigation Methodology of a Nonholomic Indoor Autonomous Mobile Robot.," Journal of Applied Sciences, 12(23): 2376-2382, 2012.

[6] Ole Bischoff, Nils Heidmann, Jochen Rust, Steffen Paul, "Design and Implementation of an Ultrasonic Localization System for Wireless Sensor Networks using Angle-of Arrival and Distance Measurement", Procedia Engineering, Vol. 47, pp 953-956, 2012

[7] Byung June Choi, Bumsoo Kim,Sung Moon Jin,JaChoon Koo, Wan Kyun hung, HyoukRyeol Choi, Hyungpil Moon, "Magnetic landmark-based position correction technique for mobile robots with hall sensors," Intelligent Service Robotics, April 2010, Volume 3, Issue 2, pp. 99-113.

[8] Toshifumi Tsukiyama, "Navigation System for Mobile Robots using RFID tags," Proceedings of International Conference on Advanced Robotics. Coimbra, Portugal, June 30-July 3, 2003.

[9] Wail Gueaieb, Md. SuruzMiah, "A modular Cost-Effective Mobile Robot Navigation System Using FRID Technology," Journal of Communications, Vol.4, NO.2, March 2009.

[10] D. H¨ahnel, W. Burgard, D. Fox, K. Fishkin, and M. Philipose. Mapping and Localization with RFID Technology. In Proc. of the IEEE International Conference on Robotics and Automation (ICRA), 2004.

[11] Kodaka, K., Niwa, H. ; Sakamoto, Y. ; Otake, M. ; Kanemori, Y. ; Sugano, S. Proc. of IEEE/RSJ International Conference on Intelligent Robots and Systems. Pages 1385-1390, Sept. 2008

[12] Cory Hekimian-Williams, Brandon Grant, Xiuwen Liu, Zhenghao Zhang, and Piyush Kumar, "Accurate Localization of RFID Tags Using Phase Difference," IEEE International Conference on-RFID, 2010.

[13] Masashi Sugano, Tomonori Kawazoe, Yoshikazu Ohta, Masayuki Murata. Target, Vol. 538 (050), 2006

[14] Qian Dong, Waltenegus Dargie. Evaluation of the Reliability of RSSI for Indoor Localization. The Third International Conference of Wireless Communications in Unusual and Confined Areas, Aug. 2012

[15] Jiuqiang Xu, Wei Liu, Fenggao Lang, Yuanyuan Zhang, Chenglong Wang. Distance Measurement Model Based on RSSI in WSN. Wireless Sensor Network, Vol. 2, No. 8, Aug. 2010

[16] Ya-Chuan Chen, Jung-Hua Chou. Mobile Robot Localization by RFID Method. The Seventh International Conference on Digital Telecommunications, 2012

[17] Lionel M. NI, Yunhao Liu, Yiu Cho Lau, Abhishek P. Patil, Wireless Networks, Vol. 10 Issue 6, Nov. 2004

[18] Nosaiba A. Sabto, Khalid Al Mutib, Autonomous mobile robot localization based on RSSI measurements using an RFID sensor and neural network BPANN, Journal of King Saud University-Computer and Information Sciences, Vol. 25 Issue 2, pp 137-143, July, 2013

[19] Hui Zhang, Joseph Chen, Kai Zhang, Reliable and Efficient RFID-based Localization for Mobile Robot. IEEE International Symposium on Robotic and Sensors Environments, 2013.

[20] Kai Zhang, Emmanuel G. Collins Jr., Dongqing Shi, " Centralized and distributed task allocation in multi-robot teams via a stochastic clustering auction," TAAS 7(2): 21 (2012)

[21] Kai Zhang, Emmanuel G. Collins Jr., Adrian Barbu, "An Efficient Stochastic Clustering Auction for Heterogeneous Robotic Collaborative Teams," Journal of Intelligent & Robotic Systems, Volume 72, Issue 3 (2013) , Page 541-558.

[22] S. Thrun, W. Burgard and D. Fox, Probabilistic Robotics, Cambridge, MA: MIT Press, 2005.

[23] Adam M. Johansen, SMCTC: Sequential Monte Carlo in C++. Journal of Statistical Software, Vol. 30, Issue 6, pp 1-41, April, 2009

[24] B. S. Choi, J. M. Yun, and J. M. Lee, "An efficient localization scheme for an indoor mobile robot," in *Proc. SICE Annual Conf.*, 2005, pp. 2008–2013.