A Practical Evaluation of Radio Signal Strength for Mobile Robot Localization

Lingfei Wu, Max Q.-H. Meng, Fellow, IEEE, Zijing Lin, Wu He, ChaoPeng, and Huawei Liang

***Abstract*—This paper dealt with localization of a mobile robot using received signal strength (RSS) and detailed a practical evaluation about the suitability of the RSS based localization. RSS technique is especially appealing for localization in WSN due to its simplicity such as low cost, size and power constraints, despite of the fact that RSS may bring in very noisy range estimates. We conducted numerous ranging experiments to quantify the effects of various environmental factors on RSS both in the indoor environment and in the outdoor environment. To further improve the localization performance of mobile robot, we proposed a novel improvement—-mean filtering technique to reduce the effect of radio irregularity and optimized the localization results. A series of localization experiments were performed to validate the proposed methods, with achieving the localization error to 1.2m in the outdoor basketball field.**

I. Introduction

China's "Chang'e" moon exploration projects will carry out the "orbiting", "landing", and "returning" three step procedures. An unmanned lunar rover will be part of the essential equipment for moon exploration in the second phase of the Chinese "Chang'e" mission [1] [2]. Since we have to know where the information is collected, and to begin with, the rovers have to reach destination, the rovers must know their position on the surface. Localization is one of the most fundamental problems in mobile robotics.

According to Moore's law, each year electronic devices become cheaper and smaller. Connecting huge numbers of small embedded systems, one is able to create powerful massively distributed systems. The best-known examples are wireless sensor networks. A wireless sensor network is a wireless network consisting of spatially distributed autonomous devices using sensors to cooperatively monitor physical or environmental conditions, such as temperature, sound, vibration, pressure, motion or pollutants, at different locations.

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Lingfei Wu, Zijing Lin, Wu He, and ChaoPeng are with Center for Biomimetic Sensing and Control Research, Institute of Intelligent Machines, Chinese Academy of Sciences, Department of Automation, University of Science and Technology of China and The Key Laboratory of Biomimetic Sensing and Advanced Robot Technology, Hefei, Anhui Province, China, (e-mail: Teddy.lingfeiwu@gmail.com)

Max Q.-H. Meng, and Huawei Liang are with Center for Biomimetic Sensing and Control Research, Institute of Intelligent Machines, Chinese Academy of Sciences, Hefei, Anhui Province, China (e-mail: {max, hwliang}@iim.ac.cn).

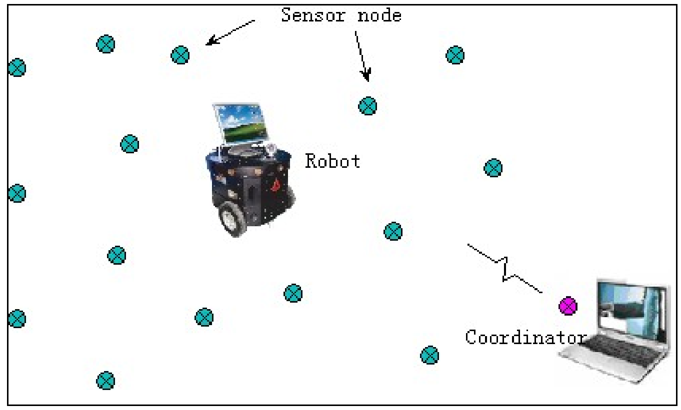


Fig. 1 Mobile Robot Navigation System

In this paper, we performed a series of localization experiments to evaluate the suitability of the RSS based localization and proposed a novel improvements---mean filtering technique, for mobile robot localization and navigation, as shown in the Fig, 1. In many ways, radio signal strength (RSS) is an ideal modality for range estimation in wireless networks because RSS information can be obtained at no additional cost with each radio message sent and received. Theoretically, the power of a radio wave decreases with the square of the distance from the transmitter under line of sight conditions. This relationship allows deducing the position of the receiver. In practice, this is impeded by the radio irregularity. In our ranging experiments, we conducted different measurements indoors and outdoors while collecting RSS data from the transmitter to the receiver by varying the time and the space, characterizing a total of 24 different environment combinations. Based on the ranging results, we analyzed the characteristics of RSS such as reflection and scattering, and different path losses, depending on different propagation.

The rest of this paper is organized as follows: Section II depicts the related work. Section III introduces the radio model for the ranging experiments and analyzes the radio irregularity due to the direction of propagation. Our ranging experiment setup and results are described in Section IV. Section V depicts the localization setup, introduces the mean filter to improve the localization performance and describes a set of mobile robot localization results. The section VI draws the conclusions.

II. Related Work

Since the received signal strength is available without any additional hardware, there have been a lot of research activities during the last years, thoroughly investigating its use for localization.

A. Analysis of the RSS Variability

Radio irregularity is a common phenomenon that arises from multiple factors, such as variance in RF sending power and different path losses, depending on the direction of propagation. Researchers working on RSS based localization are aware of this problem and have considered it in their algorithms. In [3], Gang Zhou et al. investigate the impact of radio irregularity on wireless sensor networks. They establish a RIM radio model and explored the impact of radio irregularity on MAC, routing, localization and topology control performance. Jari et al. [4] proposed an additive model as an alternative physical basis for shadow fading within an area where path loss is constant. It shows that under mild conditions on the statistics of the powers of the impinging plane waves, the shadow fading of the received signal will have approximately lognormal distribution.

Neal patwari et al. [5] considers the physical radio channel of a M2M network, presents a M2M measurement campaign conducted in an open-plan office, and shows that using existing RSS channel model result in inaccurate results. In [6][7], Kamin Whitehouse et al. present a study of how empirical ranging noise affecting the multihop range-based localization and demonstrate RSS can be used to localize a mutihop sensor network. They quantify the effects of various environmental factors on the resulting localization error.

B. RSS based Localization Algorithm

Over the past few years, many solutions based on RSS have been proposed for localization in wireless sensor networks, which can be basically divided into two main categories: range-based algorithm and range-free algorithm [8].

Centroid algorithm [9] is a simple range-free location algorithm. In this technology, the node receives RF signals of anchor messages in its communication area which containing location information and then estimates its position as the centroid of these anchor nodes. APIT [8] is area-based range-free location estimation. In this technology, it divides the neighbor area of a sensor node into many overlapped triangles according to performing numerous PIT tests with different audible anchor combinations. And then calculates the center of gravity of the intersection of all of the triangles in which a node resides to determine its estimated position. A different approach is taken by Kiran Yedavalli et al. they have elaborated the Ecolocation Algorithm [10] and its further development sequence-based localization (SBL) [11]. They determine the location of unknown nodes by examining the ordered sequence of received signal strength measurements taken at multiple reference nodes. This algorithm is robust to RSSI variability, but has an inherent limit regarding the resolution of the position. The authors report an average localization error of 1.22m for outdoor settings.

DV-distance [12] is classical range-based algorithm, which approximates the distance between a node i and an anchor node j to be the shortest path distance d_{ij} based on RSS measurements. Then each node executes the trilateration or multilateration to obtain location information. Another range-based algorithm based on RSS range technique is MDS-MAP [13]. It firstly computes shortest paths between all pairs of nodes in the region of consideration, and then applies classical MDS to the distance matrix to construct a relative map. At last, the coordinates of the anchors are mapped to their absolute coordinates through a linear transformation. The approach [14] applies the maximum likelihood estimation (MLE) to deduce the distance from the measured RSSI. The estimated position is the one which minimizes the error for multilateration of the distances.

Another methodology for localization using the RSSI is the scene analysis. RADAR [15] is a RF-based user tracker system, which achieves an average error of about 2m. This approach operates by recording and processing signal strength information at multiple base stations and combines empirical measurements to determine user location.

III. THE RADIO MODEL

There are many radio propagation models known for wireless communications that predict signal strength loss with distance in which the received signal levels decrease as the distance between the transmitter and the receiver increase. There are three classical models widely used for wireless sensor networks [16]: free space propagation model, two-ray ground model and log-distance model.

At present, the most widely used simulation model to generate RSS samples as function of distance in RF channels is the log-normal shadowing model [10]:

$$RSS(d) = P_T - PL(do) - 10\eta \log_{10}\frac{d}{do} + X\sigma \tag{1}$$

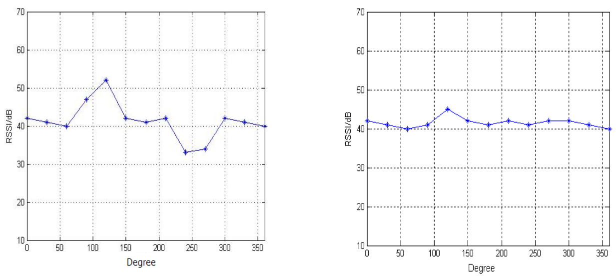
where, P_T is the transmit power and $PL(do)$ is path loss for a reference distance of do. η is the path loss exponent and the random variation in RSS is expressed as a Gaussian random variable of zero mean and σ^2 variance, $X\sigma = N(0,\sigma^2)$. The path loss exponent depends on the environment and terrain structure and can vary between 2 in free space to 6 in heavily built urban areas [17]. All powers are in dBm and all distances are in meters.

In real world channels, multipath signals and shadowing are two major sources of environment dependence in the measured RSS. In this paper, in order to simplify the RF channels model in the real experiment, we used our experimental model without considering channel fading:

$$RSSI = -(10n\log_{10} d + A) \tag{2}$$

where A is RSSI value when the distance between transmitter and the receiver is 1 m. n is also the path loss exponent. These RF channel characteristics are obtained from the experiments depending on the environments.

Gang Zhou et al. [3] investigated the impacts of radio irregularity on wireless sensor networks. In the real channel, radio irregularity is a common phenomenon that arises from multiple factors, such as devices and the propagation media, especially anisotropic path losses and heterogeneous sending powers. In order to explore these factors, we conduct some experiments both in the indoor environment and outdoor environment.



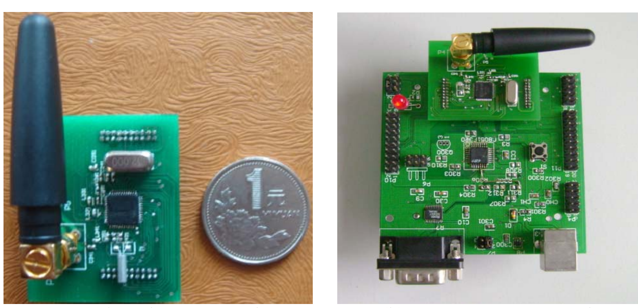
(a) Indoor Environment (b) Outdoor Environment
Fig. 2 Radio Irregularity in Different Direction

As shown in the Fig.2, the radio signal from a transmitter has different path losses in different directions in the indoor environment and the outdoor environment. In addition, the variability of radio signal strength in the indoor environment is larger than that in the outdoor environment. We guess the reason is that the refection and scattering have more effect on the RSS values in the indoor environment, especially in the case where the sensor node is close to the wall or other large obstacle.

IV. RANGING EXPERIMENTAL RESULTS

This section describes the setup of the localization system and the experimental results in the indoor environment and outdoor environment.

A. Ranging Experimental Setup



(a) Designed Sensor Node (b) Gateway Sensor Node
Fig. 3 Hardware Setup

The basic setup is shown in Fig. 3 (a) and Fig. 3(b). Our experiment test platform consists of an ASR mobile robot, 10 sensor nodes, a sensor sink node and a laptop computer. The wireless sensor node designed by us is shown in Fig. 3 (a) and Fig. 3 (b). This node mainly consists of a temperature control module, an energy control module, a CC2431, extra ROM&RAM, an RF circuit, a USB controller & interface and a user interface [18]. The temperate on the moon changes from about 102K to 384K [19]. A temperate control module is needed to protect the sensor node from the bad temperatures. A vacuum multiplayer insulation structure is used to passively control the temperature variation. Electric heater and heat pipes are used to increase the temperature actively if possible [20]. The energy control module is used to make the voltage stable and select the power source. The USB interface is an optional part that is used to communicate with computer. The power can be supplied by either USB or battery. The user interface is an interface that is used for installing various sensors according to the needs of the application. It also gives some communication interfaces such as I2C and UART. CC2431 is the heart of the node, which contains an RF transceiver, a high performance and low-power consumption 8051 based microcontroller, and a location engine based on RSSI. It controls all the other components in the node.

We designed several experiments to identify the extent to which RSS ranging is affected by various environmental factors. We deployed the nodes indoors and outdoors with different topology. We collect the RSS data in each environment in different days in order to observe the possible variability of RSS data. We repeated the experiments four times, at three different times of different day, for a total of 12 different environment characteristics.

Fig.4 Indoor Gymnasium Field

Indoors, in a large 12×12 m2 gymnasium that was filled with chairs, sport equipments and other items, as shown in Fig. 4, we conducted the experiments to measure the RSS data of different distance between the transmitter and receiver. The CC2431 node was placed in the ground as a transmitter with the distance 1.0m, 1.6m, 2.5m, 4.0m, 5.0m, 6.3m, 8.0m, and 10.0m from the receiver. A sensor sink node played as the receiver, which read corresponding RSSI and forward them to a laptop computer for storage. Outdoors in an open field known as Basketball Field (BF) shown in Fig. 5, the BF is empty and surrounded with a big house, lots of grass, and a pond. Similarly, we conducted the experiments in different direction of BF to measure the RSS date with the distance like 1.0m, 1.6m, 2.5m, 4.0m, 5.0m, 6.3m, 8.0m, 10.0m, 12.6m, 15.9m, and 20.0m from the transmitter to the receiver. Then we repeated the experiments and rerecord the

RSS date as raw data to derive the appropriate system parameters n and A shown in equation (2).

Fig. 5 Outdoor Basketball Field

B. Ranging Results

After successful ranging experiment setup and node programming, we started to monitor data representing RSS. We analyzed the data sets collected in the experiments describe above in terms of the different characteristics defined above. A comparison of the different data sets allowed us to identify the effect on RSS of each environment factor.

In the indoor environment, we carried out sets of measurements using the CC2430 Zigbee nodes. The experiments were repeated as previously detailed and produced about 100 measurements, which we chose to average to represent the RSS values. In the Fig. 6, a graph is shown for scattering every distance (1.0m, 1.6m, 2.5m, 4.0m, 5.0m, 6.3m, 8.0m and 10m) indoors. It can be seen that scattering is quite high. For this reason, we calculated the average value of the RSS, the minimum RSS, the maximum RSS and standard deviation for every distance measured. We used standard formula for it.

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \overline{x})^2} \qquad (3)$$

Measurements were done in a real environment, not in an ideal laboratory. This is because we wanted to place the nodes within real working environment, in which they would normally be operating when deployed.

In the outdoor environment, we carried out similarly lots of measurements to obtain the RSS values with different distance from the transmitter and receiver. Because the BF is bigger than indoor gymnasium, so we also measured further distance such as 12.6m, 15.9m and 20m. However, unfortunately, in our initial experiment, we found that when the distance between the transmitter and the receiver was more than 15.9m, the RSS values became bad distance indicator. The reason we analyzed was that the ground made the RF signal very small by absorbing most of its signal strength. So we tried to put the nodes in the higher elevation to observe its measurements, which technique was chosen to reduce the influence on RSS characteristics [6]. The measurements validated our ideas due to its good distance indicator again. As shown in Fig 7, we similarly pictured the average value of the RSS, the minimum RSS, the maximum RSS and standard deviation for every distance measured outdoors.

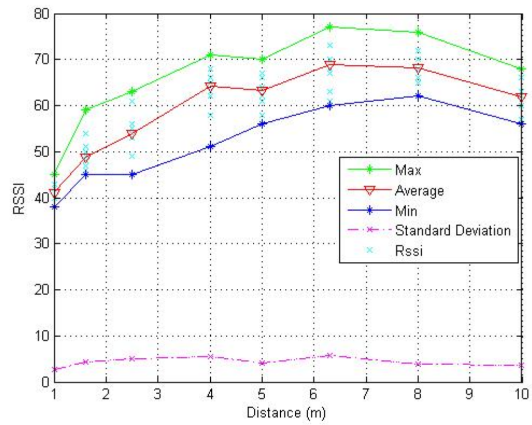


Fig. 6 RSSI Values Measured Indoors

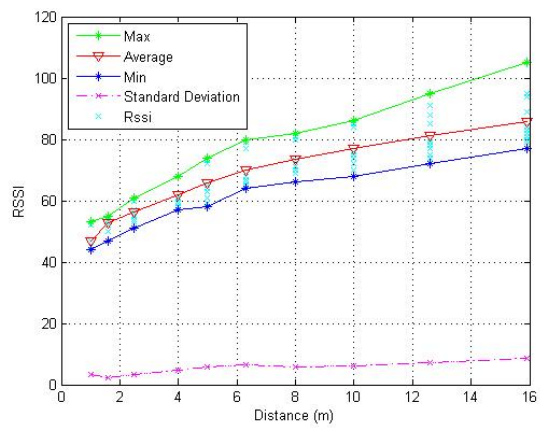


Fig. 7 RSSI Values Measured Outdoors

As many people had observed, moving two radios farther away from each other indoors did yield predictable attenuation in signal strength. However, our study of indoor signal strength revealed that, without any pre-existing knowledge of the radio's position within a room, signal strength was not related with distance, especially when the transmitter is near the wall or other bigger obstacles. The reason is that the refection and scattering had sort of influence on RF signal such as increasing the RSS. We also found that the variation of RSS data outdoors was smaller than that indoors with the same closer distance. It because the RSS date was affected less due to much larger space without any obstacles. Thus, the RF signal is sort of more suitable for outdoor application. However, when the distance between the transmitter and the receiver was more than 12m, the variation of RSS data began to increase. It seems that RSS is better distance indicator in the short distance than that in the long distance when sensor nodes are placed on the ground.

V. LOCALIZATION EXPERIMENTAL RESULTS

In our localization experiments, we used the maximum likelihood estimation localization algorithm based on our CC2431 inline location engine module to evaluate the performance of the ASR mobile robot localization.

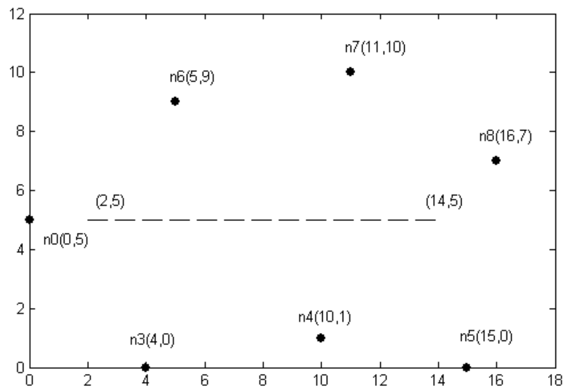


Fig. 8 Localization Experiment Topology

A. Localization Experiment Setup

The experiment field and experiment topology are respectively shown in Fig. 5 and Fig. 8. The experiment field is a square of 12 m by 18 m with 7 sensor nodes and a mobile robot deployed in it. The anchor nodes are deployed at (0, 5), (5, 9), (4, 0), (10, 1), (11, 10), (14, 5), (15, 0) and (16, 7). A sensor node is fixed on the mobile robot for the robot's localization and navigation. Both the static and mobile sensors (robot) have a communication range of 10m. The location error $LE = \|X_{est} - X_{real}\|$ is defined, where X_{real} represents the actual position and X_{est} the estimated position. In our initial localization experiment, the robot traveled from the coordinates (2, 5) to the destination position (14, 5) with a constant speed of 0.05m/s. The anchor nodes broadcasted every three seconds periodically their ID information and position to the mobile sensor so that it could obtain their position information and calculate their distance by using RSSI techniques. Then the mobile sensor executed MLE localization algorithm to get its estimate position.

For each run of the localization algorithm, we used linear regression and uniform linear calibration on all nodes to infer distance from RSS. The RSS parameters were derived from linear model using the ranging date collected in the environments corresponding to that in which localization was to take place. To initiate each experiment, the network was flooded with parameters such as path losses exponent n and empirical transmit power A . During each experiment, all experiment process was kinescoped through human-machine interface and the mobile node (robot) forwarded all location information to the link node, then by the link node, at last was forwarded to a laptop and recorded for storage. The mobile robot was controlled remotely through the controlling buttons in the right of the human-machine interface, as shown in the Fig. 9.

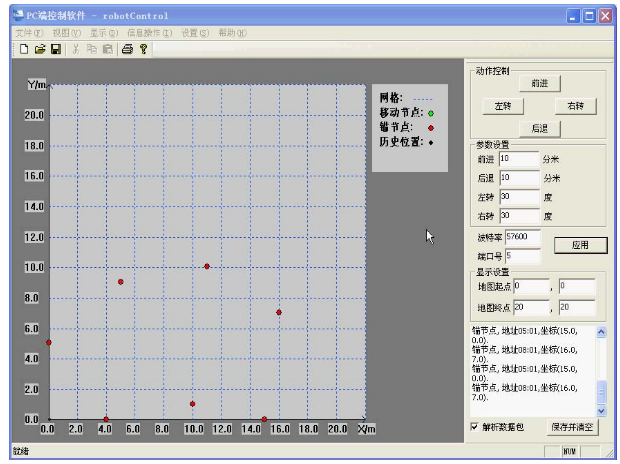
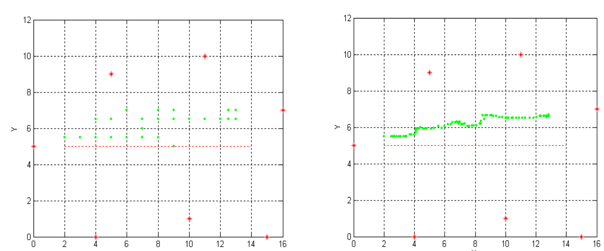


Fig. 9 Human-Machine Interface

B. Mean Filter

We conducted the initial experiments and found that the mobile robot localization results were discrete and only several location results, shown in the Fig. 10(a). In order to better tracking the mobile robot, we adopted mean filter technique to reduce the environment noise and achieve better localization results.


(a) Before Mean Filter (b) After Mean Filter
Fig. 10 Initial Mobile Robot Localization Experiments

Mean filter and median filter are both effective filtering technique to reduce the environment noise. Mean filter is the most common used linear filter technique for reducing Gauss noise, while median filter is a non-linear signal enhancement technique for the smoothing of signals, the suppression of impulse noise, and preserving of edges. Because people commonly modeled RSS channel noise as a zero mean Gauss noise, we chose mean filter technique to help us reduce the location noise. In the one-dimensional case it consists of sliding a window of a set of elements along the signal, replacing the centre sample by the mean of the samples in the window. Mean filter is windowed filter of linear class, that smoothes signal (image). The filter works as low-pass one. We will simply introduce the principle and characteristics of mean filter.

The idea of Mean filter is to calculate the mean of an array, called the window, or take an average across its neighborhood. Suppose that a sampling list is $x(1)$, $x(2)$, …., $x(n)$, then store them in an array. Set that window length is number L. If we adopt L number of sampling $x(i-k)$,…, $x(i-1)$, $x(i)$, $x(i+1)$, …, $x(i+k)$, where $x(i)$ is the centre of the window, and $k=(L-1)/2$. Thus the mean is the output of this window.

$$y(i)=Mean\{x(i-k),...,x(i),...,x(i+k)\} \quad (4)$$

When we get the location information forwarded from the mobile robot, we do not adopt this result as current mobile robot location but the current output result by mean filtering. The localization results after mean filtering are shown in Fig. 10(b). The pink line is the actual moving path of the robot, and the green line is estimated positioning trajectory of the robot. The positioning result in the experiment is relative continuous and more smoothing than the previous. And the localization error is about 1.5m. Obviously, mean filter can effectively reduce the situation of discrete location results and track the mobile robot. It because that this technique reduces the effect of RF signal radio irregularity due to variation of node hardware and environment such as RF sending power and different path losses [3] .

C. *Random Localization Experiments*

In above preliminary experiment, we verified the validity of the proposed method. To test mean filtering technique fully, we further conducted some localization experiments. Firstly, the mobile robot was controlled remotely to run randomly in the BF. The moving speed is 0.05m/s and the robot reported its position every three seconds. The RSS parameters are the same as the above experiment.

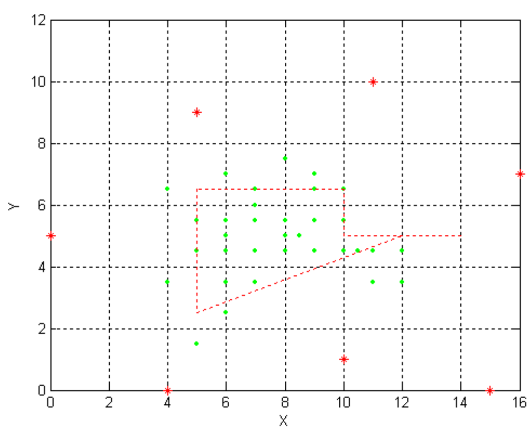


Fig. 11 Raw Random Location Results

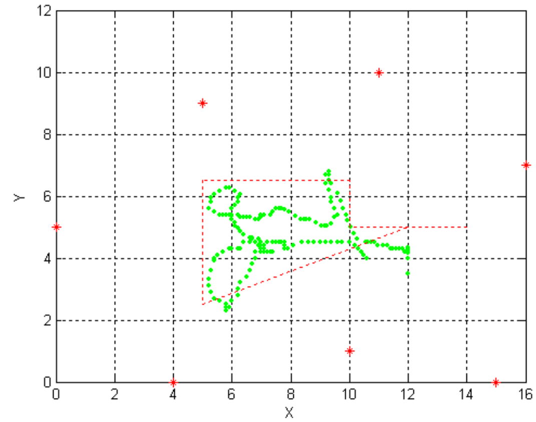


Fig. 12 Random Location after MF, Window = 10

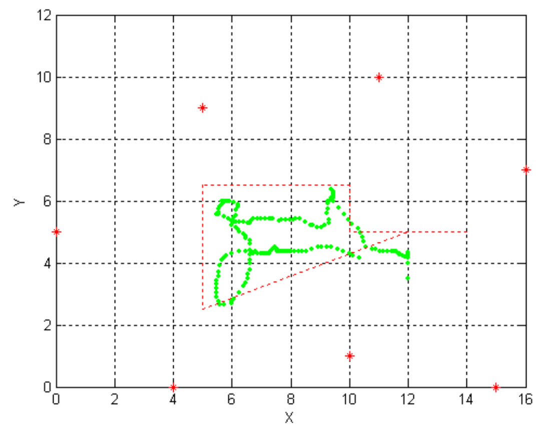


Fig. 13 Random Location after MF, Window = 15

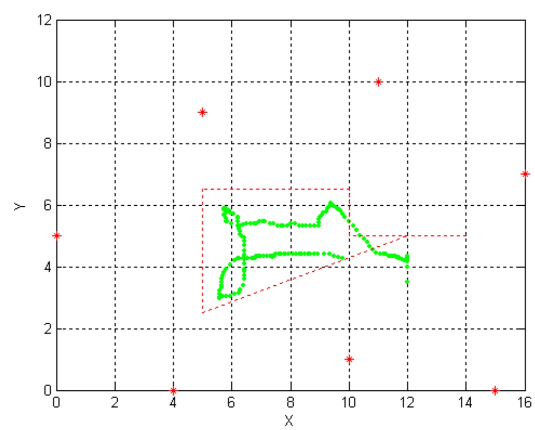


Fig. 14 Random Location after MF, Window = 20

As shown in above Figures, red star represents anchor nodes. The pink broken line is the actual moving path of the mobile robot, and the green line is tracking trajectory of the robot. In the Fig. 11, when the mobile robot move along the pink path, its raw location results distributed on both sides of pre-planed path. But we almost can not distinguish its regularity in the small moving region. Fig 12, 13, and 14 show the location results after mean filter with the window size 10, 15, and 20 respectively. We can obviously see a tracking path responding to the pre-planed path. The tracking localization error is from about 1m to 2m, and average is about 1.6m. The localization results after mean filter with the bigger window size is sort of better than that with the smaller. However, the tracking trajectory after mean filter brought in abrupt changes and swing over, when the mobile robot began to swerve. We analyzed the reason that when the mobile robot began to veer off, the antenna direction of mobile node followed to change sharply. It may cause radio propagation parameters to change, which brings in RSS values in each direction varying sharply. It also illustrates the RF signal is very sensitive to slight change whether in the device or in the environment.

D. Localization Experiments with Collision-Avoided

We continued to conduct other localization experiments when the obstacle (the chair) was placed in the center of BF. Similar as the above, RSS parameters is constant and location report and robot moving speed stay the same.

As shown in above Figures, red star represents anchor nodes. The pink broken line is the actual moving path of the mobile robot, and the green line is tracking trajectory of the robot. The black box represents the obstacle. Differ from the location results in the Fig. 11, the moving direction of mobile robot was loom seen but not distinct in the Fig. 15. It seems that the location results were improved to some extent when the mobile robot moved in a larger region although there is some obstacle near the pre-planed path. From Fig. 16, 17, and 18 show the location results after mean filter with the window size 10, 15 and 20. The tracking trajectory was basically good and location error was in about 1.2m. The mobile robot can be controlled remotely to avoid the obstacle based on RSS, especially with the window 20. When the window was 10 and 15, some trajectory entered into the black box, which meant it was sort of dangerous for mobile robot to avoid the obstacle fully. However, when the window was 20, it was totally safe for mobile robot moving. In order to ensure absolutely collision avoided in any situation, the obstacle could be magnified appropriately to control robot to move safely, at the cost of the shortest path.

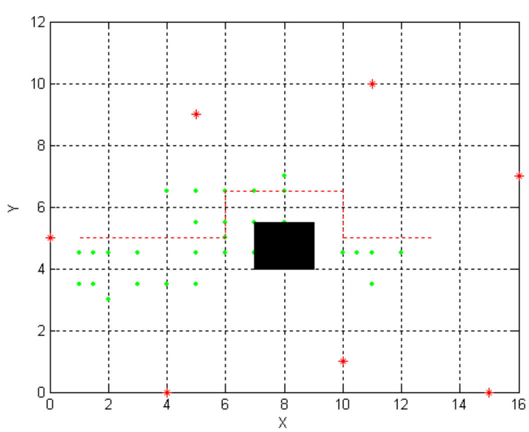


Fig. 15 Raw Collision-Avoided Location Results

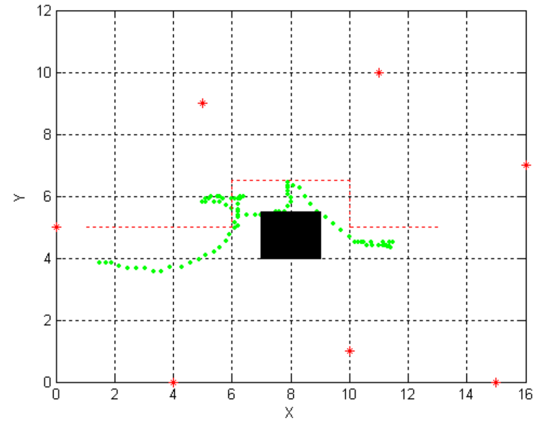


Fig. 16 Location Results after MF, Window = 10

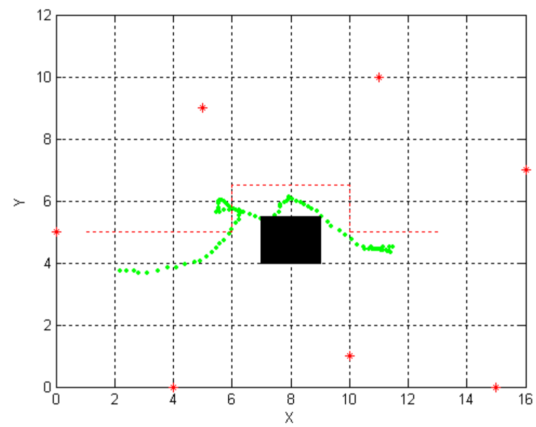


Fig. 17 Location Results after MF, Window = 15

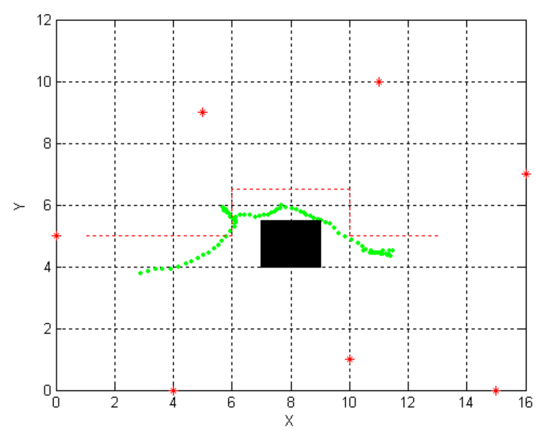


Fig. 18 Location Results after MF, Window = 20

VI. CONCLUSIONS

We performed a series of localization experiments to evaluate the suitability of the RSS based localization and proposed a novel improvement, mean filtering technique, for mobile robot localization and navigation. We firstly introduced the most widely used radio propagation models, the log-normal shadowing model, and then we gave our experimental channel model considering the RF signal complexity of real experiment. Then a lot of ranging experiments were conducted to analyze the characteristics of RSS such as reflection and scattering, and different path losses depending on different propagation both in the indoor environment and in the outdoor environment. In order to track the mobile robot better, we adopted mean filtering technique to reduce the effects of environment on RF signal and optimized the mobile robot localization performance. We performed different kinds of localization experiments to prove the validity of the proposed method using our test designed platform. Our future work is to use much larger scale sensor networks for the navigation and localization of real lunar rover.

REFERENCES

[1] Deng, Z.; Fang, H.; Dong, Y.; Tao, J. Research on wheel-walking motion control of lunar rover with six cylinder-conical wheels. IEEE International Conference on Mechatronics and Automation 2007, Harbin, China, 388-392.

[2] Friedman, L.; Huntress,W. Proposal for an International Lunar Decade. 36th COSPAR Scientific Assembly 2006, Beijing, China, 2006.

[3] GANG ZHOU, TIAN HE, SUDHA KRISHNAMURTHY, and JOHN A. STANKOVIC. Models and Solutions for Radio Irregularity in Wireless Sensor Networks, ACM Transactions on Sensor Networks, Vol. 2, No.2, May 2006, Page(s): 221-262

[4] Jari Salo, Lasse Vuokko, Hassan M. EI-Sallabi and Pertti Vainikainen, An Additive Model as a Physical Basis for Shadow Fading, IEEE Transactions on Vehicular Technology, Volume 56, Issue 1, Jan. 2007 Page(s):13 – 26

[5] Neal Patwari, Yanwei Wang, Robert J. O' Dea, The Importance of the Multipoint-to-Multipoint Indoor Radio Channel in Ad Hoc Networks, 2002 IEEE Wireless Communications and Networking Conference, 2002. Volume 2, March 2002 Page(s):608 – 612

[6] Kamin Whitehouse, Chris Karlof, David Culler, A practical Evaluation of Radio Signal Strength for Ranging–based Localization, SIGMOBILE Mobile Computing and Communications Review, Jan, 2007, Volume 11 Issue 1

[7] Kamin Whitehouse, Chris Karlof, David Culler, The Effects of Ranging Noise on Multihop Localization: An Empirical Study, IPSN 2005, April 2005 Page(s):73 – 80

[8] T. He, C. Huang, B. M. Blum, J. A. Stankovic, and T. F. Abdelzaher, "Range-Free Localization Schemes in Large Scale Sensor Networks," in MobiCom, 2003.

[9] Bulusu N, Heidemann J, Estrin D. "GPS-less low-cost outdoor localization for very small devices", Personal Communications, IEEE, 2000, 7(5):28 – 34.

[10]K. Yedavalli, B. Krishnamachari, S. Ravula, and B. Srinivasan, "Ecolocation: a sequence based technique for RF localization in wireless sensor networks," Proceedings of the 4th international symposium on Information processing in sensor networks, 2005

[11]Y. K. and K. B., "Sequence-based localization in wireless sensor networks," IEEE Transactions on mobile computing, 2007

[12]D. Niculescu, B. Nath. "Ad Hoc Positioning System (APS)," Proc. of the IEEE GLOBECOM 2001, San Antonio, pp. 2926-2931, 2001.

[13]Y Shang, W. Ruml , K. Zhang , and M. Fromherz . Localization from mere connectivity[C]//ACM MobiHoc, Annapolis, MD, June 2003: 201-212.

[14]M. Sugano, T. Kawazoe, Y. Ohta, and M. Murata, "Indoor Localization System using RSSI Measurement of Wireless Sensor Network based on ZigBee Standard," Proceeding of Wireless Sensor Networks, vol. 7, pp. 54–69, 2006.

[15]P. Bahl, and V. N. Padmanabhan, RADAR: An In-Building RF-based User Location and Tracking System, IEEE INFOCOM 2000, pp. 775-784

[16]Benkic, K., M. Malajner, et al., Using RSSI value for distance estimation in wireless sensor networks based on ZigBee. Systems, 15th International Conference on Systems, Signals and Image Processing, 2008

[17]T. Rappaport, Wireless Communications, Principles and Practice. Prentice Hail, 1999

[18]Chen, W.M, Liang, H.W, Mei, T. Design and implementation of wireless sensor networks for robot navigation. International Journal of Information Acquisition 2007, 4, 77-89.

[19]Heiken. G, Vaniman. D, French. B. Lunar Sourcebook: A User's Guide to the Moon. Cambridge Univ Press, 1991.

[20]Miao, S.F, Liang, H.W, Meng, M. Q.-H, Chen, W.M, Li, S. Design of wireless sensor networks nodes under lunar environment. Transducer and Microsystems Technologies 2007, 26, 117-120.