Distance Estimation of Smart Device using Bluetooth

Joonyoung Jung, Dongoh Kang, Changseok Bae
Personal Computing Platform Research Team
Electronics and Telecommunications Research Institute
Deajeon, Korea
{jyjung21, dongoh, csbae}@etri.re.kr

***Abstract*— Distance estimation identifies the distance between two machines in wireless network. The Received Signal Strength Indication (RSSI) of Bluetooth can be used to estimate distance between smart devices. The characteristic of Bluetooth RSSI value is different as environments. So, we have tested the relation between distance and Bluetooth RSSI value in several environments, such as indoor hall, meeting room, and ElectroMagnetic Compatibility (EMC) chamber environment. This paper shows the distance characteristic of Bluetooth RSSI from these experiment results. There are a lot of measurement errors at Bluetooth RSSI raw data. The minimum RSSI value is -88 dBm and the maximum RSSI value is -66 dBm at 11m of the indoor hall environment. The difference between maximum value and minimum value is 22 dBm. So, it is hard to estimate the distance using Bluetooth RSSI raw data. Therefore, we use the Low Pass Filter (LPF) for reducing the measurement errors. The minimum RSSI value is -80.6 dBm and the maximum RSSI value is -71 dBm in the same environment. The difference between maximum value and minimum value is just 8.4 dBm. The measurement error is significantly reduced. We compare the distance estimation between the Bluetooth RSSI raw data and LPF data at the EMC environment. This paper shows that the distance estimation is possible with small error rates using Bluetooth RSSI LPF data.**

Keywords-Distance Estimation; Bluetooth; RSSI

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are one of the essential research domains. There are many applications for WSNs in military and civil applications [1]. The Machine to Machine (M2M) distance estimation is a fundamental issue for a lot of applications of indoor WSNs, such as a Bluetooth and Zigbee. Distance estimation identifies the distance between two machines in wireless network. Such estimates are an important component of systems' localization, because they are used by the position computation and localization algorithm components. Different methods, such as RSSI, Time of Arrival (ToA), and Time Difference of Arrival (TDoA), can be used to estimate a M2M distance. Nowadays, lots of location systems have tried to estimate M2M distance using different models in wireless networks. For example, the Active Badge System used an infrared signal [2]. Cricket, developed at MIT, uses TDoA method [3]. Global Positioning System (GPS) uses ToA [4]. RADAR, developed at Microsoft, uses RSSI to estimate M2M distance [5]. SpotON is a RSSI-based ad-hoc localization system [6]. In this paper, we discuss the M2M distance estimation using Bluetooth RSSI.

The rest of the paper is organized as follows. Section II describes related work. In Section III, we describe distance characteristic of Bluetooth RSSI. In Section IV, we describe Bluetooth RSSI using a low pass filter. Section V provides the experimental results, and some concluding remarks are finally given in Section VI.

II. RELATED WORK

A. RSSI

RSSI can be used to estimate the M2M distance based on the received signal strength from another machine. The longer the distance to the receiver machine, the lesser the signal strength at received machine. Theoretically, the signal strength is inversely proportional to squared distance, and there is a known radio propagation model that is used to convert the signal strength into distance. However, in real environments, it is hard to measure distance using RSSI because of noises, obstacles, and the type of antenna. In these cases, it is common to make a system calibration [7], where values of RSSI and distances are evaluated ahead of time in a controlled environment. The advantage of this method is its low cost, because most receivers can estimate the received signal strength. The disadvantage is that it is affected by noise and interference. So, distance estimation may have inaccuracies. Some experiments [8] show errors from 2 to 3 m in some scenarios. Distance estimation using RSSI in real-world applications is still questionable because of inaccuracy [9]. However, RSSI could become the most used technology of distance estimation from the cost/precision viewpoint because of low cost [10]. A. Awad et al. [1] discuss and analyze intensively some approaches relying on the received signal strength indicator. The most important factor for proper distance estimation is to choose a transmission power according to the relevant distances. It was showed that even for noisy indoor environments an average positioning error of 50cm on an area of 3.5 x 4.5 m is possible by choosing the RF and algorithm parameters carefully based on empirical studies. S. Feldmann et al. [11] also presented an indoor positioning system based on signal strength measurements, which were approximated by the received RSSI in a mobile device. The functional dependence between the received RSSI and the distance was achieved by a well fitted polynomial approximation.

 ISBN: 978-1-61208-305-6

B. *ToA*

In ToA, the M2M distance is directly proportional to the time the signal takes to propagate from one machine to another, as shown in Fig. 1 [12]. ToA needs precisely synchronized machines.

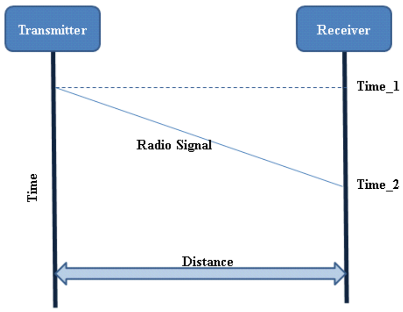


Figure 1. ToA distance estimation method

The distance between two machines is proportional to the signal transmitted time. That is, if a transmitter sends a signal at time time_1 and a receiver receives the signal at time time_2, the distance between transmitter and receiver is d = P_r(time_2 – time_1), where P_r is the propagation speed of the radio signal, and time_1 and time_2 are the times when the signal was transmitted and received. S. Schwarzer et al. [13] presented a concept to measure the distance between two IEEE 802.15.4 compliant devices using ToA. It shows that compared to signal correlation in time, the phase processing technique yields an accuracy improvement of roughly an order of magnitude.

C. *TDoA*

TDoA is based on the difference in the times at which multiple signals from a single machine arrive at another machine. The machines must have extra hardware for sending two types of signals simultaneously, as shown in Fig. 2. These signals must have different propagation speeds, like RF and ultrasound. N. Priyantha et al. [14] presented a TDoA method using different propagation speed signals, like radio/ultrasound. K. Whitehouse et al. [7] used radio/acoustic signals. Usually, the first signal propagation speed is light, while the second signal has slower propagation speed. The second signal is six orders of magnitude slower than the first signal.

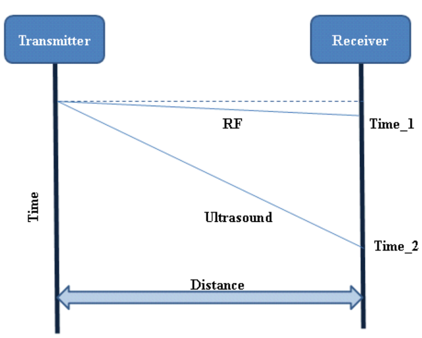


Figure 2. TDoA distance estimation method

An example of TDoA suitable for WSNs is used in [8] and depicted in Fig. 2, where the ultrasound pulse and radio signal are sent simultaneously. A receiver machine computes the difference time of the two signals. The distance can now be computed by the formula d = (P_r – P_u)*(time_2 – time_1), where P_r and P_u are the propagation speed of the radio signal and ultrasound pulse, and time_1 and time_2 are the received times of the radio signal and ultrasound pulse, respectively. Another different and interesting way of computing distance among machines using the TDoA is proposed by Fu et al. [15], and is based on the Direct Sequence Spread Spectrum (DSSS) modulation technique. The distance estimation errors using TDoA are several centimeters. Experiments error with ultrasound performed in [8] is about 3 cm, where M2M distance was 3 m. In [16], the experiments error with acoustic sound is about 23 cm, where M2M distance was 2 m. TDoA system has precise distance estimation accuracy. However, it also has disadvantages. It needs extra hardware to send the second signal, which increases cost. And it has limited range of the second signal, which is about between 3 and 10 m according as transmitter power. To save a cost, Y. Fukuju et al. [17] presented a TDoA system that reduces configuration cost.

D. *Location System using M2M Distance Estimation*

The Active Badge System finds location information using an infrared signal [2]. Each person wears a small infrared badge. The badge sends a unique packet periodically or on demand. A server receives badge data using fixed infrared sensors in building and gathers this data. The Active Badge system provides absolute location information using this infrared distance information. Infrared signal has an effective range of several meters because of diffusion. Therefore, infrared signal range is limited to small or medium rooms. As mentioned above, drawbacks are limited range of infrared sensors and usage of diffused infrared in fluorescent lighting or direct sunlight.

Cricket uses TDoA method [3]. M2M distance error is about 3 cm, but this causes a huge burden on the receiver machine due to distributed computation and processing of ultrasound pulses and RF signal. The Cricket Location Support System finds location information using ultrasound pulse and RF signal. The RF signal is used for synchronization of the time measurement. Cricket estimates distance using TDoA and then finds location information using distance information. However, Cricket does not require a grid of ceiling sensors with fixed locations because its mobile receivers perform the timing and computation functions. A receiver receives multiple beacons, so it triangulates its position. Cricket has advantages that it has privacy and decentralized scalability. It also has disadvantages that it does not have centralized management and more it has the computational and power burden for timing and processing both the ultrasound pulses and RF signal on the mobile receivers.

RADAR was developed at Microsoft and used RSSI to estimate M2M distance [5]. It is based on an 802.11 Wireless LAN. A building-wide tracking system based on the IEEE 802.11 LAN wireless networking technology. RADAR

 ISBN: 978-1-61208-305-6

measures the signal strength and signal-to-noise ratio at the base station, and then it computes the position within a building using these data. RADAR's scene-analysis implementation has position error within about 3 meters with 50 percent probability, while the signal strength lateration implementation has position error about 4.3-meter with 50 percent probability.

SpotON is a RSSI-based ad-hoc localization system [6]. The SpotON system implements ad-hoc lateration with low cost tags. SpotON tags estimate distance between tags using radio signal attenuation. It can be used for relative and absolute position determination. In an ad-hoc location system, all of the machines become mobile machines with the same sensors and capabilities. To estimate their locations, machines cooperate with other nearby machines by sharing RSSI data. Machines in the cluster are located relative to one another or absolutely if some machines in the cluster have known locations. The techniques for building ad-hoc systems include triangulation, scene analysis, or proximity. Location sensing with ad-hoc infrastructure has a high scalability.

III. DISTANCE CHARACTERISTIC OF BLUETOOTH RSSI

We tested the relation between distance and Bluetooth RSSI in indoor hall, meeting room, and EMC chamber environment. These experiment results show the distance characteristic of Bluetooth RSSI in several environments

A. *Indoor hall*

We have measured Bluetooth RSSI with a notebook and a Nexus 7 in indoor hall environment as shown in Fig. 3. We measured 200 samples at each meter from 0m to 15m.

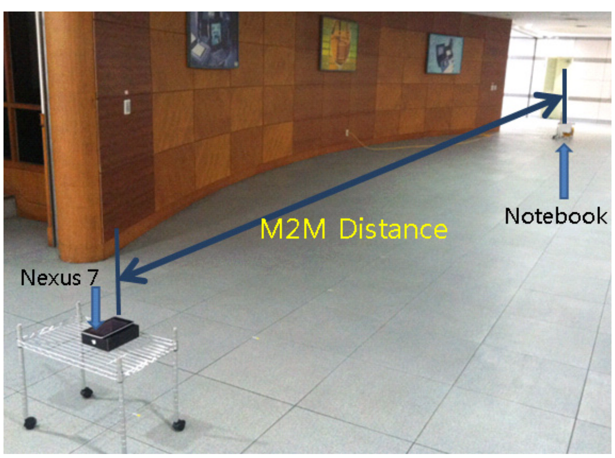
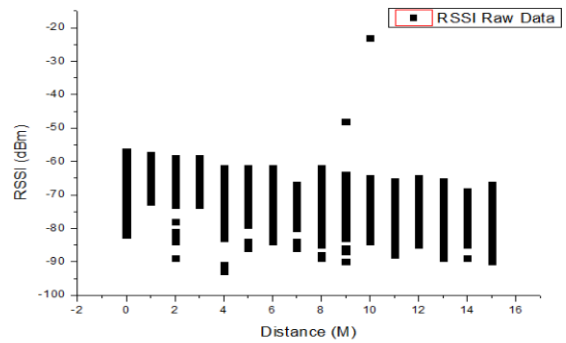
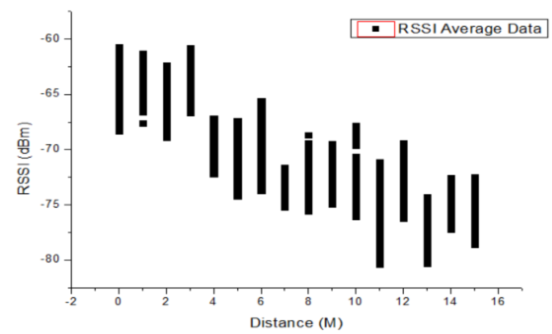


Figure 3. Bluetooth RSSI mesurement test in indoor hall environment

The result of these experiments is shown in Fig. 4. The RSSI raw data and average data are shown in Fig. 4 (a) and Fig. 4 (b). The RSSI average data average 10 RSSI raw data. The distance estimation is impossible with the RSSI raw data. However, the distance estimation may be possible coarsely with the RSSI average data. The RSSI average value is similar from 0m to 3m, from 4m to 6m, and from 7m to 15m.



(a) RSSI raw data



(b) RSSI average data

Figure 4. The Bluetooth RSSI measurement result in indoor hall environment

B. *Meeting Room*

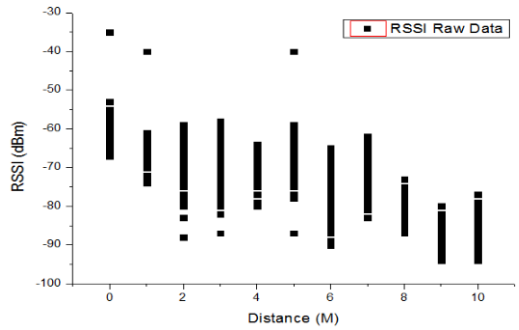
We have measured Bluetooth RSSI with a notebook and a Nexus 7 in meeting room environment, as shown in Fig. 5. We measured 200 samples at each meter from 0m to 10m. The meeting room door is located between 7m and 8m from the notebook. When Bluetooth RSSI value is measured from 8m to 10m, the meeting room door is closed.

Figure 5. Bluetooth RSSI mesurement test in meeting room environment

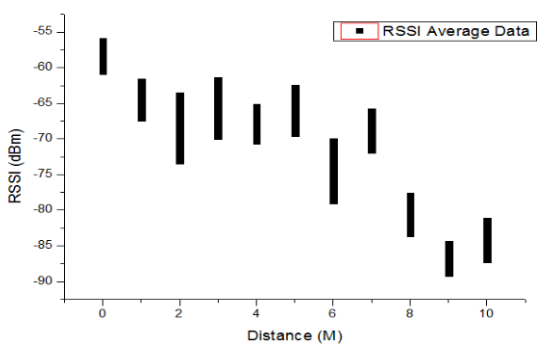
The RSSI raw data and the RSSI average data are shown in Fig. 6 (a) and Fig. 6 (b), respectively. It is hard to classify into inside and outside of the meeting room with the RSSI raw data. However, the minimum RSSI average value from 0m to 7m is -78.6 dBm and the maximum RSSI average value from 8m to 10m is -77.9 dBm. So, it may be possible

 ISBN: 978-1-61208-305-6

to classify into inside and outside of the meeting room with the RSSI average data.



(a) RSSI raw data



(b) RSSI average data

Figure 6. The Bluetooth RSSI mesurement result in meeting room environment

C. EMC Chamber

We have measured Bluetooth RSSI with a notebook and a Nexus 7 in EMC chamber environment as shown in Fig. 7. We measured 200 samples at each meter from 0m to 15m.

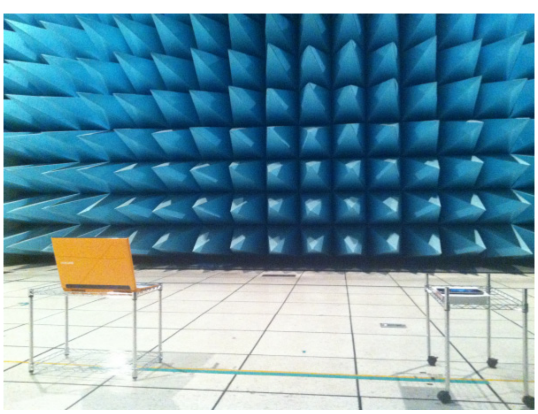
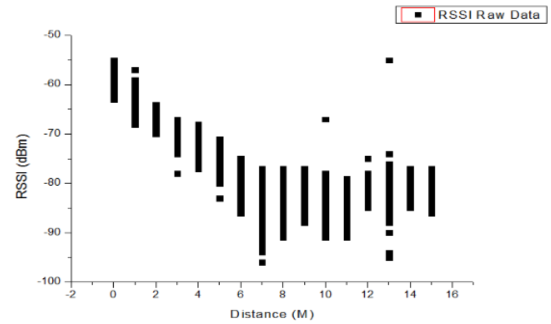
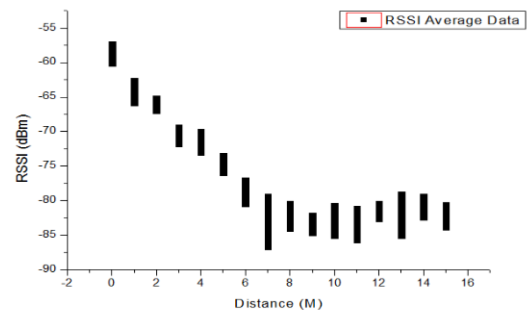


Figure 7. Bluetooth RSSI mesurement test in EMC chamber environment

The RSSI raw data and the RSSI average data are shown in Fig. 8 (a) and Fig. 8 (b), respectively.



(a) RSSI raw data



(b) RSSI average data

Figure 8. The Bluetooth RSSI mesurement result in EMC chamber environment

The RSSI value decreases linearly from 0m to 7m and has similar value from 7m to 15m. The distance estimation is performed well from 0m to 7m using the RSSI average value in EMC chamber environment.

IV. BLUETOOTH RSSI USING LOW PASS FILTER

The Bluetooth RSSI raw data at 11m of indoor hall environment is shown in Fig. 9. There are a lot of measurement errors at Bluetooth RSSI raw data. The minimum RSSI value is -88 dBm and the maximum RSSI value is -66 dBm. The difference between maximum value and minimum value is 22 dBm. So, it is hard to estimate the distance using Bluetooth RSSI raw data.

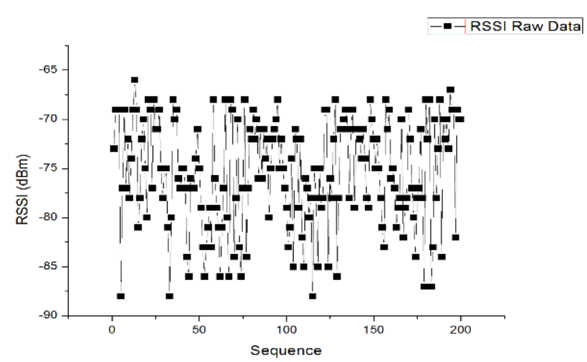


Figure 9. The Bluetooth RSSI raw data at 11m of indoor hall environment

 ISBN: 978-1-61208-305-6

LPF equation is (1). When the LPF is used, the RSSI deviation is reduced as seen Fig. 10, where ($\alpha = 0.8$).

$$P_n = \alpha P_{n-1} + (1-\alpha) T_n \ . \quad (1)$$

The received signal strength (T_n) is the RSSI value receiving from the other smart device at k. And the LPF value (P_n) is the RSSI value of LPF at k. The constant (α) has a value that is bigger than 0 and lower than 1.

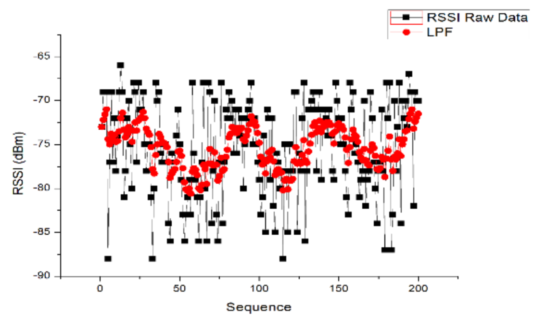


Figure 10. The Bluetooth RSSI LPF data at 11m of indoor hall environment

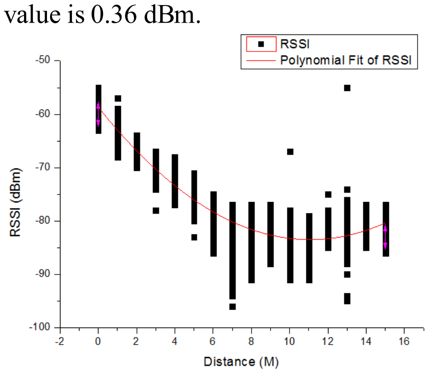
The minimum RSSI value is -80.6 dBm and the maximum RSSI value is -71 dBm. The measurement errors are significantly reduced. The difference between maximum value and minimum value is just 8.4 dBm.

V. EXPERIMENT RESULT

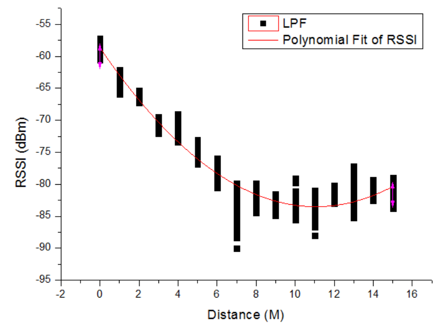
A. *Distance estimation comparision in EMC chamber*

We compare the distance estimation between the Bluetooth RSSI raw data and LPF data. The Bluetooth RSSI values are measured from 0m to 15m in EMC chamber.

Polynomial Regression (order 2) is used to estimate the distance as shown in Fig. 11. The R-square value of RSSI raw data is 0.867 and the standard deviation is shown in Fig. 12. The maximum value and the minimum value of standard deviation are 4.94 dBm and 1.26 dBm. The R-square value of RSSI LPF data is 0.958, which is better than R-square value of RSSI raw data significantly. The standard deviation is shown in Fig. 12. It shows also better result than those of RSSI raw data. The maximum value is 1.77 dBm and the minimum value is 0.36 dBm.



(a) Regression with RSSI raw data



(b) Regression with RSSI LPF data

Figure 11. Distance estimation comparision between RSSI raw data and LPF data in EMC chamber environment

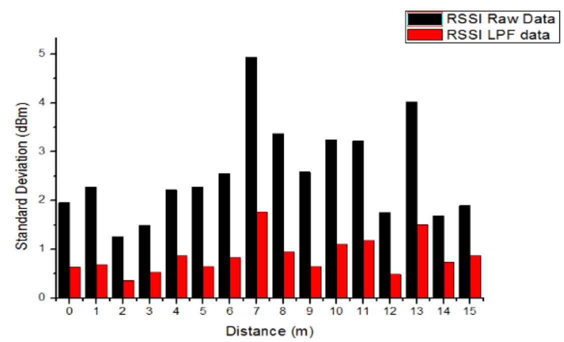


Figure 12. Standard deviation comparision between RSSI raw data and LPF data in EMC chamber environment

B. *Distance estimation application in meeting room*

One device is located in the meeting room statically and the other device is moved around inside and outside of the meeting room. The distance from 0m to 5m is inside of the meeting room and the distance from 6m to 10m is outside of the meeting room.

The standard deviation of RSSI value is too broad at each meter to estimate distance when the RSSI raw data are used, as shown in Fig. 13. So, we cannot distinguish between inside and outside of the meeting room.

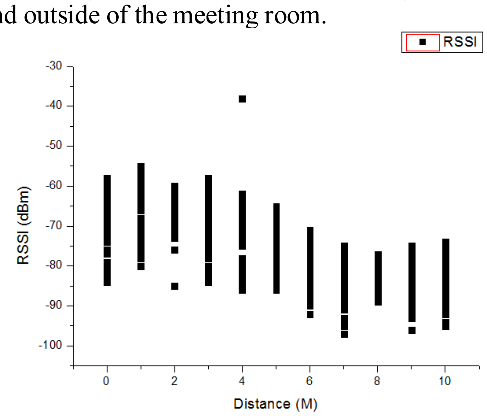


Figure 13. The RSSI raw data for distinguish between inside and outside of the meeting room

 ISBN: 978-1-61208-305-6

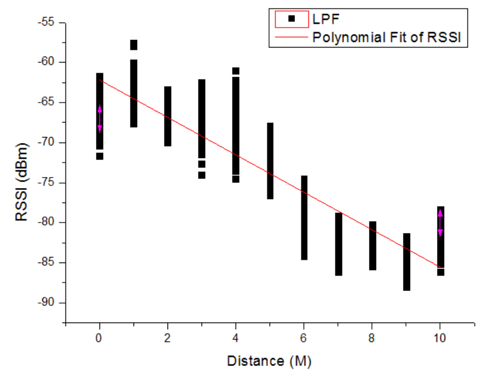


Figure 14. The RSSI LPF data for distinguish between inside and outside of the meeting room

The RSSI LPF data of the RSSI raw data are shown in Fig. 14 (α : 0.8). The R-square value is 0.838. The minimum RSSI value from 0m to 5m is -76.6dBm and the maximum RSSI value from 6m to 10m is -74.5dBm. The overlap region is only 2.1dBm. So, we can distinguish between inside and outside of the meeting room.

VI. CONCLUSION AND FUTURE WORK

This paper addressed the distance estimation method and distance characteristic of Bluetooth RSSI. The distance estimation is impossible with the RSSI raw and may be possible coarsely with the RSSI average data in indoor hall environment. In meeting room environment, it is hard to classify into inside and outside of the meeting room with the RSSI raw data and may be possible to classify into inside and outside of the meeting room with the RSSI average data. The RSSI value decreases linearly from 0m to 7m and has similar value from 7m to 15m in EMC chamber environment. This paper considers the LPF for reducing the measurement errors. The measurement errors are significantly reduced. We compare the distance estimation between the Bluetooth RSSI raw data and LPF data at EMC chamber environment. With RSSI raw data, the R-square value is 0.867 and the maximum standard deviation value is 4.94 dBm. With RSSI LPF data, the R-square value is 0.958 and the maximum standard deviation value is 1.77 dBm. The LPF data shows better result than RSSI raw data. However, LPF data need to be improved for estimating distance more exactly. So, we will design a new algorithm to estimate distance with Bluetooth RSSI.

ACKNOWLEDGMENT

This work was supported by the IT R&D program of MKE/KEIT, [K10041801, Zero Configuration Type Device Interaction Technology using Device Sociality between Heterogeneous Devices].

REFERENCES

[1] A. Awad, T. Frunzke, and F. Dressler, “Adaptive Distance Estimation and Localization in WSN using RSSI Measures,” 10th Euromicro Conference on Digital System Design Architectures, Methods and Tools, Aug. 2007, pp. 471-478.

[2] R. Want, A. Hopper, V. Falcao, and J. Gibbons., “The Active Badge Location System,” ACM Transactions on Information Systems, vol. 40, no. 1, Jan. 1992, pp. 91-102.

[3] N. B. Priyantha, A. Chakraborty, and H. Balakrishnan, “The Cricket Location-Support System,” Mobile Comp. and Networking, Aug. 2000, pp. 32–43.

[4] P. Enge and P. Misra, “Special Issue on GPS: The Global positioning System,” Proc. of the IEEE, vol. 87, no. 1, Jan. 1999, pp. 3-15.

[5] P. Bahl and V. N. Padmanabhan, "RADAR: An In-Building RF-based User Location and Tracking System," Proceedings of IEEE Infocom 2000, vol. 2, Mar. 2000, pp. 75-84.

[6] J. Hightower, C. Vakili, G. Borriello, and R. Want, "Design and Calibration of the SpotON Ad-Hoc Location Sensing System," University of Washington, Seattle, Technical Report UW CSE 01-08, Aug. 2001.

[7] K. Whitehouse and D. Culler, “Calibration as Parameter Estimation in Sensor Networks,” Wireless Sensor Networks and Apps., 2002, pp. 59-67.

[8] A. Savvides, C.-C. Han, and M. B. Strivastava, “Dynamic Fine-Grained Localization in Ad-Hoc Networks of Sensors,” 7th ACM/IEEE Int’l. Conf. Mobile Computing and Networking, Rome, Italy, 2001, pp. 166–179.

[9] T. He, C. Huang, B. M. Blum, J. A. Stankovic, and T. Abdelzaher, “Range-Free Localization Schemes for Large Scale Sensor Networks,” MobiCom ’03, ACM Press, 2003, pp. 81-95.

[10] J. Bachrach and C. Taylor, “Localization in Sensor Networks,” Handbook of Sensor Networks: Algorithms and Architectures, I. Stojmenovic, Ed., Wiley, Sept. 2005.

[11] S. Feldmann, K. Kyamakya, A. Zapater, and Z. Lue, “An indoor Bluetooth-based positioning system: concept, implementation and experimental evaluation,” International Conference on Wireless Networks, 2003, pp. 109–113.

[12] B. Hofmann-Wellenho, H. Lichtenegger, and J. Collins, “Global Positioning System: Theory and Practice,” Springer-Verlag, 1997.

[13] S. Schwarzer, M. Vossiek, M. Pichler, and A. Stelzer, “Precise Distance Measurement with IEEE 802.15.4 (ZigBee) Devices,” IEEE Radio and Wireless Symposium, Mar. 2008, pp. 779-782.

[14] N. B. Priyantha, A. K. L. Miu, H. Balakrishnan, and S. Teller, “The Cricket Compass for Context-Aware Mobile Applications,” 7th ACM Int’l. Conf. Mobile Computing and Networking, Jul. 2001, pp. 1-14.

[15] Y. Fu et al., “The Localization of Wireless Sensor Network Nodes Based on DSSS,” Electro/Infor. Tech., 2006 IEEE Int’l. Conf., May 2006, pp. 465–469.

[16] K. Whitehouse, “The Design of Calamari: An Ad Hoc Localization System for Sensor Networks,” Master’s thesis, UC Berkeley, 2002.

[17] Y. Fukuju, M. Minami, H. Morikawa, and T. Aoyama, “DOLPHIN: An Autonomous Indoor Positioning System in Ubiquitous Computing Environment,” Workshop on Software Technologies for Future Embedded and Ubiquitous Systems, 2003, pp. 53-56.

 ISBN: 978-1-61208-305-6