International Journal of Smart Home
Vol.10, No.10 (2016), pp.9-22
http://dx.doi.org/10.14257/ijsh.2016.10.10.02

Bluetooth-Tracing RSSI Sampling Method as Basic Technology of Indoor Localization for Smart Homes

Jun-Ho Huh[1]*, Yohan Bu[2]* and Kyungryong Seo*

[1]*Senior Research Engineer of SUNCOM Co.*
[2]*Developer & Manager, Gameberry Inc.*
** Dept. of Computer Engineering, Pukyong National University at Daeyeon*
72networks@pukyong.ac.kr, yhbu@stdc.so, krseo@pknu.ac.kr

Abstract

In recent years, smart homes have become the center of interest for IT companies and construction companies and various types of smart homes have been made currently available on the market. Yet, these equipment are costly and it is not easy to convert existing equipment for smart home application as they may require additional resources which could also inflict much costs. The extra costs involving the remodeling of existing housing structure and installment of new equipments can be avoided by using advanced wireless technologies. As an example, this paper proposes an indoor localization system that adopts Bluetooth technology and uses RSSI values for localization. Researchers have configured a system where the central control device will recognize all other devices or equipments in the system, communicate with each other, and respond to the commands or the information provided. However, despite the efforts of many researchers, existing RSSI-based indoor localization systems do not show a satisfactory level of accuracy such that we have devised a system that traces the trend in the RSSI samples. The RSSI sampling algorithm uses Delta values obtained from the Delta sampling process to improve system accuracy and to lower the costs. The analysis results led us to believe that our algorithm has a reduced localization error rate by 12%-point compared to the algorithm that used raw sampling method.

Keywords: *Bluetooth, RSSI, Smart Home, RSSI-based indoor localization system, Python*

1. Introduction

Like many other IT-advanced countries, smart homes are attracting more and more customers in recent years, with devices and equipment associated with Smart Homes continually increasing, presenting more convenient or novel functions. Contrary to such an environment, the cost of constructing or remodeling existing households to adapt smart functions is increasing as these works (*i.e.*, installing new equipments, setting up new systems and adding new functions) often involve time-consuming and costly operations. Such being the case, we have devised a system that can recognize the conditions of present household appliances, analyze the data and place appropriate commands, and initiate the movements according to them. Here, the 2 most important factors were 'Cost Saving' and 'Accuracy'. The former is related to reducing or avoiding additional device installments and the latter is associated with developing a better algorithm.

As an example of achieving these goals, we have designed an Indoor Localization System that displays a higher level of accuracy than GPS and other similar positioning systems by incorporating Bluetooth technology and RSSI-based algorithm without costly structural changes.

ISSN: 1975-4094 IJSH

Our system will pinpoint the target objects inside the household by triangulating the signals from the reference terminals (*e.g.*, beacons or other signal-generating devices). Figure 1, shows Bluetooth BLE-based location tracking. Bluetooth Low Energy (BLE) technology has been applied for the beacons considering energy efficiency.

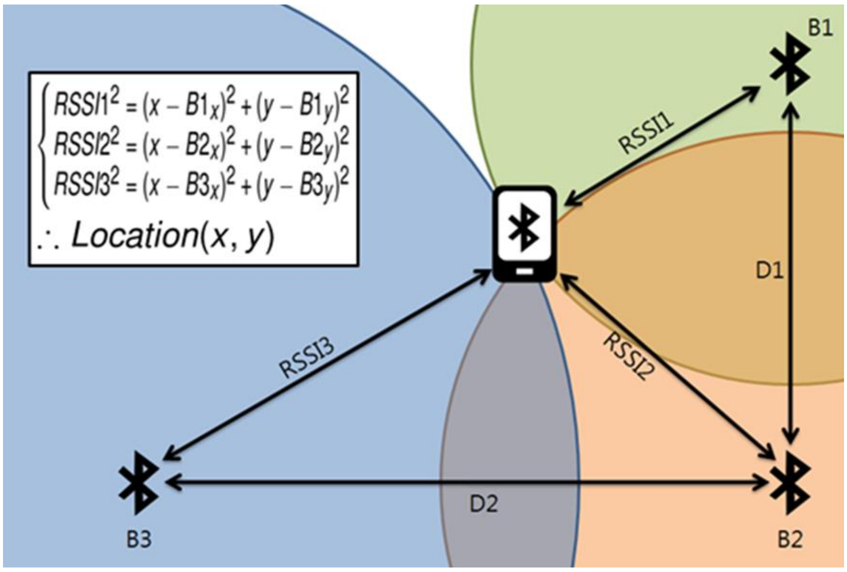

Figure 1. Bluetooth BLE-based Location Tracking

With Bluetooth technology, the intensity of signals and their unique identifiers can be distinguished and the position of a certain beacon can be identified through the relevant identifier. Additionally, the distance between the beacon and a fixed point can be estimated using RSSI so that by accumulating and analyzing such information from all of the beacons, the user's position can be approximated. Since most smart phones are embedded with Bluetooth function nowadays, one can avoid purchasing another one to use it as a measuring tool. There are some other products that have a similar function as Bluetooth but they often need to be calibrated with the smooth filter or field data such that they may not provide accurate data. To deal with this problem, we proposed an RSSI sampling method with a trend tracing function.

2. Related Research

2.1 iBeacon

The iBeacon is a wireless beacon protocol that has been proposed by Apple, Inc. It is built on the principle of BLE technology and designed to broadcast a beacon's information on a regular cycle to let the device to receive them and make decisions. The information to be broadcasted is listed in the following [Table.1].

Table 1. Information to be Broadcasting

Condition	Information
iBeacon Protocol Prefix	Indicating that the iBeacon protocol is in use
iBeacon UUID	Unique identifier of the installed beacon
Major Code	Major value (*e.g.*, main building) of the installed beacon
Minor Code	Minor value (*e.g.*, 1st lobby) of the installed beacon

Basically, iBeacon was designed and used for product arrangement guidance for offline shopping so that it included a function of measuring rough distances to a beacon using each beacon's RSSI. However, the measurements are classified into only 3 categories (*i.e.*, Close, Away, Far), and only the adjacent information of the relevant beacon is provided after establishing one-to-one relationship. Currently, many hardware companies manufacture and sell the beacons that follow iBeacon protocol.

2.2 Estimote

Estimote, Inc., is a company that supports hardware sales and carries out application service development for iBeacon. They provide the Software Development Kit (SDK), which facilitates information collection processes following the iBeacon standards, for iOS and Android and recently, they've announced a new SDK called 'the Indoor-SDK' that traces indoor position with iBeacons. However, it only supports iOS and provides basic equipments and SDK, not the application services. Additionally, it only traces and offers 2-dimensional information of indoor space.

2.3 Market Situation

A lot of companies are currently developing and selling the indoor positioning system, however, most of their products are based on the different types of technologies and even if they would use similar ones, the markets are still divided by using different types of standards so that the wider use of the solutions is limited, preventing market expansion. Also, there are no domestic companies specializing in this kind of service and most of the time, the similar service will only be developed by the SI development companies if there are any demands in the market. Under such environment, both the accumulation of technological know-how and standardization are far from realization and market growth is contracting in both the short and long terms. Therefore, it is essential to let users benefit from this technology through its standardization and introduction.

2.4 Comparison with Other Studies

The idea of using distance measured by RSSI-based method for indoor localization started early [1] and is still ongoing. Researchers try to improve accuracy by enhancing data processing [2]. However most of them had to recognize the uncertainty of RSSI [3]. For instance, they applied different types of smooth filters [4], complemented the system by using a network of multiple beacons [5] and so forth. While these studies prove to be effective for RSSI-based localization, they don't seem effective enough to produce higher-accuracy products. Thus, we need to further the study for RSSI-based localization technique.

3. Delta Trace Sampling for RSSI-Based Distance Estimation for Smart Homes

3.1 RSSI

The abbreviated term RSSI (Received Signal Strength Indication) refers to the value of the electrical power received by the wireless receivers. Since it describes the signal powers, both the antenna gain and the circuit loss are not considered. In most cases, the unit dBm, which indicates the gain and attenuation, is used.

3.2 Decibel

Equation (1) shows decibel. Decibel is a dimensionless relative system unit that indicates the ratio between a specific reference volume of A and measured volume of B. Below is a formula to calculate the decibel.

$$\mathrm{dB} = 10 * \log_{10}\left(\frac{\mathrm{B}}{\mathrm{A}}\right) \tag{1}$$

3.3 dBM

Although dB is the dimensionless unit, a reference value of A for the target medium should be set to be used in the engineering field. Thus, 0dBm is defined by setting the reception power that will incur 0dB as 1mW.

3.4 RSSI Model

Equation (2) represents the RSSI model [6].

- D : the distance(m) between signal transmission equipment and measuring equipment.
- $P_r(D)$: measured RSSI value on D
- $P_r(D_0)$: measured RSSI value (dBm) when D=1
- N : the signal attenuation constant. In an ideal condition, the number would be 2 but it can be amplified or attenuated depending on the radio environments.

$$\frac{P_r(D_0)}{P_r(D_0)} = \left(\frac{D}{D_0}\right)^n \tag{2}$$

3.5 RSSI-based Distance Estimation

Relation model between the distance and RSSI can be obtained from.

- OFFSET: $P_r(D_0)$
- RSSI: $P_r(D)$

$$D[m] = 10^{\left(\frac{OFFSET-RSSI}{10*N}\right)} \tag{3}$$

Calibration of OFFSET and N: Measure the RSSI value from 1m distance and designate the value as OFFSET. Next, measure the RSSI value again from a different distance and substitute it to the formula derived from above.

- OFFSET: RSSI value measured from 1m distance
- RSSI: the RSSI value currently measured
- D: the distance between the place of RSSI measurement and the equipment

$$N = \frac{OFFSET - RSSI}{10 * \log_{10}(D)} \tag{4}$$

3.6. RSSI Sampling

RSSI values show considerable fluctuations even in a static condition. This phenomenon is usually caused by multiple reasons such as signal interferences with other signals, unstable power level of transmitting equipments, current fluctuations during data transmission and the radio wave strength in surrounding environments. Thus, if the sample errors are not calibrated, exact calibration for the OFFSET or N will also be impossible, causing the problem of not being able to obtain an exact sample that will be used for the distance measurement

Smooth Filter: The simplest way to calibrate the errors for the samples is to perform smooth filtering for the samples.

However, since the smooth filter works targeting entire samples, it is easily affected by the changes in the RSSI values, which appear from the momentary signal distortions or other electromagnetic disturbances. For this reason, the margin of error will be larger so that the reliability of measurements themselves cannot be secured easily. Nevertheless, if it's possible to secure enough reliability, the smooth filter can be quite suitable for deducting a trend value among the measurements obtained. Thus, a new approach is needed to secure the reliability for the measured values. Since we will not be dealing with the smooth filters and relevant studies in the development research area, the range average calculation, which is the simplest form of smooth filtering, will be used.

Delta-based RSSI Sampling: The reason for the low reliability of measured RSSI values is that each measurement results in a different outcome even if the smooth filtering method has been applied because the range of fluctuation is too wide even in a static condition. Moreover, most of the results obtained from the smooth filtering showed that better accuracy can be achieved when more data samples are available. However, the process speed will be poor as it requires a longer time to measure the samples.

In this regard, we suggest using another sampling method in which only the effective samples will be collected comparing the deltas of measurement values from a small number of samples.

The basic idea of the delta-based sampling is that when the current measurement variations are excessively larger when compared to the recent trends, it will be most likely that the current value is an irregular sample extraneous to recent variation in the measurements.

Following this idea, an algorithm that identifies the effective samples by distinguishing them through checking the ratio (*i.e.*, proportion between the delta of current sample value and that of recent samples) that falls below a certain level, is described next. Smooth filter will be used to determine sample trend and for our algorithm, the range average will be used - the simplest smooth filtering method.

- SAMPLE_LIST: List of time-sequenced samples to be measured (size(SAMPLE_LIST) >= 2)
- SAMPLE: Currently measured sample
- THRESHOLD: Variation tolerance compared to the tendency (0 < THRESHOLD)

```
    var DELTA_LIST = new LIST;
for (var index = 0; index < size(ALL_LIST) - 2; index++)
var delta = ALL_LIST[index + 1] - ALL_LIST[index];
DELTA_LIST.add(delta);
end for
var averageDelta = average(DELTA_LIST);
var currentDelta = SAMPLE - ALL_LIST.last();
var deltaRatio = abs(currentDelta / averageDelta);
var effective;
if (deltaRatio < THRESHOLD)
```

effective = TRUE;
else
effective = FALSE;
return effective;

The merit of this algorithm is that we will be able to read off whether the next measurements would be included in the overall changing trend by determining the fluctuation tendency of the values obtained from a small-sized sample group of 20 or so.

Accordingly, even for the real-time measurements, it will be possible to seek out valid samples relatively exactly using recent available samples.

On the other hand, in cases wherein the size of the targeted SAMPLE_LIST is too large, or measuring interval for the samples is too long, one should pay particular attention to setting the size or range for these factors at the time of an actual implementation because there's a possibility of overlooking the fact that the trend may have changed for a short period of time and returned to normal afterwards.

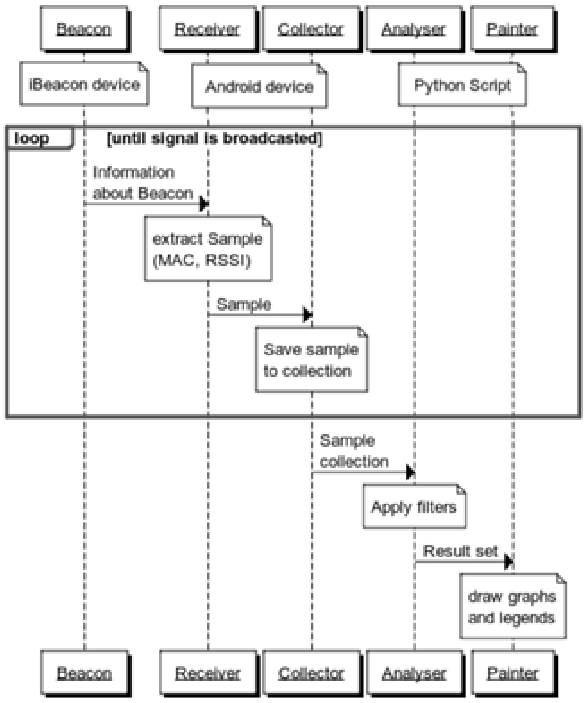

Figure 2. Sampling/Analysis Mechanism

Figure 2, shows the sampling/analysis mechanism. The process and the core algorithm are as follows:

Set A with the sequential RSSI values is,

$$S = \{s_1, s_2, \ldots, s_n\} \tag{5}$$

and, Set D, which consists of deltas between neighboring elements in the Set A, is defined as,

$$D = \{d_1 = 0, d_2 = s_2 - s_1, \ldots, d_n = s_n - s_{n-1}\} \tag{6}$$

Function T(n), which estimates the trend of elements in the Set D, is an arithmetic mean of the Set D.

$$T(n) = \frac{1}{n}\sum_{k=1}^{n} d_k \tag{7}$$

Then, when s_k has been provided, a Function R(s_k) that estimates the trend of s_k will be defined as,

$$R(s_k) = \frac{d_k}{T(k-1)} \tag{8}$$

When a random value R_{max} is given, a Function V(s_k) which determines the validity of s_k will be defined as,

$$V(s_k) = \begin{cases} False \Leftarrow R(s_k) < 0 \\ True \Leftarrow 0 \leq R(s_k) \leq R_{max} \\ False \Leftarrow R(s_k) > R_{max} \end{cases} \tag{9}$$

∵ Since the directions will be opposite when R (s_k) is negative, s_k does not coincide with the trend.

∵When 0 ≤ R(s_k) ≤ R_{max}, the directions of d_k and T(k) will be the same so that s_k coincides with the trend.

∵When R_{max} ≤ R(s_k),d_k and T(k) will bear the same direction but their variations differ much so that s_k does not coincide with the trend.

If n becomes large enough, the accuracy of the trend estimation T(n) will be decreased. Thus, the improved T(n) is defined as,

$$T'_n = \begin{cases} \frac{1}{n}\sum_{k=1}^{n} d_k \Leftarrow n \leq T_{count} \\ \frac{1}{T_{count}}\sum_{k=n-T_{count}}^{n} d_k \Leftarrow n > T_{count} \end{cases} \tag{10}$$

Here, T_{count} sets the random values that represent the number of elements used to estimate the trend. T'(n) is similar to the average-based smoothing filters.

4. Delta Trace Sampling for RSSI-Based Distance Estimation for Smart Homes

For the Android platform, we've test-implemented the above-mentioned algorithm by following its rules to perform sampling, distance measurement and calibration of N and OFFSET using a BLE device. For the embodied test system, a function of reading that the BLE device has moved more than a certain distance from the designated position has been added to check whether the variation measuring function is working properly.

Figure 3 shows TI CC2540 Module. A communication module manufactured with TI CC2540 (small BLE SoC) was used as a transmission device for the implementation.

Figure 3. TI CC2540 Module

Additionally, in order to measure the device's RSSI periodically, a firmware was compiled and installed on the ROM to broadcast information in accordance with the iBeacon standard.

Figure 4 shows a conceptual diagram for implementation. For the measurement, an application that registers/measures broadcasting information and RSSI by using an android device (phone) and that sends them to the server was developed. Both the server that collects/ stores the transmitted sample measured with the device and the Delta Sampling algorithm, which is to process stored data, were implemented using the Python Script.

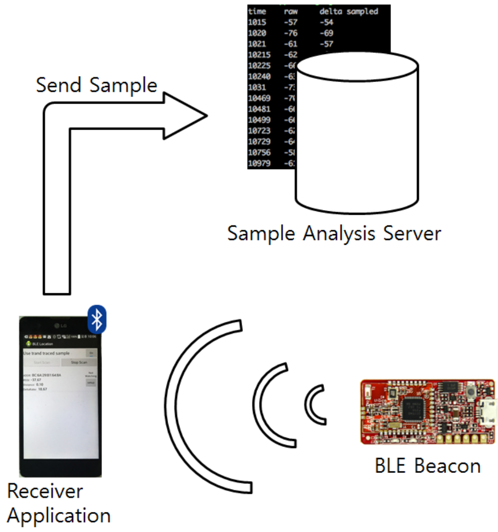

Figure 4. A Conceptual Diagram for Implementation

5. Performance Evaluation

5.1 Experiments

Figure 5 shows actual embodiment. For the measurement, a test was conducted by setting the range size and threshold as 20 and 7.5 (test-1), respectively following the small-scale preliminary test. During the test, collection of the RSSI samples every 100ms was conducted shifting the distance the range from 1m to 3m over 70 seconds. The test was repeated several times and the results were collected for the calculation. For the measurement, a test was conducted by setting the range size and threshold as 5 and 7, respectively following the small-scale preliminary test. During the test, RSSI samples were collected every 375ms. The test was repeated several times and the results were collected for the calculation.

We have two types of tests. In test-2, we collected 100 RSSI samples while the device was fixed at 3 meters from beacon. In the test-3, the RSSI samples were conducted shifting the distance the range from 1m to 3m over 30 seconds.

Figure 5. Actual Embodiment

5.2 Analysis

As shown in Figure 6, we were able to confirm that the range of fluctuation was more stable than the case of raw samples, which had shown a wide fluctuation range. From this result, we learned that finding the valid values with our algorithm is not only effective in correct sampling but also effective in extracting more precise data during the smoothing process. The result shows better performance levels than other available methods.

The Figure 6, shows the comparison of measurements collected with the raw sampling and Delta sampling methods. It can be observed that the range of fluctuation in the measurements collected with the Delta sampling method is more stable than that of the raw sampling method. The minimum and maximum values and their standard deviation obtained from the raw sampling were -90, -54 and approx. 5.95 respectively while they were -81, -57 and approx. 5.02 each from the Delta sampling. Thus, one can assume that the delta sampling collects a little more stable RSSI measurements compared to the raw sampling method.

Furthermore, if it's possible to find a suitable threshold depending on the usage environment through repetitive experiments, a higher degree of precision could be expected. Therefore, as a future work, we shall pursue experimental studies for an algorithm that is suitable for the trend estimation of raw data as well as finding an appropriate threshold for each different usage environment.

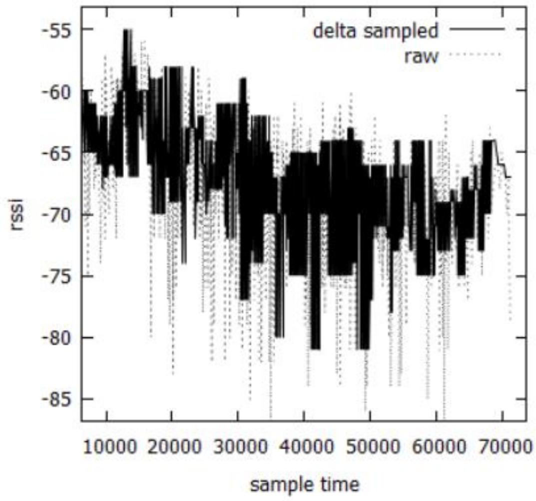

Figure 6. Comparison of Raw Sample and Delta based Sample (Test-1)

As shown in Figure 7, 8, we were able to confirm that the range of fluctuation was more stable than the case of raw samples, which had shown a wide fluctuation range. The Figure 7, 8, shows the comparison of measurements collected with the raw sampling and Delta sampling methods. It can be observed that the range of fluctuation in the measurements collected with the Delta sampling method is more stable than that of with the raw sampling method.

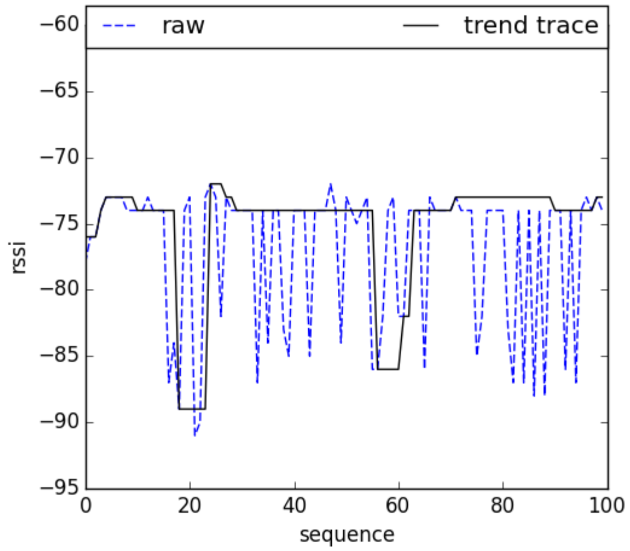

Figure. 7 Comparison of Raw Sample and Delta based Sample in the(Test-2)

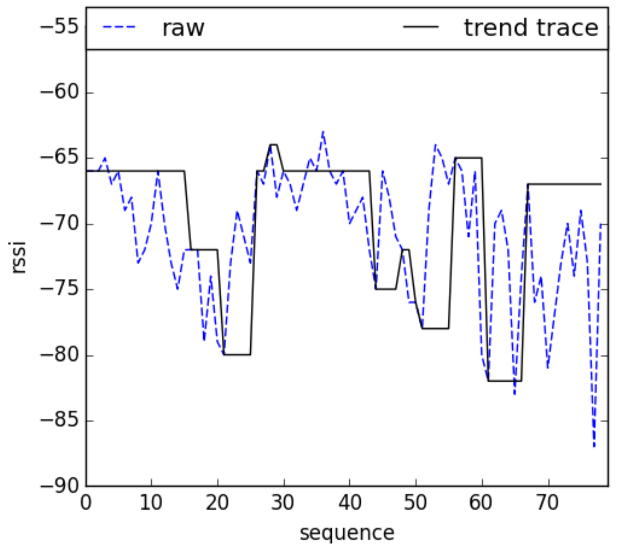

Figure 8. Comparison of Raw Sample and Delta based Sample in the (test-3)

Figure 9, 10 shows comparison of average smoothing filter, delta based trend trace sampling, and a combination of both methods. The graph is smoother than raw RSSI samples when using the average smoothing filter. However, the graph spiking, even though the values are decreasing, because it was exposed to an error of the RSSI samples, and it followed the trend. In other cases that used delta based trend tracing that combined with average smoothing, the graph is stable and less affected by the error.

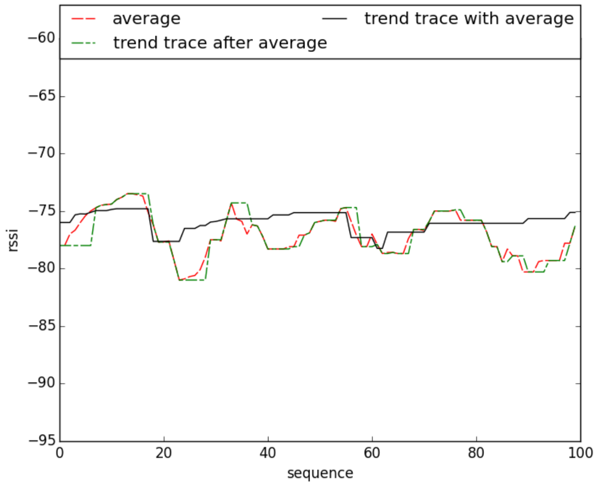

Figure 9. Comparison of Average Filter, Trend Tracing and MIX in the (Test-2)

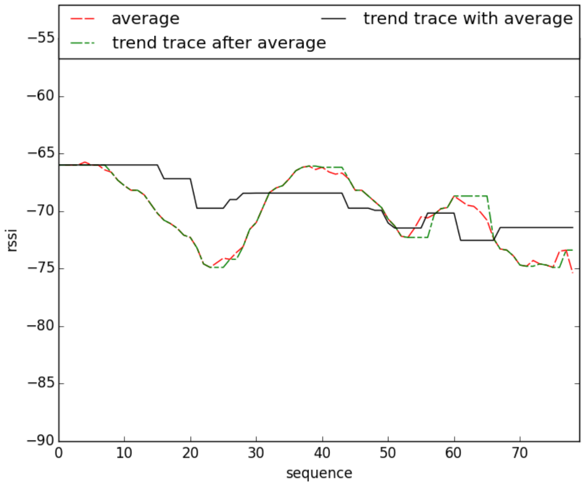

Figure 10. Comparison of Average Filter, Trend Tracing and MIX in the (Test-3)

In a last case that used delta-based trend tracing after average smoothing, it was not effective. From this result, we learned that finding the valid values with our algorithm is not only effective in correct sampling, but also effective in extracting more precise data during the smoothing process. The result shows better performance levels than other available methods when it was mixed with others.

6. Conclusion

Our experiment results have shown that the proposed algorithm was effective and efficient in extracting usable and valid samples in an RSSI data set but there were a few limitations. That is, to trace the trend, researchers used the range average algorithm, but it was clear that the measurements tended to depend on the sample sizes and the number of valid samples varied in each sampling rate or sampling environment. Moreover, a raid position shifting affects the measurement results so that the trend estimation becomes inaccurate. Another notable problem was that it was anticipated that when the threshold value in the experiment was too high, the noise would have more impacts on the result and when it was kept low, low accuracy could be expected.

Therefore, researchers plan to find a more sophisticated algorithm to improve the accuracy of the system in our future research to deal with these problems. While integrating the Delta-based RSSI sampling method with other complementary methods may improve the accuracy, proving its effectiveness in smart homes will require much work. Additionally, it is important to mention the BLE-exclusive devices. For example, researchers suggest that the beacons with CR2045-model batteries should be used for the experiments and in actual smart homes for their low power consumption nature and a long service life (1.8 ~ 28.7 months). In addition to this research, our future study will consider these 2 factors more seriously.

Lastly, our method can be applied to many other fields (*e.g.*, theft prevention, warehouse management, and etc.) as a base technology and we expect that we will be able to enhance it to deal with a more complex environment.

Acknowledgements

The first draft of this thesis was presented in 2015 at The 11th International Conference on Multimedia Information Technology and Applications (MITA 2015), June 30-July 2, 2015, Tashkent, Uzbekistan, IEEE Region 10, Changwon Section. The researchers are grateful to 5 anonymous commentators who have contributed to the enhancement of our thesis with their valuable suggestions at the conference.

References

[1] B. Nissanka, Priyantha., Anit Chakraborty., Hari Balakrishnan, The Cricket Location-Support System, In Proceedings of the 6th annual international conference on Mobile computing and networking, USA, **(2000)** pp. 32-43.

[2] A. Ault, E. Coyle, X. Zhong, "K-nearest-neighbor analysis of received signal strength distance estimation across environments", Proceedings of the First Workshop on Wireless Network Measurements, **(2005)**

[3] J. Joonyoung, D. Kang, C. Bae, "Distance Estimation of Smart Device using Bluetooth", The Eighth International Conference on Systems and Networks Communications, Italy, **(2013)** , pp. 13-18.

[4] Dong., Qian., Waltenegus Dargie., Evaluation of the Reliability of RSSI for Indoor Localization, IEEE International Conference, Clermont Ferrand, **(2012)** , pp. 1-6.

[5] Botta., Miroslav., Milan Simek., Adaptive distance estimation based on RSSI in 802.15 4 network, Radioengineering. vol. 22, No. 4, **(2013),** pp.1162- 1168.

[6] Jihoon Kang. Daeyoung Kim. Youngsoo Kim, RSS Self-calibration Protocol for WSN Localization, IEEE 2nd International Symposium on Wireless Pervasive Computing, **(2007)**, pp. 181-184.

[7] Kumareson. P., Rajasekar. R., Prakasam. P., Accurate Location Identification Using Bluetooth in Android Smartphone,"The International Daily journal, India, **(2015)**, pp. 81-86.

[8] J.-H. Huh., K. Seo., PLC-Based Smart grid Home Network System Design and Implementation using OPNET Simulation, Journal of Multimedia and Information Systems, **(2014)**, pp.113-120.

[9] J.-H. Huh., T. Koh., N.-J. Kim., K. Seo., Design and Test Bed Experiments of Smart Grid-based PLC Slient node problem Using OPNET, Proceedings of the 11th International Conference on Multimedia Information Technology and Applications (MITA 2015), Tashkent, Uzbekistan, IEEE Region 10, Changwon Section, (2015), pp. 317-322.

[10] Y. Bu., J.-H Huh, H., H. Jeong., K. Seo., Trend Trace RSSI Sampling as Basic Technology of Indoor Localization for IoT, Proceedings of the 11th International Conference on Multimedia Information Technology and Applications (MITA 2015), Tashkent, Uzbekistan, IEEE Region 10, Changwon Section, (2015), pp.153-157.

[11] J.-H. Huh., D. Lee., K. Seo., "Implementation of Graphic Based Network Intrusion Detection System for Server Operation", International Journal of Security and Its Applications, SERSC, vol. 9, no. 2, (2015), pp. 37-48.

[12] J.-H. Huh., K. Seo., Hybrid Advanced Metering Infrastructure Design for Micro Grid Using the Game Theory Model, International Journal of Software Engineering and Its Applications, SERSC, Vol. 9, No. 9 (2015), pp. 257-268

Authors

Jun-Ho Huh, He finished his Cooperative Marine Science and Engineering Program at the Texas A&M University at Galveston, United States of America in Aug. 2006.

He received B.S. in Science Degree from the Department of Major of Applied Marine Sciences (Marine Aquaculture, Oceanography, Marine Life Sciences), B.S. in Engineering Degree (Double Major) from Department of Major of Computer Engineering from Jeju National University at Ara, Jeju, Republic of Korea in Aug. 2007 and completion of the Secondary School (Middle and High schools) Teacher Training Curriculum in accordance with Republic of Korea Secondary Education Act.

He received his M.A. in Education Degree from Department of Major of Computer Science Education, Graduate School of Education, Pukyoug National University at Daeyeon, Busan, Republic of Korea in Aug. 2012 and completion of the Secondary School (Middle and High schools) Teacher Training Curriculum in accordance with Republic of Korea Secondary Education Act.

He fi=inished the Ph.D. Program in Computer Engineering, Graduate School, Pukyoug National University at Daeyeon, Busan, Republic of Korea in Aug. 2015.

He also received the Best Paper Award from Korea Multimedia Society thrice (Nov. 2014, May. 2015, Nov. 2015).

Currently, he is Senior Research Engineer of SUNCOM Co., Republic of Korea.

His research interests are Green IT, Smart Grid, Network Security, Curriculum of Computer, High Availability Computing.

Yohan Bu received his Bachelor of Engineering Degree from the Department of Major of Computer Engineering from Pukyoug National University at Daeyeon, Busan, Republic of Korea in Feb. 2016. From January 2014 to June 2015, he served as a Developer and Manager at Bobcat Studio. Currently, he is Developer & Manager at Gameberry Inc.

His research interests are Green IT, Network Security, Smart Home Device, High Availability Computing.

Kyungryong Seo received his B.S. in Engineering Degree from the Department of Major of Electrical Machinery Engineering from Pusan National University, Busan, Republic of Korea in Feb. 1983.

He received his M.S. in Degree in Electrical Engineering from Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Republic of Korea in Feb. 1990.

He received his Ph.D. Degree in Electrical Engineering from Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Republic of Korea in Aug. 1995.

Currently, he is a Full Professor (Tenure) of Computer Engineering Departments, Pukyong National University at Daeyeon, Busan, Republic of Korea. His research interests are High Speed Computer Network, Network Security, High Availability Computing.