

An Indoor Localization System Considering Channel Interference and the Reliability of the RSSI Measurement to Enhance Location Accuracy

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Abstract— An indoor localization system in wireless sensor networks has become a hot development area. Received signal strength indicator (RSSI)-based localization is a promising technique since it requires a relatively low configuration, battery power and easy control. However, the received signal strength is influenced by channel interference and propagation environments. This characteristic affects channel stability and location accuracy in RSSI-based localization. As a result, we propose a novel indoor localization system consisting of a pre-processing method and a post-processing method. To improve channel stability, the pre-processing method selects an optimal channel in terms of the smallest distance error. The optimal channel is less affected to IEEE 802.11. To develop location accuracy, the post-processing method performs maximum likelihood estimation-based location tracking scheme considering the reliability of the RSSI value measurement. We apply three methods to the existing MLE to improve the reliability of the RSSI value. By using this indoor localization system with pre-processing and post-processing, the location error can be reduced. We also proved the performance of the indoor localization system by conducting experiments in a real indoor environment.

Keywords— IEEE 802.15.4, Localization, IEEE 802.11, RSSI, Location Error, Channel Interference

I. INTRODUCTION

Wireless Sensor Networks (WSNs) offer a diverse range of applications in many fields including localization, health-care, environmental monitoring, military, and smart homes. However, the concept of designing and connecting many small and low cost devices leads to nodes in WSNs with limited processing and communication capabilities as well as limited memory and energy resources. Therefore, one of the main concerns in this area is to design and deploy highly reliable sensor networks with excellent energy efficiencies. To do so, there are several power saving protocols but the quality and stability of the wireless channels are also critical. In reality, most wireless networks including WSNs are deployed using the default or a random channel since most people assume that all channels in a standard have identical characteristics (reliability, signal strength, etc...). However, a defining characteristic of wireless communication is the varying signal strength as functions of time and frequency,

which leads to an unsteady radio signal strength with losses. Furthermore, the radio frequency (RF) wave is influenced by multiple factors such as interference, noise, multi-path, and shadowing. These factors affect the error rate, delay, and signal strength in the WSNs and therefore, the reliability and quality of the service. Consequently, it is necessary to have mechanisms to evaluate and measure the quality and stability of a wireless channel. Although there are numerous models available to theoretically predict the channel variations as functions of time and frequency, it is very difficult to develop an applicable model for accurately estimating and evaluating the reliability and characteristics of different channels in a wireless standard. As a result, experimentation can be considered as the most suitable method for measuring and evaluating the differences between channels in a wireless network.

Location-based service (LBS) is an area of particular interest for wireless networks. Global positioning systems (GPS) are an example of a location-based service and many GPS application programs include a location-based service. GPS has good accuracy in the outdoors, but has poor line of sight (LoS) accuracy indoors and localization is very poor. For this reason, indoor localization studies are in progress. IEEE 802.15.4 was intended to be the key enabler for a low complexity, ultra-low power consumption, and low data rate wireless connectivity among inexpensive fixed, portable, and moving devices.

The studies conducted involving indoor localization systems can be subdivided into two groups. One group includes studies of techniques to measure position. The other group includes studies of position accuracy improvements to optimize position coordinates. Triangulation, trilateration, fingerprint, and maximum likelihood estimation (MLE) are representative measurement techniques. Moving average filters, median filters, and Kalman filters are examples of methods used to improve the positioning accuracy.

Generally, the studies mentioned above use the received signal strength indicator (RSSI). Because additional devices are not needed for using the RSSI, the system design is relatively simple. However, IEEE 802.15.4 wireless sensor networks typically operate on the 2.4 GHz ISM band, which is

used by IEEE 802.11 (wireless LAN) networks as well. Overlap between the channels used by IEEE 802.15.4 and IEEE 802.11 networks may adversely impact the operation of IEEE 802.15.4 since it is a low power protocol with a low channel width compared to the transmitted power levels and channel width used by IEEE 802.11. For that reason, the measured value from every channel from a RSSI differs. In fact, some instances are impossible to measure. Therefore, the location accuracy of RSSI-based indoor localization systems decreases and is unstable.

In this paper, we propose a method to improve the positioning accuracy of an indoor localization system. This method considers channel interference and the reliability of the RSSI measurement. The indoor localization system consists of a pre-processing method and a post-processing method. The pre-processing method selects an optimal channel in terms of the smallest distance error. The post-processing method performs a maximum likelihood estimation (MLE)-based location tracking scheme considering the reliability of the RSSI measurement.

The remainder of this paper is organized as follows. First, we present related works in section 2. In sections 3 and 4, we propose the pre-processing and post-processing methods of the indoor localization system, respectively. In section 5, we analyse the performances of the pre-processing method and post-processing method. Finally, we conclude the paper in section 6.

II. RELATED WORK

This paper proposes a new indoor localization system. The proposed indoor localization system has two goals. First is developing channel stability of IEEE 802.15.4, second is improving location accuracy of indoor localization system.

Wireless sensor network is very useful and flexible but, on the other hand, it is also susceptible to noise, interference, multi-path, obstacles, among other problems. Because of the limited battery of sensor nodes, it is required that the radios transmit at very low power. Therefore, the effects of the above factors are more severe than in other wireless networks. Above all, the indoor localization system is most affected by the interference.

Some related papers investigate the performance of IEEE 802.15.4 considering channel interference [3] ~ [6]. In [3], some experimental researches about the characteristic of IEEE 802.15.4 channels in ISM band are performed. This paper shows that it is very difficult to predict the quality and stability of the different channels in sensor networks, as the environment conditions greatly and influence the network performance. Researchers in [4] investigate to what extent the positioning accuracy is affected by channel interference between access points. This paper analyzes how the positioning accuracy is affected in three different channel assignment schemes (ad-hoc, sequential, and orthogonal data). Chieh-Jan Mike Liang in [5] examines the interference patterns between ZigBee and WiFi networks at the bit-level granularity. He found the symmetric interference regions where the ZigBee signal is too weak to be detected by WiFi

senders. So, he proposes BuzzBuzz to mitigate WiFi interference through header and payload redundancy. Finally, Researches in [6] study degrading effects (Bluetooth, IEEE 802.11, microwave ovens and other devices) on IEEE 802.15.4 network installed in an industrial environment. They simulate the physical layer of the IEEE 802.15.4 and used their channel measurements from different industrial sites to choose a reasonable channel model to measure the link Packet Error Rate (PER).

These papers [3] ~ [6] are related to channel interference of IEEE 802.15.4. However, they don't consider each channel of IEEE 802.15.4. IEEE 802.15.4 has 26 channels (11 ~ 26). Each channel is influenced by various factors. The effects for each channel may be different. Pre-processing that we propose considers each channel of IEEE 802.15.4 to find an optimal channel. Many localization researches use maximum likelihood estimation (MLE) method [7] ~ [9]. In statistics, MLE is a method of estimating the parameters of a statistical model. The MLE-based localization algorithm uses a probability distribution to improve the location accuracy. Researchers in [7] propose a new MLE-based localization algorithm to improve performance. This algorithm includes four steps to estimate location, and doesn't require to any extra hardware and it has the less complexity and results the less RMSE (Root Mean Square Error) than the original MLE. Masahiro Takashima in [8] proposes a method considering a probabilistic model of wireless propagation characteristics in a real IEEE 802.15.4-based wireless sensor network environment, and the location of sensor node is estimated by MLE using the model. A method of position estimation by the MLE method is proposed on the basis of a probabilistic model of the wireless propagation characteristics in a real environment. Finally, based on the contaminant attenuation model, Researchers in [9] propose a wireless sensor network to estimate the plume source location in a sensor field using the MLE method and the Direct Triangulation method respectively. This paper analyzes the effects of the number of sensor nodes and noise on location accuracy.

Post-processing uses MLE method to improve location accuracy of indoor localization system, too. However, we consider the reliability of RSSI measurement. Because RSSI is source data for MLE method, our indoor localization system have high accuracy of location compared to existing MLE method.

III. PRE-PROCESSING OF AN INDOOR LOCALIZATION SYSTEM

IEEE 802.15.4 sensor networks typically operate in the 2.4 GHz ISM band, which is used by popular IEEE 802.11 (wireless LAN) networks as well. An overlap between the channels used by IEEE 802.15.4 and IEEE 802.11 networks may adversely impact the operation of IEEE 802.15.4 since it is a low power protocol with a low channel width compared to the transmitted power levels and channel width used by IEEE 802.11. If the localization system uses the overlapped channel between IEEE 802.15.4 and IEEE 802.11, channel interference will be occurred.

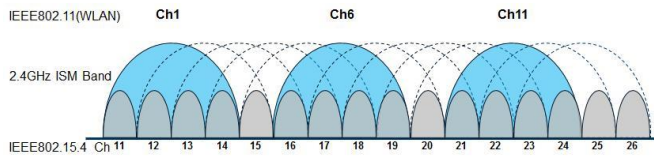


Figure 1. IEEE 802.15.4 and IEEE 802.11 channels in the 2.4 GHz ISM band

Fig. 1 represents IEEE 802.15.4 and IEEE 802.11 channels in the 2.4GHz ISM band. IEEE 802.11 channel 1 uses the same frequency band as IEEE 802.15.4 channel 11, 12, 13, and 14. If the RSSI value between the IEEE 802.15.4-based sensor nodes is measured in environments with various IEEE 802.11 APs (Access Point), the RSSI value will be measured differently for each channel.

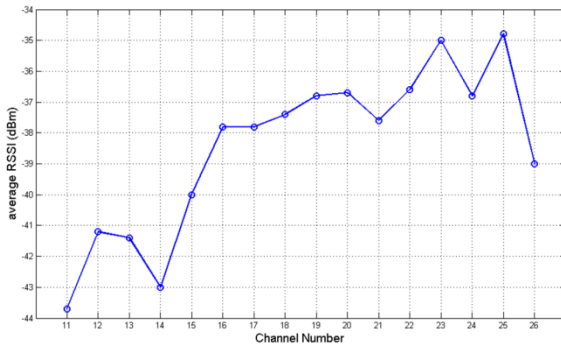


Figure 2. RSSI value for each channel measured indoors

Fig. 2 shows the average RSSI values for each channel of an IEEE 802.15.4-based sensor node in an environment containing various IEEE 802.11 APs. 5,000 RSSI values were measured for each channel and the average values were calculated. The distance between the reference node and sink node is the same, but the average RSSI values were different (the reference node transmits packets and the sink node receives packets). The maximum difference of the average RSSI values was approximately 10 dBm.

Also, the channel is generally time-varying. However, we think that if surrounding environments (indoor, the number of IEEE 802.11 AP, distance between two sensor nodes, no obstacles) are identical, the estimated RSSI value in the same channel is similar. Generally, the location of installed IEEE 802.11 AP is not changed, and the distance between sensor nodes of indoor localization system is not altered. Therefore, we think the surrounding environments of indoor localization system are almost identical. To study the variation of signal strength over time in different channels of IEEE 802.15.4 based sensor networks, a continuous experiment over 24h was performed. In this experiment, the sensor network switched to new channel every 10 min, which means that each channel was measured nine times ($t_1 \dots t_9$).

Fig. 3 shows the temporal variation of signal strength for each channel at different periods. The RSSI value at each period is the mean of the measurements over 10 min. As we can see, channel 19 has a greater variation than others. The other way, most of the channels have less variation. The

varying behavior of the received signal strength over time shows that the reliability of the most channels is stable.

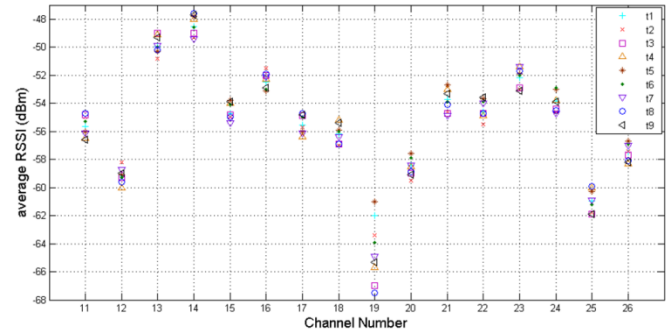


Figure 3. Time varying of RSSI value indoor environment

If a RSSI-based indoor localization system is operated in environments with various IEEE 802.11 APs, the performance of the RSSI-based indoor localization system can be different for each channel. So, an optimal channel selection process is needed before operating the RSSI-based indoor localization system.

In this paper, we propose a pre-processing method that utilizes the difference between the actual distance and the measured distance for each channel before operating the RSSI-based indoor localization system.

Fig. 4 presents a block diagram of the procedure of pre-processing method. First, the RSSI measurement between a reference node and sink node is performed for each channel (Ch11~26). This measurement is conducted at various distances (1m, 2m, and 5 m). Also, various IEEE 802.11 APs operate near the test environments. The IEEE 802.11 APs use different channels (Ch1~11). Second, the parameter calculation is performed to obtain the distance between the reference node and sink node. The parameter A is the received signal strength at a distance of one meter. And the parameter n is the signal propagation constant, which is also referred to as the path loss exponent. Third, the distance error calculation between the actual distance and measured distance is conducted. Finally, the optimal channel selection process is performed. The optimal channel is the channel resulting in the smallest distance error.

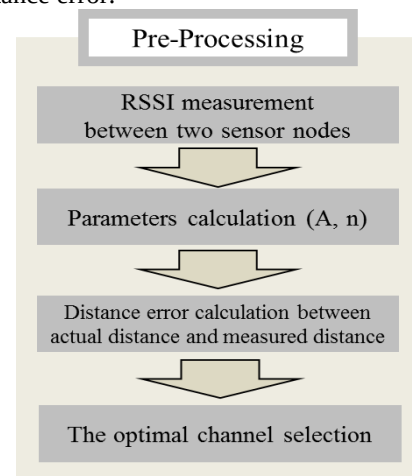


Figure 4. Block diagram of the pre-processing method

A. Parameters Calculation

The calculation of the parameters is performed after the RSSI measurement process. The parameters are the elements that are needed when translating a RSSI value into a distance where the elements are 'A' and 'n'. The parameter A is an empirical parameter which is determined by measuring the RSSI value one meter from the transmitting unit. The parameter n is a parameter that describes how the signal strength decreases when the distance from the transmitter increases. The relationship of the distance between the reference node and sink node and the associated RSSI value can be expressed as follows.

$$\text{RSSI} = -(10 \times n \times \log_{10} d + A) \quad (1)$$

CC2431 data sheet includes equation (1) [10]. We use CC2420 RF as a transmitter-receiver for performance evaluation. However, CC2431 uses CC2420 RF too, so we can use equation (1).

The parameters A and n are calculated for each channel because the parameters differ depending on measurement channel environments. The parameter A can be obtained by calculating the average RSSI value for a sensor node as follows,

$$A = -\frac{\sum_{k=1}^m x_k}{m} \quad (2)$$

where x_k is the measured RSSI value and m is the sample number.

The distance between the reference node and sink node can be varied within a meter. The measured RSSI value is then used to determine the parameter n. The parameter n is calculated by substituting the measured RSSI value and the parameter A is calculated using equation (2) into equation (3).

$$n = \frac{-(mA + \sum_{k=1}^m x_k)}{10m \log_{10} d} \quad (3)$$

In this way, the parameter n is calculated for each of the 16 channels (Ch 11~26).

B. Optimal Channel Selection

The optimal channel in the pre-processing method is the channel with the smallest distance error compared to the measured distance between the reference node and sink node and the actual distance. The measured distance is calculated by using the predetermined parameters (A, n) and the difference between the measured distance and the actual distance. Finally, the channel with the smallest distance error is selected. The distance between the reference node and sink node can be determined as the following.

$$d = 10^{-\frac{x_k + A}{10n}} \quad (4)$$

The difference between the measured distance and the actual distance can be expressed as

$$E = \frac{\sum_{k=1}^a |d - r|}{a} \quad (5)$$

where a is the sample number and r is the actual distance.

IV. POST-PROCESSING OF THE INDOOR LOCALIZATION SYSTEM

In this section, we discuss post-processing of the indoor localization system to improve the location accuracy. Post-processing refers to the process used to estimate the location of a mobile node. Generally, the received signal strength varies with distance in wireless sensor networks (Fig. 5). This received signal strength is changed because of the transmission power, the antenna of the transmitter-receiver, and environments factors. We assumed a fixed transmission power and used the Omni-antenna beacon mode, in which the reference node periodically sends a beacon message to the mobile node. Therefore, the reference nodes transmit beacon messages to a mobile node and measure the received signal strength using the received beacon messages. The method used to estimate the location varies. The most popular methods of location are the angle of arrival (AoA), time of arrival (ToA), time difference of arrival (TDoA), trilateration, triangulation, and maximum likelihood estimation (MLE) [11], [12].

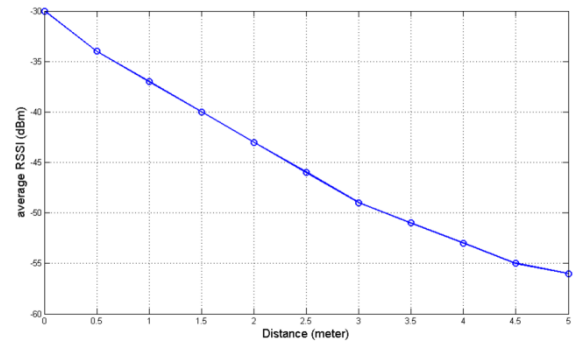


Figure 5. RSSI versus Distance

In statistics, MLE is a method of estimating the parameters of a statistical model. When applied to a data set and given a statistical model, the MLE provides estimates of the model's parameters.

The MLE-based localization algorithm uses a probability distribution to improve the location accuracy. Fig. 6 represents a probability distribution of MLE. If a distance between reference node and mobile node is estimated 5m, Gaussian distribution has the highest probability at 5m.

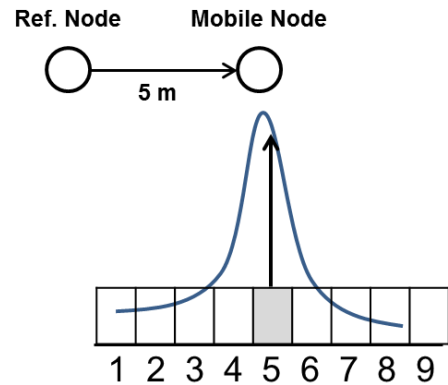


Figure 6. MLE-based localization algorithm (probability distribution)

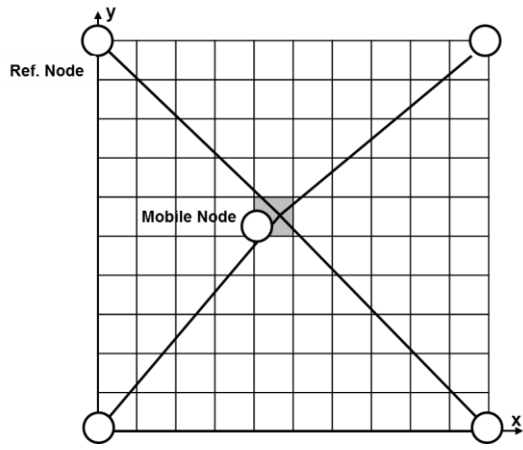


Figure 7. MLE-based localization algorithm (location estimation)

Fig. 7 shows how the location of mobile node is estimated using MLE method. The MLE-based localization algorithm uses a probability distribution to improve the location accuracy. The MLE-based localization algorithm divides a region into many cells and finds the cell with the highest probability of the mobile node being located.

$$p(s_i|\theta_j) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-(x - \mu)^2}{2\sigma^2}\right) \quad (6)$$

In equation (6), $p(s_i|\theta_j)$ is probability of blind node being located at j -th cell in a view of reference node i . x is estimated RSSI value at distance of sender to a cell. μ is measured RSSI value at receiver. σ is variance of RSSI measurements.

$$\mathcal{L}(\theta_j) = \prod_{i=1}^m p(s_i|\theta_j) \dots \quad (7)$$

In equation (7), $\mathcal{L}(\theta_j)$ is probability of blind node being located at j -th cell, and m is the number of reference node.

In this study, the post-processing is based on the maximum likelihood estimation because if the number of reference nodes is changed, the method to estimate the location almost isn't changed. So, we applied the following three methods to the existing maximum likelihood estimation.

(1) Method 1: Learning-based direction path loss exponent method.

(2) Method 2: The weight method using variation of the RSSI value.

(3) Method 3: The weight method considering the possible moving area.

Fig. 8 shows the block diagram of the procedure of the post-processing method. The three methods are applied at different stages. The collected direction loss coefficient based on learning is set up before operating the indoor localization system. In the next stage, a probability distribution is generated using the RSSI value between the reference node and the mobile node. Finally, the possible moving area of the mobile node is applied because the indoor localization system has to consider the mobility of the mobile node.

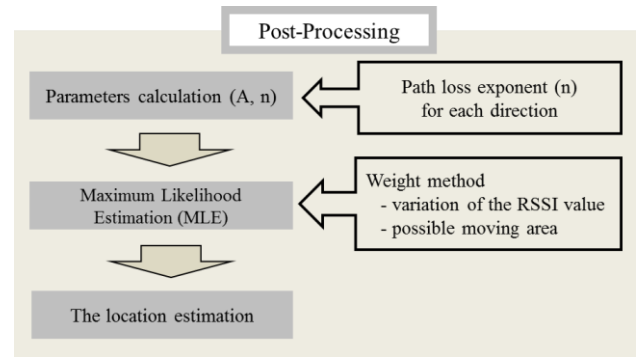


Figure 8. Block diagram of the post-processing method

A. Learning-based direction path loss exponent method

Here, the reference nodes have to consider the wall because the reference nodes are mounted on the wall. The location of wall is fixed and the wall weakens the signal strength. Also, the received signal strength varies according to direction of sensor node because the performance of the sensor node differs depending on the direction of the antenna. Fig. 9 shows path loss exponent for each direction (1°). Because of various obstacles (e.g. tables, wall, etc.), path loss exponent varies for each direction.

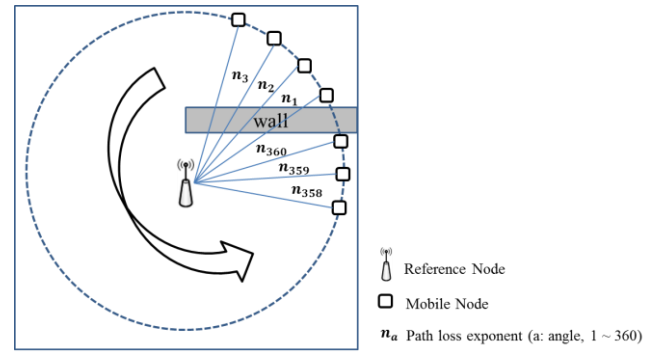


Figure 9. Path loss exponent considering obstacles

First stage in the post-processing method, the mobile node learns path loss exponent for each direction. Path loss exponent is influenced by the received signal strength. Path loss exponent is important factor to estimate distance between the reference node and mobile node. We first measured path loss exponent for each direction before operating post-processing. And the mobile node stores 360 path loss exponents, angles, distance and the received signal strength. In general, if there is no obstacles, path loss exponent is 2.5. However, if there is obstacle between the reference node and the mobile node, path loss exponent can be changed. This method improves location accuracy of mobile node by considering obstacles. Path loss exponent can be calculated by equation (3).

$$D = \sqrt{(Ref_x - M_x)^2 + (Ref_y - M_y)^2} \quad (8)$$

$$X = Ref_x - M_x, Y = Ref_y - M_y$$

$$\left\{ \begin{array}{l} \text{if}(X > 0) \\ \quad \angle = 180 + \text{Atan}\left(\frac{Y}{X}\right) \\ \text{if}(X < 0) \\ \quad \angle = \text{Atan}\left(\frac{Y}{X}\right) \\ \text{if}(X = 0) \\ \quad \angle = 180 + (\text{Sin}(Y) * 90) \end{array} \right.$$

Equation (8) shows the expression of the angle between the reference node and mobile node where Ref_x and Ref_y refer to the x and y coordinates of the reference node, respectively, and M_x and M_y refer to the x and y coordinates of the mobile node, respectively. To utilize this method, the indoor localization system knows path loss exponent of mobile node for each direction, and angle between the reference node and the mobile node.

B. The weight method using variation of the RSSI value

First a probability distribution is generated using the signal strength before applying the weight. RSSI value variation depending on the distance is used to generate the probability distribution. The post-processing of the indoor localization system calculates the distance between the mobile node and reference node using the received signal strength of the mobile node. Also, the indoor localization system generates a circle with a radius equal to the calculated distance, centered on the location of the reference node.

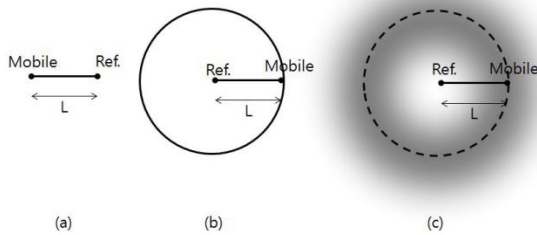


Figure 10. Probability distribution generation

Fig. 10 represents the probability distribution of the mobile node. The arc of the circle represents the highest probability of the mobile node being located. The area of the highest dark shadow means the highest probability of the mobile node being located.

The received signal strength of the reference node is different even if the transmission power of the reference node is same because obstacles affect communication between the reference node and the mobile node. Therefore, a mobile node continuously stores the received signal strength and calculates its standard deviation. The standard deviation corresponds to the reliability of the measured RSSI values. If the standard deviation of the received signal strength is small, the reliability of the measure RSSI values high. On the other hand, if the standard deviation of the received signal strength is large, the reliability of the measure RSSI values is low.

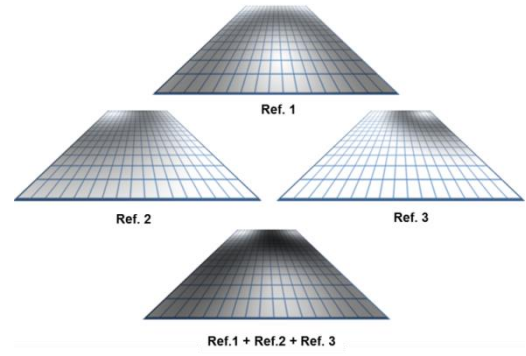


Figure 11. Probability distribution accumulation

$$S = \sqrt{\frac{\sum_{i=0}^t (d_i - m)^2}{t}} \quad (9)$$

In equation (9), S is the standard deviation of the RSSI value of the reference node, d_i is the RSSI value, t is the number of the collected RSSI value (In this paper, t value is 10), and m is the average of the RSSI values.

$$\mathcal{N}(\theta_j) = \prod_{i=1}^m (p(s_i|\theta_j) \times S_r) \quad (10)$$

In equation (10), $\mathcal{N}(\theta_j)$ is the value of S applied to $p(s_i|\theta_j)$. $p(s_i|\theta_j)$ is probability of blind node being located at j -th cell in a view of reference node i (cf. equation(9)), and r is the number of reference node.

$$\vartheta = \text{argmax } \mathcal{N}(\theta_j) \quad (11)$$

ϑ refers to the cell with the highest probability of the mobile node being located.

C. The weight method considering the possible moving area

The indoor localization system estimates the location of the mobile node. So, the indoor localization system has to consider the mobility of the mobile node. Fig. 12 shows possible moving area of mobile node. If we can know speed of the mobile node, we can predict possible moving area of the mobile node.

The indoor localization system can calculate the possible moving area of a mobile node for a period time. The indoor localization system gives weight to the cell including the possible moving area and then, the indoor localization system can reduce the location error. In this paper, a packet is transmitted one per 0.1 second, and speed of mobile node is approximately 1m/s. So, the indoor localization system can predict possible moving area of mobile node considering time and speed of mobile node.

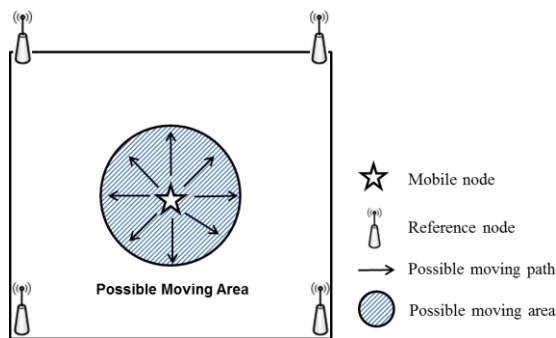


Figure 12. Possible moving area of mobile node

V. PERFORMANCE EVALUATION

A. Pre-processing of indoor localization system

The pre-processing test was performed in a building with many IEEE 802.11 WLAN APs. The test bed environment chooses TelosB affiliation as the platform for the sensor network and the wireless module uses CC2420 RF as a transmitter-receiver. The microprocessor used is the sensor node loading MSP430 (8 MHz) from Texas Instruments (TI). The network size of the test bed is 5 m x 5 m.

Fig. 13 represents the environment of pre-processing test. There are two kinds of sensor nodes. One is a reference node, which transmits a packet once per 0.1 second. The transmission power of the reference node is set to 0 dBm in the experiments. The other kind is a sink node, which is like a base station node. This node receives a packet from a reference node and transmits the packet to a task manager PC. The sink node is connected to a task manager PC in order to collect and record the packet for analysis. The task manager PC measures the RSSI value using the received packets.

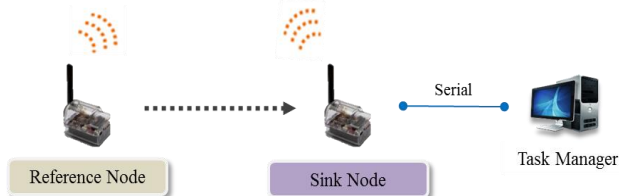


Figure 13. Pre-processing test set up

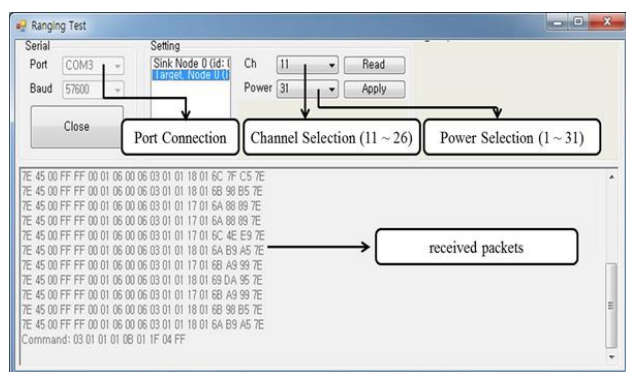


Figure 14. Task manager UI

Fig. 14 shows the test UI that runs on the task manager PC. The target node means a reference node. The sink node and

task manager PC are connected by a serial cable. The connection is confirmed by the 'Port' combo box. The channel of the sensor nodes is selected by a 'ch' combo box. Also, the transmission power of the reference node can be selected by a 'power' combo box. However, we set the 'power'.

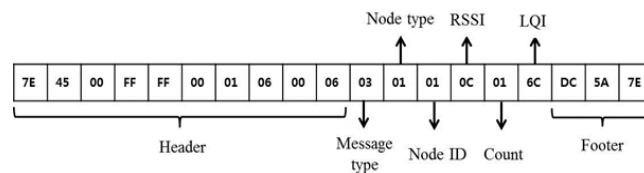


Figure 15. Packet format

Fig. 15 represents the format of a received packet. The total size of the packet is 19 bytes where the header size is 10 bytes, the footer size is 3 bytes, and the payload size is 6 bytes. The payload is comprised of Message type, Node type, Node ID, RSSI, Count, and LQI where each field size is a byte.

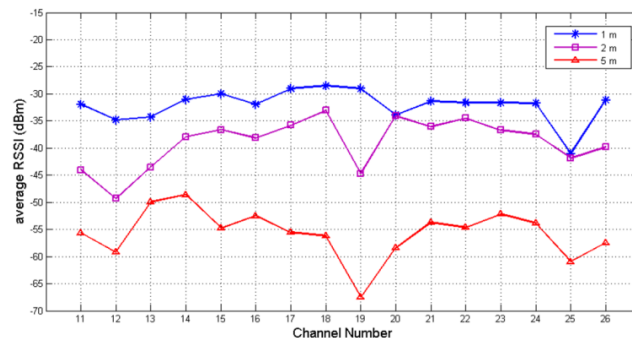


Figure 16. RSSI value for each channel indoor at distances of 1, 2, and 5m

Fig. 16 shows the average RSSI value for each channel indoors at distances of 1m, 2m, and 5m. First, the parameter A, which is an empirical parameter, can be determined by measuring the RSSI value 1-meter from the reference node (equation 2). Second, the parameter n, which is also an empirical parameter, can be determined by measuring the RSSI value 2-meter from the reference node (equation 3). Table 1 represents parameter A and n for each channel.

TABLE 1. PARAMETERS A AND N FOR EACH CHANNEL

Ch	11	12	13	14	15	16	17	18
A	-31.9	-34.7	-34.2	-31.0	-30.0	-31.9	-29.0	-28.4
n	4.7	5.2	4.8	4.2	4.1	4.3	4.0	3.8
Ch	19	20	21	22	23	24	25	26
A	-29.0	-33.8	-31.3	-31.6	-31.6	-31.7	-41.0	-31.1
n	4.5	4.2	4.1	4.1	4.2	4.2	5.1	4.4

Finally, the distance error is calculated using the RSSI value with a distance of 5 m to select the optimal channel (equations 4 and 5). The distance error refers to the difference between the measured distance and actual distance. The optimal channel is the channel with the smallest distance error.

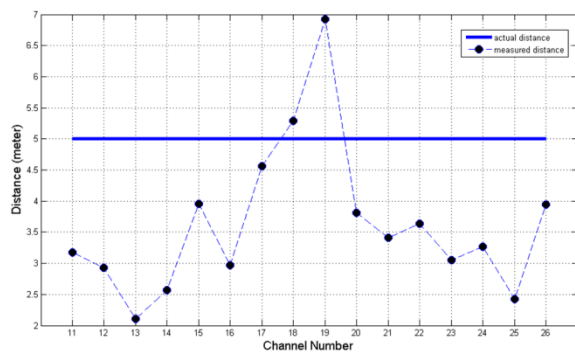


Figure 17. Comparison of the actual and measured distances

Fig. 17 shows the comparison of the actual and measured distances.

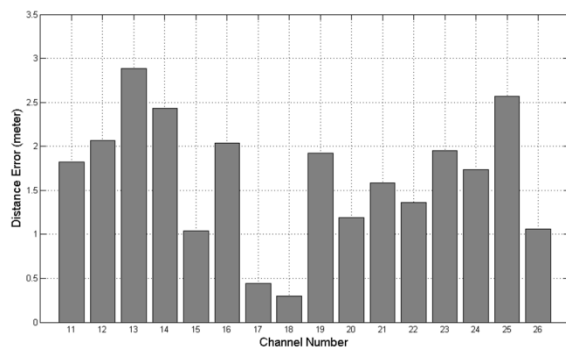


Figure 18. The distance error for each channel

Fig. 18 shows the distance error for each channel. As can be seen in Fig. 17, the RSSI-based distance error differs from channel to channel. The largest distance error is 2.9 m (channel 13) and the smallest distance error is 0.3 m (channel 18). Therefore, the optimal channel is channel 18.

B. Post-processing of the indoor localization system

The post-processing test environments are similar to those of the pre-processing method. The post-processing test was performed in a building with many IEEE 802.11 WLAN APs. The test bed environment chooses TelosB affiliation as the platform for the sensor network and the wireless module uses CC2420 RF as a transmitter-receiver. The microprocessor used is the sensor node loading MSP430 (8 MHz) from Texas Instruments (TI) and the network size of the test bed was 5 m x 5 m.

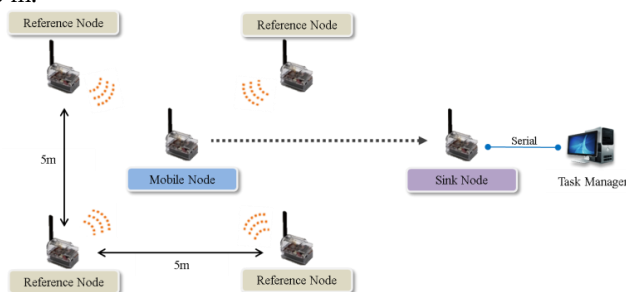


Figure 19. Post-processing test set-up

Fig. 19 shows a representation of the experimental environment. The distance between the reference nodes is 5 m. There are obstacles present such as a wall, chairs, tables, and an experimenter. Also, we used channel 18 of IEEE 802.15.4 because channel 18 was selected by the pre-processing method.

We developed a test UI program based on C# to confirm the performance of the proposed post-processing of the indoor localization system. This program is shown in Fig. 20.

The three proposed methods were applied to this test UI program. The post-processing is based on the maximum likelihood estimation. We compared the trilateration method, existing MLE method and MLE-based post-processing. We also tested the localization of a fixed mobile node and a mobile node.

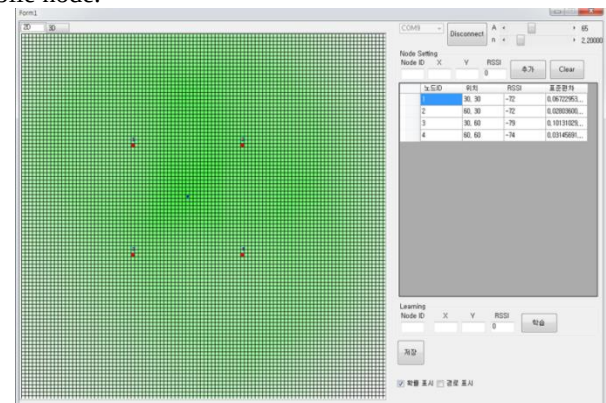


Figure 20. Test UI program

Fig. 21 shows the comparison of the localization of trilateration, the existing MLE and post-processing techniques (fixed mobile node). The mobile node is placed on a table, and the location of fixed mobile node is estimated for 10 seconds. As displayed in Fig. 21, the location accuracy of the post-processing method is higher than that of trilateration and the existing MLE. Fig. 22 shows the comparison of the localization of trilateration, the existing MLE and post-processing methods (straight movement). A person holding the mobile node moves straight. The task manager UI estimates the location of mobile node and displays it. As shown in Fig. 22, the location accuracy of the post-processing method is higher than that of trilateration and the existing MLE. In trilateration method, because it doesn't consider anything (obstacles, reliability of RSSI value, etc.), the location error of mobile node is very high. Fig. 23 shows the comparison of the localization of the existing MLE and post-processing methods (square movement). A person holding the mobile node moves square. The task manager UI estimates the location of mobile node and displays it. As seen in Fig. 23, the location accuracy of the post-processing process is higher than that of the existing MLE.

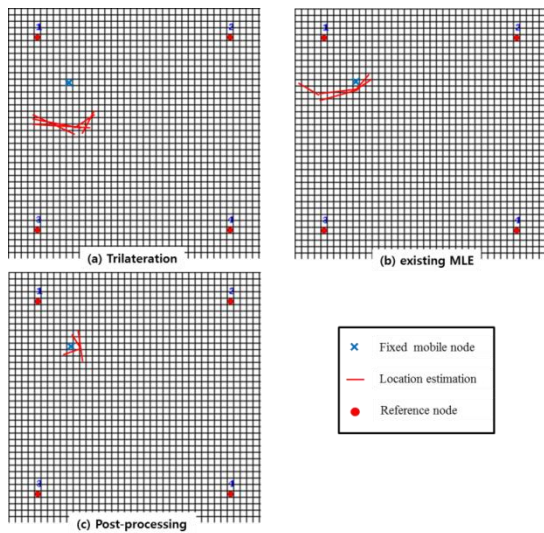


Figure 21. Localization comparison of trilateration, existing MLE, and post-processing (fixed location)

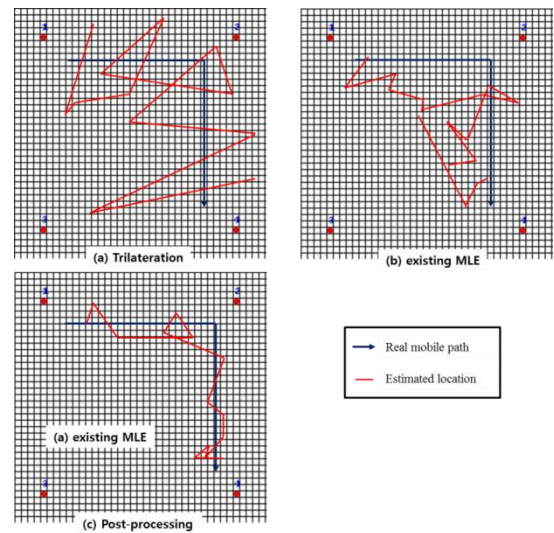


Figure 23. Localization comparison of trilateration, existing MLE, and post-processing (square movement)

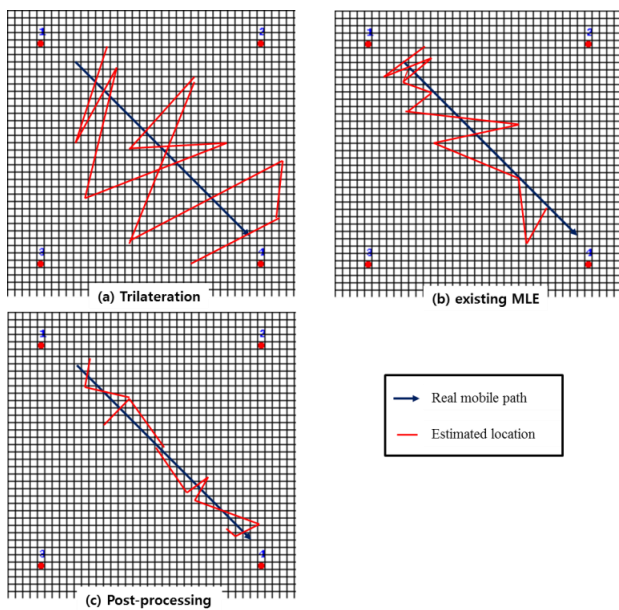


Figure 22. Localization comparison of trilateration, existing MLE, and post-processing (straight movement)

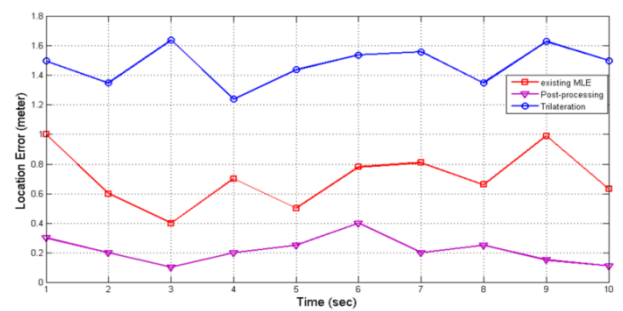


Figure 24. Comparison of the location error with the trilateration and the existing MLE (fixed location)

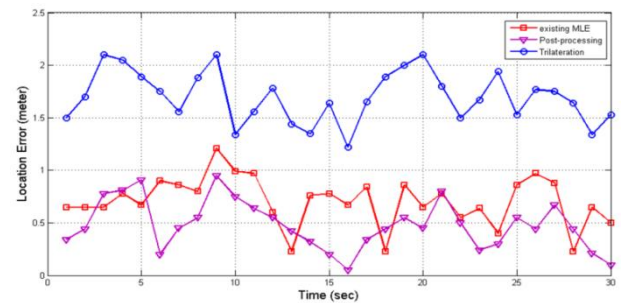


Figure 25. Comparison of the location error with the trilateration and the existing MLE (straight movement)

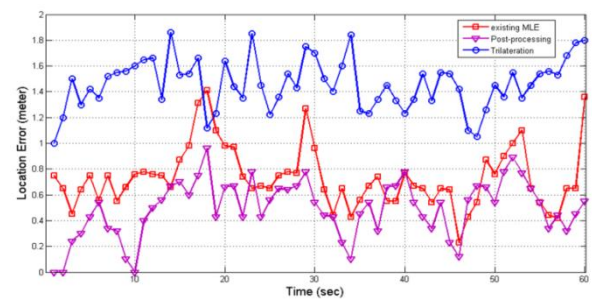


Figure 26. Comparison of the location error with the trilateration and the existing MLE (square movement)

Fig. 24, 25, and 26 show comparisons of the location error with trilateration and the existing MLE method. In all cases (fixed, straight, square), the location error of trilateration method is higher than other methods. As shown in Fig. 24, 25, and 26, we can conclude that the location error of our post-processing technique is lower than that obtained from trilateration and the existing MLE.

Fig. 27 shows the comparison of the location errors obtained using our method with trilateration and the existing MLE in each situation (fixed location / straight movement / square movement). In the fixed location situation, the location error of localization using pre-processing and post-processing method is smaller than localization using trilateration (approximately 1.505m) and the existing MLE (approximately 0.49m).

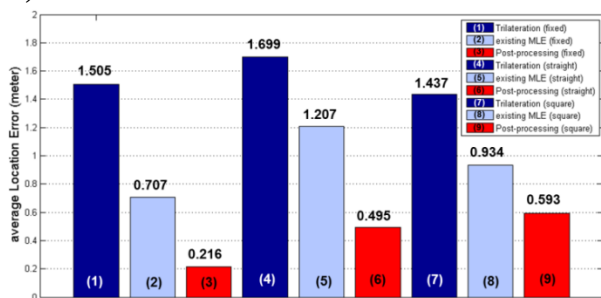


Figure 27. Comparison of the location error with the trilateration and the existing MLE (fixed/straight/square movement)

In the straight movement situation, the location error of localization using proposed indoor localization system is smaller than localization using trilateration (approximately 1.699m) and the existing MLE (approximately 0.71 m). In the square movement situation, the location error of localization using proposed method is smaller than localization using trilateration (approximately 1.437m) and the existing MLE (approximately 0.34 m). In all cases, the location error of indoor localization system is lower than other methods (0.216m, 0.495m, and 0.593m). Because our proposed pre-processing and post-processing method of the indoor localization system uses the optimal channel in terms of the smallest distance error and considers the reliability of the RSSI measurement, the location accuracy of sensor node is higher than other methods.

VI. CONCLUSIONS

Nowadays, many IEEE 802.11 APs operate in indoor environments. The signal of an IEEE 802.11 AP influences the performance of a RSSI-based indoor localization system. In this paper, we propose pre-processing and post-processing of an indoor localization system. These methods are based on the received signal strength indicator. First, we propose a pre-processing method to select the optimal channel. The pre-processing method considers channel interference between IEEE 802.15.4 and IEEE 802.11. Therefore, this method selects the optimal channel in terms of the smallest distance error. We also propose a post-processing method to improve the performance of the maximum likelihood estimation

localization algorithm. The post-processing method considers the reliability of the RSSI measurement and possible moving area. The experimental results demonstrate that the proposed method (pre-processing and post-processing) results in a higher location accuracy than trilateration and the existing maximum likelihood estimation localization algorithm.

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