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Path Loss Exponent Autocalibration Using UWB and ZigBee in Indoor Environment

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ABSTRACT

The path loss exponent, whose value is dependent on the particular propagation environment, is a parameter that indicates the rate at which the received signal strength indicator (RSSI) weakens with distance. Path loss exponent calculation is crucial in distance-based wireless sensor network localization, where distance is inferred from the RSS data. Estimating the path loss exponent is helpful for various tasks, such as distance measurement. Current methods for path loss exponent estimation use distance and RSSI measurements from the same environment to calibrate the path loss exponent. However, in certain circumstances, obtaining a distance measurement can be expensive and complicated. In this study, a novel method for the autocalibration of the path loss exponent in ZigBee is proposed. The combination of Zigbee and UWB is introduced to improve accuracy and a comprehensive path loss exponent calculation. This paper's main contribution is to show that the path loss exponent may be estimated using a joint ultrawideband (UWB) and ZigBee in the designated area and also create the logarithm function from scratch due to the limitation of the application used. The result indicates the measurements and calculations on the error in the distance are improved.

Key Words : Distance, path loss exponent, RSSI, UWB, ZigBee

Ⅰ. Introduction

The positioning system is usually provided by global navigation satellite systems, such as the global posi- tioning system (GPS) or the European satellite naviga- tion system Galileo. Meanwhile, GPS offers precise positioning resolution in outdoor environments due to its line-of-sight (LoS) capabilities, it encounters difficulties when employed for indoor localization, particularly due to non-line-of-sight (NLoS) issues[1].

NLoS refers to the phenomenon wherein wireless signals indoor bounce off surfaces, resulting in multiple signal paths reaching the receiver, as illustrated in Fig. 1. This multipath propagation or NLoS can lead us to high interference, signal degradation, and inaccuracies during position estimation[2].

Various techniques and methodologies are employed for indoor localization systems to overcome these challenges and achieve accurate positioning

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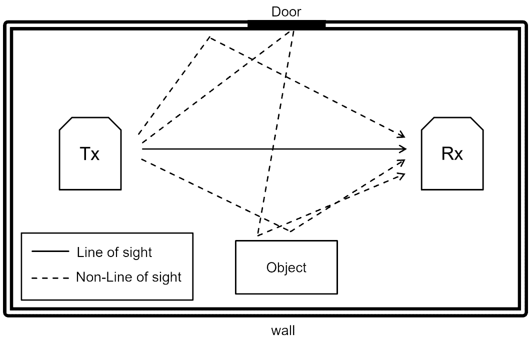


Fig. 1. The multipath illustration between two devices in indoor environments

within an indoor environment. In indoor localization systems, different devices such as Wi-Fi[3], bluetooth[4], ultrawideband (UWB)[5], radio frequency identification (RFID)[6], and ZigBee[7] are utilized. In this study, ZigBee is considered an indoor localization device. ZigBee introduces distinct advantages for indoor localization through its capability to enable longterm operation without frequent battery replacement, support wireless mesh networking where devices can act as routers, form self-organizing networks, and provide a reliable and efficient means of communication in indoor settings. These capabilities introduce ZigBee as one of the capable devices for indoor localization. ZigBee indoor localization system solutions frequently rely on received signal strength indicator (RSSI) approaches[7,8].

RSSI is a technique used to measure the strength or power level of the received signal in wireless communication systems. This measurement can be utilized to estimate the distance of a device. RSSI-based localization uses the RSSI measurements obtained from wireless signals to infer the proximity or distance between the target device and a reference point in the environment. This allows distance calculation, especially in indoor environments. However, the accuracy of distance calculation using ZigBee is affected by an unknown propagation environment.

Generally, in an RSSI-based localization system, there are several parameters that are essential for obtaining accurate distance measurements. A critical parameter to consider is the path loss exponent, which can vary depending on the total propagation in the indoor environment. The value of the path loss exponent is influenced by specific environmental characteristics, including obstacles, building materials, and interference sources.

To accurately calculate the path loss exponent, a reference distance is one critical point to get the accurate value. The value of the reference distance is typically obtained through a controlled scheme, such as calculating the distance within one meter[9]. ZigBee, classified as a communication device, has inherent limitations that prevent it from direct distance measurements[10]. However, incorporating devices that can directly calculate distances as reference values for ZigBee can provide an advantage in distance calculation. This motivation has led us to combine communication and sensing devices. In this study, we propose utilizing ZigBee as a communication device and UWB as a sensing device to calibrate the path loss exponent.

Furthermore, the combination of ZigBee and UWB leads us to several advantages. UWB sensing provides accurate distance measurements, while ZigBee facilitates data exchange and coordination among nodes or devices. In essence, the combination of Zigbee and UWB enables simultaneous communication and sensing. The UWB will be used in the calibration stage, after that ZigBee can measure the distance by itself. This multi-modal approach capitalizes on the strengths of each technology, resulting in improved accuracy and a comprehensive path loss exponent calculation, as opposed to relying solely on UWB or ZigBee.

Accordingly, the main contributions of this study are as follows:

- UWB and ZigBee are utilized to obtain appropriate values for the path loss exponent in any given indoor environment for distance measurement.
- A logarithm from scratch is proposed due to limitations in micro-Python libraries.

However, in [11] ZigBee is utilized for implementing the distance measurement for application in the emergency underground navigation system.

The remaining sections of the paper are structured as follows: Section II presents the proposed autocalibration path loss exponent system. Section III discusses the experimental results of this paper. Finally, Section IV concludes the study.

Ⅱ. Proposed System

2.1 Devices

The proposed system, as depicted in Fig. 2, utilizes wireless sensor network (WSN) nodes comprising two Digi XBee 3 RF modules and two UWB DWM1001CDEV modules, as shown in Fig. 3. The programming platform is based on micro-python and Tera Term. The parameters of the XBee module are presented in Table 1.

To perform the distance measurements, as shown in Fig. 2b, we developed an original program in the Python language adapted for micro-python. This program enables a connection between two XBee

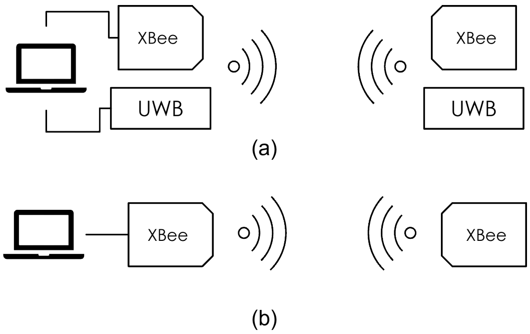
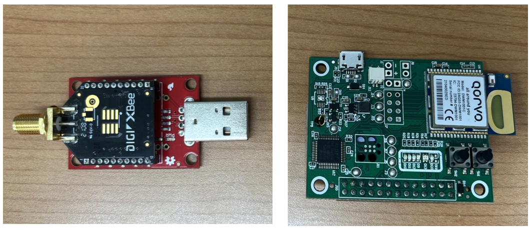


Fig. 2. The proposed system:(a) autocalibration (b) distance measurement.



(a) (b)

Fig. 3. The experiment utilized the following hardware: (a) Digi XBee 3 (b) UWB DWM1001C-DEV.

Table 1. Summary of Digi XBee 3 parameters.

Model	Digi XBee 3 RF Module
Protocol	ZigBee
Indoor range	Up to 60m
Outdoor range	Up to 1200m
Frequency	2.4-2.4835 GHz

modules with functionalities for measuring RSSI and distance. It's worth noting that micro-python has limitations in libraries compared to Python libraries. In micro-python, due to its minimalist Python implementation for embedded systems and microcontrollers, not all Python standard library functions are available, including the logarithm function. However, the distance measurement problem necessitates logarithmic calculations. Therefore, we propose a logarithm calculation method to overcome the limitations of micro-python, as presented in Algorithm 1.

Algorithm 1 Logarithm scratch

Input: value x, base of logarithm b
Output: logarithm value r
$n \leftarrow$ length of string(x)
$v \leftarrow$ "99"
for $j \leq n$ **do**
  $v \leftarrow v$ + "9"
$v \leftarrow$ integer(v)
$x_{\text{val}} \leftarrow v \times (x^{\frac{1}{v}-1})$
$b_{\text{val}} \leftarrow v \times (b^{\frac{1}{v}-1})$
$r \leftarrow \frac{x_{\text{val}}}{b_{\text{val}}}$
return r

2.2 Auto Calibration Path Loss Exponent

As mentioned in Section. I, signal propagation is one of the parameters that can be used to maintain a reliable wireless connection. In indoor scenarios, the propagation environment can be a factor in reliable wireless connection affected by the signal propagation.

Path loss exponent is used to indicate the rate at which the received signal strength decreases with distance, and its value depends on the specific propagation environment[12]. Based on [13], the path loss exponent can be determined as shown in Table. 2.

In spite of this, it can be determined that choosing

Table 2. Path loss exponent on different environments.

Path loss exponent	Environment
2.0	Free space
1.6 - 1.8	Inside a building, LoS
2 - 3	Inside a factory, NLoS
2.7 - 4.3	Inside an office building, NLoS

the best path loss exponent value for a specific environment is one of the challenging problems that require multiple experiments. To address this issue, the combination of a sensing device with a communication device on a calibration stage is proposed in this study. By leveraging the accurate distance measurements of UWB, this study utilizes UWB as a reference value to calibrate the path loss exponent for ZigBee distance measurements in indoor environments. The autocalibration setup can be shown in Fig. 2a. Initially, the UWB will measure the distance and RSSI several times. Then, the ZigBee module will calibrate the path loss exponent with distance and RSSI reference from UWB. Based on [14] path loss exponent can be expressed as

$$\eta = -\frac{P_z - P_u}{10\log d_u}, \tag{1}$$

where P_Z, P_U, and d_U denote RSSI from ZigBee, RSSI from UWB, and distance from UWB, respectively. After getting the path loss exponent that is already calibrated, the distance for ZigBee can be measured. Based on [13], the following equation is needed to be a parameter for measuring the distance of ZigBee

$$\delta = \frac{P_o - F_m - P_z - 10 \times \eta \times \log_{10}(f) + 30 \times \eta - 32.44}{10 \times \eta}, \tag{2}$$

where P_O is transmit power, F_m is fading margin, and f is frequency. Finally, the distance of ZigBee can be expressed as

$$d_z = 10^{\delta}, \tag{3}$$

The implementation of the autocalibration is summarised in the Algorithm. 2.

Algorithm 2 Path loss exponent autocalibration

Input: Distance UWB $\mathbf{D}_{\mathrm{uwb}}$, number of reference N_d
Output: Average path loss exponent η
  PLE $\leftarrow$ empty list
  $\mathbf{D}_{\mathrm{ref}} \leftarrow$ get N_d last distance from $\mathbf{D}_{\mathrm{uwb}}$
  $\mathbf{RSSI}_{\mathrm{ref}} \leftarrow$ get N_d last RSSI from UWB
  $P_z \leftarrow$ RSSI from ZigBee
  for $j \le N_d$ **do**
    $d_u \leftarrow \mathbf{D}_{\mathrm{ref}}[j]$
    $P_u \leftarrow \mathbf{RSSI}_{\mathrm{ref}}[j]$
    PLE $\leftarrow$ append calculation from Eq. 1
  $\eta \leftarrow$ average PLE
  return η

For checking the error distance from distance calculation can be expressed as

$$e = |d_R - d_z|, \tag{4}$$

where |•| denotes as absolute operation and dR denotes the real distance.

Ⅲ. Experimental Results

The proposed algorithm was validated by selecting two experimental environments, the classroom and the indoor corridor in the building as the experimental indoor environment, as illustrated in Fig. 4. In this

(a) The classroom experimental environment.

(b) The indoor corridor experimental environment.

Fig. 4. The indoor experimental environment during distance measurement.

indoor environment, the scenario involves propagating the signal through walls and poles. The experiment was conducted by averaging the RSSI and distance measurements from 10 samples taken at each distance and environment.

In order to validate the proposed system, distance measurement experiments were conducted using two schemes, with distances from 1 to 5 meters (short distances) and distances from 30 to 45 meters (long distances) being covered, respectively. In the experiment, several parameters that need to be considered are shown in Table 3. Subsequently, for each distance, the system calculates the path loss exponent. This means that every distance and different environment has a unique value for path loss exponent, as presented in Table 4.

However, the value of the autocalibration path loss exponent aims to adaptively change as the distance increases and the environment changes. This allows for more accurate distance measurement in a specific environment and improves the accuracy of distance estimation in localization.

The experimental area resembles a typical classroom setting with desks, chairs, cabinets, and other elements for the short distance Fig. 4a. In Fig.

Table 3. Parameters

Parameters	Definition	Values
P_o	Transmit power	8 dBm
F_m	Fade margin	8 dB [13]
f	Signal frequency	2.483 GHz
N_d	Number of references	10

Table 4. Autocalibration path loss exponent

Real Distance (m)	Autocalibration Path-loss exponent
1	1.932975
2	2.368384
3	2.251233
4	2.277546
5	2.197469
30	2.907775
35	2.754504
40	3.027901
45	3.019531

5, the average distance measurement under two conditions is presented for each distance. The results indicate that the "ZigBee calibrate" scheme provides more accurate distance measurements compared to the "ZigBee non-calibrate" scheme. The various calibration schemes utilize the path loss exponent, as presented in Table 4. On the other hand, the non-calibrate scheme uses a static value of path loss exponent η = 3 for each distance. The noncalibrate showed a big gap between the calibrate when the distance getting far. It's shown the effect of path loss exponent can be seen at different distances. As the distance between the transmitter and receiver increases, the signal spreads out over a larger area, resulting in a decrease in received signal power.

Figure. 6 shows the average error for a short

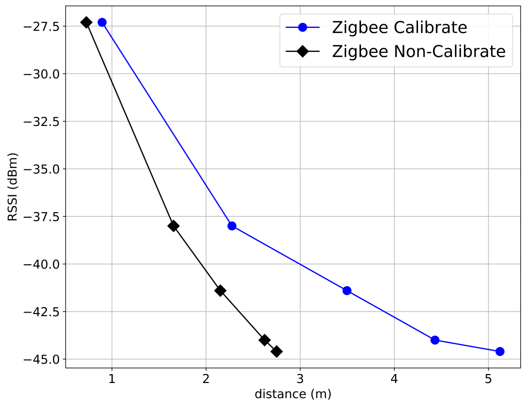


Fig. 5. The average RSSI vs. average short distance comparison.

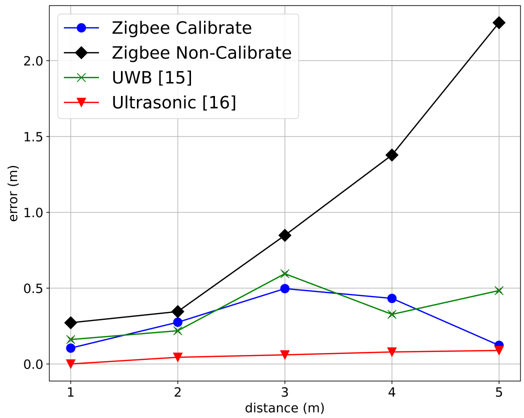


Fig. 6. The average error short distance representation.

distance. As the error from the static path loss exponent got higher, the error from the autocalibration path loss exponent can be stable below 0.5 meters and can be comparable with UWB[15] average error distance, even though the ultrasonic[16] has the best result for the short distance measurement with the error below 0.09 meters. For comparison, we also assessed the error range of two types of other sensing devices: UWB and Ultrasonic shown in Table. 5.

The experimental setup for long-distance measurements resembles a typical corridor setting with some pillars, as described in Figure 4b. The calibrate scheme utilizes the path loss exponent presented in Table 4. The non-calibrate scheme uses a static value of path loss exponent η = 2 for each distance. Fig. 7 shows the average error long-distance measurement for ZigBee with autocalibration path loss exponent and static path loss exponent and UWB[15].

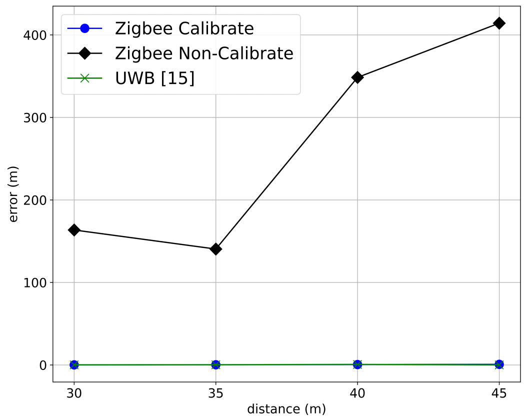


Fig. 7. The average error long-distance representation.

The details of Fig. 7 have been presented in Table 5. Table 6 presents the results of distance measurements between the ZigBee autocalibration path loss exponent and static path loss exponent. The error between ZigBee autocalibration and UWB[15]

Table 5. Average error short distance (m)

Real Distance	Autocalibration Path loss exponent error	Static Path loss exponent error	UWB [15]	Ultrasonic [16]
1	0.10446456	0.27176580	0.161	0.000
2	0.27503300	0.34550200	0.219	0.044
3	0.49680680	0.84809160	0.595	0.060
4	0.43233399	1.37779700	0.327	0.079
5	0.12267809	2.25061610	0.484	0.089

Table 6. Long distance results

Real Distance (m)	Average RSSI	Autocalibration Path loss exponent	Autocalibration average result (m)	Static Path loss exponent	Static average result (m)
30	-84.1	2.907775	30.088732	2	193.55637
35	-83.3	2.754504	35.240983	2	175.45632
40	-91.9	3.027901	42.262924	2	388.49408
45	-91	3.019531	41.362038	2	459.22005

Table 7. Average error long distance (m)

Real Distance	Autocalibration Path loss exponent error	Static Path loss exponent error	UWB [15]
30	0.088732	163.55637	0.105
35	0.240983	140.45632	0.220
40	0.467451	348.49408	0.605
45	0.693736	414.22005	0.061

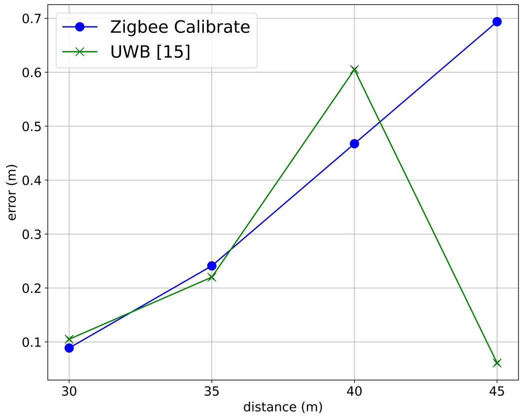


Fig. 8. The average error long-distance ZigBee calibrate vs UWB representation.

cannot be shown correctly because the error is lower compared to ZigBee with static path loss which has a much higher error. For the sake of clarity, Table 7 presents the average error for long distances, demonstrating that the autocalibration method exhibits lower errors compared to the UWB technique.

Figure 8 shows the average error long distance for ZigBee autocalibration and UWB[15]. The error distance can still be comparable but, the ZigBee autocalibration error tends to exhibit a noticeable upward trend, indicating a marked increase in error with greater distances.

Ⅳ. Conclusions

In this paper, a joint UWB and ZigBee algorithm for path loss exponent autocalibration has been proposed. By using Algorithm 2, the path loss exponent will be calibrated based on the environment using the distance and RSSI reference from UWB. Experimental results have shown the proposed system can minimize the distance error rate by calibrating the path loss exponent.

Future works will be aimed at investigating the performance of the proposed autocalibration system in indoor localization. Comparison with a Rola method is another representative distance measurement technique in the 2.4 GHz frequency band, which can be discussed in our future work. Furthermore, it can be extended with a filtering system to minimize the error rate between real distances.

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