Performance Evaluation of RSS Fingerprinting for Indoor Location using LoRa

Irsan Taufik Ali [1], Abdul Muis [2], Riri Fitri Sari [3]

Department of Electrical Engineering, Faculty of Engineering, Universitas Indonesia, Depok 16424, Indonesia.

Emails: [1] irsan.taufik@ui.ac.id; [2] muis@ui.ac.id; [3] riri@ui.ac.id

Abstract **- The complexity of the problems encountered on the Internet of Things (IoT) market increases accompanied by increasing needs including for indoor localization. The use of the fingerprint signal strength indicator (RSSI) is one of the popular techniques used in Indoor Localization Systems (ILS). Knowing the characteristics of the device and the environment in the room is needed to determine the right technique for indoor localization. LoRa (Long Range) is a Low-Power Wide Area Network (LPWAN) technology in recent years that has excelled in outdoor implementations but its performance has not been sufficiently investigated for indoor locations. We conducted a preliminary study to determine the suitability of RSS LoRa fingerprint characteristics in the indoor environment by comparing the results of the simulation and testbed. Based on experiments show that properties of room and obstacles greatly affect against of Received Signal Strength (RSS) fingerprints LoRa for indoor localization.**

Keywords – component, LoRa, RSSI, Fingerprinting, Indoor localization.

I. INTRODUCTION

LoRa is generally projected for outdoor applications. There are many publications that report successful implementations of LoRa in a variety of outdoor applications [1], [2], [3], [4]. LoRa properties can also be used for indoor scenarios [5], [6] including applications for localization [7], [8] and [9]. In general, the characteristics of the region and obstacles greatly affect the propagation of the wave of telecommunications signals whatever the technology.

Density, building height, and contours of the area greatly affect the results of IoT implementation, especially the use of LoRa for indoor localization blocking applications. B.Islam, et al [8] showes LoRa is more stable than WiFi and BLE, and is more resilient to environmental changes. LoRa operates in the sub-GHz band, which performed it more penetrating therefore it is more resistant to noise and multipath. This property makes LoRa the right choice for indoor localization.

Network Simulator 3, or better known as NS3, is a discrete event network simulator that is useful in studying the dynamic nature of communication networks. Simulation of wired and wireless networks such as routing algorithms, TCP, UDP, etc. can be done using NS-3. NS-3 is not intended for indoor localization scenarios, but by using several special simulator techniques it can be used to generate fingerprint data from nodes. The use of the LoRaWAN module in NS-3 has not yet been widely explored, especially the use of the LoRaWAN module for indoor localization scenarios.

In this paper, the NS-3 simulation has been conducted with the aim to determine the extent to which LoRa module can be implemented for indoor localization. RSS values measurement from nodes tracked based on the position of each reference node (anchor node) to produce fingerprints. The simulation scenario used 4 nodes as references and 1 node to track. The measurement results of RSS obtained from simulation are compared with the results of testing using the devices on testbed to determine the phenomena related to the use of RSS as fingerprinting in indoor localization. The structure of the paper is organized as follows. Section II gives briefly introduces. Section III review the existing literature of indoor localization systems. Section IV describes an experimental setup. Section V describes the result and problem discussions. Section VI concluded the paper.

II. LORA, INDOOR LOCALIZATION AND RSS.

A. LoRa

LoRa (Long Range) technology is a unique and a great modulation format created by Semtech operating on unlicensed bands below 1 GHz for remote communications. The core of the processing phase produces a stable frequency. LoRa technology offers an exciting blend of long-term, low power consumption, and secure data transmission. The frequency value of the LoRa varies in a different region, In Asia the frequency used is 433 MHz, In Europe, the frequency used is 868 MHz, whereas In North America the frequency used is 915 MHZ [10]. The physical layer employs LoRa modulation, which is based on Chirp Spread Spectrum (CSS) and presents the same characteristics of Frequency Shifting Keying (FSK) regarding communication range[10]. The advantage of using this method is the offset against time and frequency of sender and receiver alike, thus greatly reducing receiver complexity [11].

B. Indoor Localization Technique

The Indoor Localization System is a technology that has similarities with GPS however, but this technology does not use a satellite communication system because the Internet or satellite signals cannot be used properly in the building and can cause false information if it is still used. Localization in a room is a technology to find out an object in a room by providing information on the location of an object based on the access point placed in a predetermined coordinate.

Indoor localization technology can be done by creating a wireless infrastructure network. The creation of wireless networks for indoor localization serves to control the quality of the location sensing signals and to track the location of objects. In addition to having benefits, the wireless infrastructure also has the disadvantage of requiring an algorithm to reduce the accuracy of a system. The IoT localization approach in the room can generally be divided into two categories, namely, passive methods and active method [12]. In the passive localization approach, the tracked object does not carry any electronic devices and are not actively involved in the positioning process. In the case of active localization, the tracked object carries an electronic device that is actively involved to collect and process some information and send the localized server results for further processing. Localization systems that are relatively mature and widely used can be classified into three categories based on system requirements and techniques used, i.e, infrastructure-based systems, systems based on propagation wave modeling and fingerprint location-based systems.

C. Received Signal Strength Fingerprinting Indoor Localization

Indoor localization is a supporting technology for a wide variety of wireless applications. One of promising approach is to place users with radio frequency fingerprints. Fingerprints using RSSI are general indoor positioning techniques. Fingerprint-based localization generally consists of two basic phases [13]. First is the off-line phase, which is called the training phase, and second is the on-line phase, so called the test phase. The training phase is carried out for the construction of databases based on survey data related to sign of positions collected and processed in advance. At this stage, a comprehensive location survey is conducted to record fingerprints at the targeted location. During the location survey, the collector must stand in each training position and collect signal information scans for several rounds and be carried out at each different position. Data collection can be done by two methods, namely path-based and point-based [14], as shown in Figure 2 below.

In the path-based method, fingerprint data collection processes are carried out along the path while for point-based (base point) method, fingerprint data is collected based on certain points.

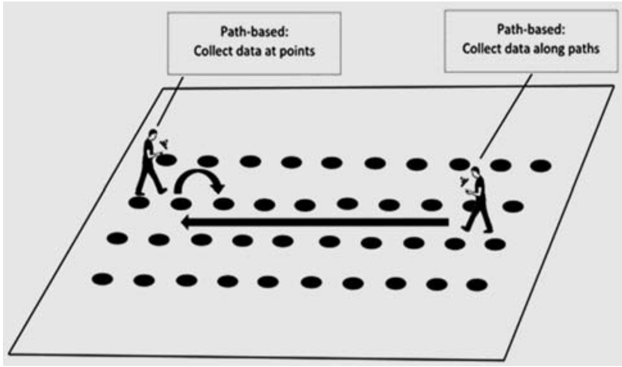

Figure 2. Fingerprint data collection method

In the off-line training stage, machine learning methods can be used to train and store fingerprints containing all Received Signal Strength (RSS) data. Such machine learning methods not only reduce the complexity of computing but also obtain core features in RSS for better localization performance. K-nearest-neighbor (KNN), artificial neural networks (ANN), and supporting vector machines (SVM), as a popular machine learning method and have been applied for indoor fingerprinting-based localization. KNN uses the mean value of the nearest K location to determine an unknown location which is inversely proportional to the Euclidean distance between the observed RSS measurements and the closest K training sample as a weight [15]. The disadvantage of K-nearest-neighbor is that it has to store all the RSS values obtained from the training results. Neural networks use backpropagation algorithms to train weights, in hidden layers to avoid propagation errors in the training phase and require labeled data as a monitoring in learning [16]. SVM is a binary classification that has extensions to non-linear classification and inseparable data. This method was introduced by Vapnik and Chervonenkis in 1963. SVM aims at finding a linear classifier,i.e., a hyperplane which maximizes the margin between two classes. It has extensions to non-linear classifiers and non-separable data too [17].

In the on-line phase, data recording is carried out in real time on mobile devices and then the data is tested using a database generated in the previous stages. The test results are then used to estimate the position of the mobile device, by looking for each training point to find the most suitable point as the target location. At the operational stage, when a user submits a location request with a particular fingerprint and then the localization server calculates and returns the results in the form of an approximate location.

III. RELATED WORK

The use of RSS information is the popular technique used in the Indoor Localization System (ILS) using both a fingerprinting database and without a database. The following is a review of related research on the use of RSS

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information on ILS. The indoor localization approach can generally be divided into two categories, namely, passive methods and active methods [12]. For the active category, there are three implementation schemes, namely infrastructure based, propagation model based and fingerprint-based. For the passive category, there are two schemes of application, namely, device free and device based. Here is some literature related to the use of RSS fingerprinting in indoor localization.

In 2016 Lin, et al. [18] proposed a Localization New Method (LNM) based on Neighbor Relative RSS (NR-RSS) and fingerprint-based Markov chain prediction algorithms and Markov chain models to provide higher accuracy of localization with calibration requirements the lower one. The existing approach to designing such a system generally uses the signal strength received by Received Signal Strengt (RSS) from WiFi to build fingerprints to get the user's position. NR-RSS is used as fingerprint data to create radio maps instead of absolute RSS. The formation of fingerprint radio maps and proposed localization techniques is based on neighboring relationships. This technique provides high and stable localization accuracy for device heterogeneity and environmental dynamics, which ensures efficiency in localization.

C. Luo *et., al* [19] introduced Pallas as a self-bootstrapping system for indoor localization that was passively localized using a non-intrusive WiFi monitor. Pallas identifies passive landmarks obtained from the WiFi WiFi trail later, statistically mapping the RSS tracks collected to the paths in a particular room. With adequate mapping, Pallas is able to bootstrap a smooth passive fingerprint database and build a Gaussian process for localization automatically without the need for additional calibration efforts. Pallas passively bootstraps the fingerprint database and builds its own GPS for its localization system.

W. Xue *et al.,* [20] improved the accuracy of the traditional weighted neighbor K-closest algorithm (WKNN) by proposing a new weighted algorithm based on the physical distance of RSSI. Experiments were conducted in office buildings and the results showed that the proposed method was far better than KNN, Euclidian-W-KNN, Manhattan-W-KNN, EWKNN, LiFS, and GPR in terms of position accuracy, which was defined as the cumulative position distribution error function.

Many studies have developed RSS fingerprinting techniques for indoor localization using a variety of approaches. As that as known from the literature that there is no research that uses LoRa technology as a device for testing. For the initial stages of this paper, we tried to implement LoRa technology for indoor localization using the fingerprinting technique in NS-3. Some references are needed to obtain an overview of the use of LoRa technology in a simulation. Several studies related to LoRaWAN use simulations for several problems, among others.

Reynders *et al*. [21] used ns-3 with a scenario evaluating the technical differences between wideband spread spectrum (like LoRa) and ultra narrowband (Like Sigfox) by investigating the impact of the MAC protocol used in Sigfox and LoRaWAN. The results show that CSS networks offer higher throughput, while UNB networks support a larger number of devices.

The work of Bor et al. [22] used LoRa Simulator (LoRaSim) to study the LoRa network scalability based on the results of previous experiments conducted. The authors study the limits on the number of transmitters supported by the LoRa system based on empirical models and conduct practical experiments that measure the communication range and capture effects of LoRa transmissions. These findings are used to build a specially built simulator, LoRaSim, with the aim of studying LoRa network scalability. The authors conclude that the LoRa network can scale quite well if they use a dynamic.

Pop *et al*., [23] expanding the LoRaSim simulator function to include LoRaWAN bi-directional communication to study the impact of two-way traffic on LoRaWAN. The resulting simulator is named LoRaWANSim. Both the ns-3 and LoRaWANSim modules make it possible to study LoRaWAN network scalability. Both functions find that the work cycle limit at the gateway limits the number of downlink messages (Ack or data) that can be sent by the gateway.

In other work, Magrin, *et al.,* [24] evaluates LoRa network performance in smart city scenarios in the form of simulation scenarios. The authors propose link measurement and link performance models for LoRa and implement a LoRaWAN system-level simulator on ns-3. Their results show that LoRaWAN provides higher throughput than the basic ALOHA scheme and that the scale of the LoRaWAN network is well in line with the increasing number of gateways.

In the paper [25] analytically evaluate LoRaWAN scalability by developing a joint model for coverage, capture effect and demodulation ability for LoRa transmission. Models are built and evaluated based on the SX1301 gateway however, the same model and methodology can be applied to any architecture. SX1301 is able to demodulate 8 frames, simultaneously, any transmission outside of this will be canceled. Finally, we evaluate the performance of several SF allocation schemes based on the developed model. The overall conclusion is that the existence of several demodulation pathways shows significant changes in the analysis and performance of LoRa random access schemes.

Each study has a different purpose with several limitations. There are several points that can be increased as part of future work. As discussed in the related work study, the modeling approach using both LoRaWANSim and NS-3 on LoRa can produce a variety of scenarios. This scenario can be used for several problems. Related of the literature on RSS fingerprints for indoor localization, the authors then tried to incorporate these ideas into other simulation scenarios and LoRa test devices. The measurement of RSS obtained from the simulation is compared to the measurement results using the actual LoRa device to determine the characteristics of the RSS generated in the room. Simulation scenarios and device testing using LoRa technology to generate fingerprint data for indoor localization scenarios become the next scenario to be discussed in this paper.

IV. EXPERIMENTAL SETUP

The experiment has been deployed in two stages, the first using the NS3 simulation and the second using the LoRa testbed device. At the initial stage simulation, four anchor nodes are positioned in each corner of the room that acts as the receiver. One node called the tracked node in line-of-sight positioned for different place from the previous four anchor nodes. The tracked node acts as the sender. RSS and distance measurements are carried out at 30 different points scattered in a room measuring 8 x 8 meters. The following Figure 3 shows the position of RSS measurement for fingerprinting.

To communicate the entire node use a frequency of 868,1 MHz with a strong signal emitted by the sender at 14 dbm and spreading factor 7. Simulation of indoor interference and attenuation from multipath, reflection, deflection, diffraction, and channel fading used the path loss of 1.5 based on the path loss exponent table [26]. The amount of signal received strength (RSS) and the distance on each anchor node are calculated.

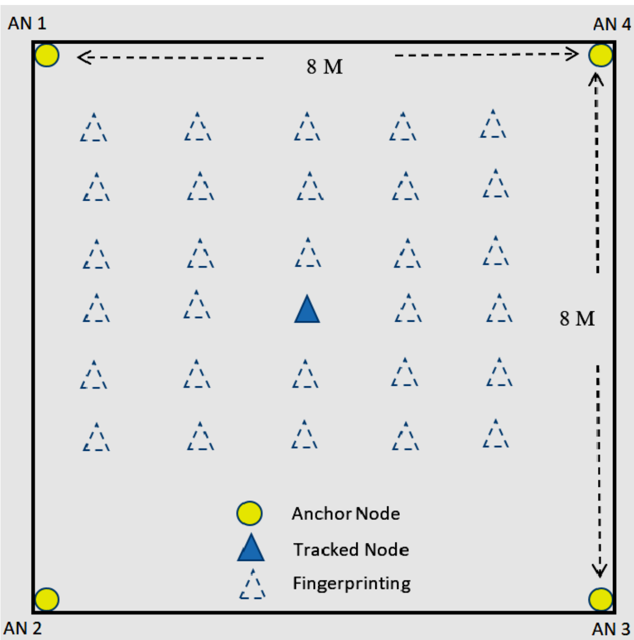


Figure 3. RSS Fingerprint position for 30 different locations.

TABLE I. PATH LOSS EXPONENT

Environment	Path loss exponent
Free space	2
Urban area	2.7 – 3.5
Suburban area	3 – 5
Indoor line-of-sight	1.6 – 1.8
Obstructed in building	4-6
Obstructed in factories	2-3

The simulation results will be compared with the testbed results using the LoRa device. The device used is 5 LoRa nodes, 4 as anchor node and 1 node as a tracked node.

TABLE II. LORA DEVICE SPESIFICATION

Parameter	LoRa Value
Radio	SX1278
Frequency band	433 MHz
Anchor height	2 m
Tracked node height	1.5 m
Radiation pattern	Omnidirectional
Sensitivity	-148 dBm, +20 dBm

The room size is 11.27 meters long and 7.86 meters wide. The building wall material is made of 70% GRC board and 30% glass with a thickness of 0.75 cm. The platform is made of gypsum with a thickness of 0.5 cm. In the room, there are 28 cubical tables with particle board material with a thickness of 2 cm and a thin steel storage cabinet with a thickness of 1.5 mm.

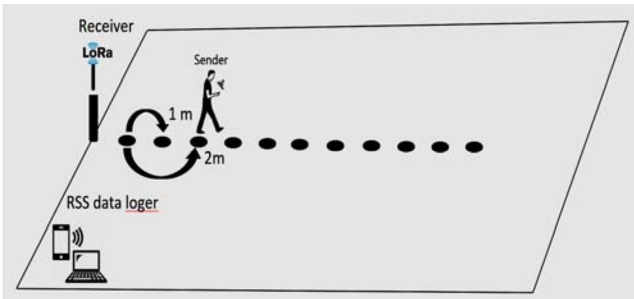


Figure 4. RSS measurement position testbed in interval 1 m and 2m.

RSS measurement is done by using 1 device as Anchor Anchor and 1 device as tracked nodes. The measurement scenario is done by shifting the tracked node away from the Anchor node at intervals of 1 meter and 2 meters in the line-of-sight. Measurements are made in several points and then recorded in the database using a computer as a data logger. Measurements are made at each point every 2 seconds with a duration of 2 minutes for each position as shown in figure 4.

The characteristics of RSS obtained from measurement results using simulation and testbed are very useful for determining the choice of the best technique for indoor localization systems.

V. RESULTS AND DISCUSSION

Following Figure 6 Execution results from the simulation. In the display, the results are RSS values from nodes that are tracked based on measurements at four different anchor node positions. This RSS value is the data for fingerprints that will be used for indoor localization. RSS measurements re carried out at different points by shifting the coordinates at 30 positions scattered in the room. The measurement results in each of these coordinates are stored in a table of RSS value information as data fingerprinting. The following Table 1 presents the results of the RSS measurement.

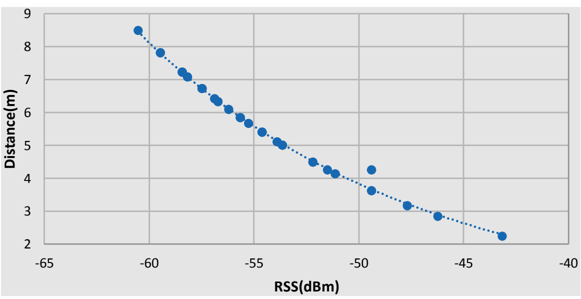
TABLE III. RSS AND DISTANCE MEASUREMENT RESULTS IN 30 POSITIONS AGAINST 4 ANCHOR NODES.

Fingerprinting position		Anchor node 1		Anchor node 2		Anchor node 3		Anchor node 4	
X	Y	Distance(m)	RSS(dBm)	Distance(m)	RSS(dBm)	Distance(m)	RSS(dBm)	Distance(m)	RSS(dBm)
6	2	6,32456	-56,7086	2,82843	-46,224	6,32456	-56,7086	8,48528	-60,5377
6	3	6,7082	-57,4759	3,60555	-49,3869	5,38516	-54,6137	7,81025	-59,4576
6	4	7,2111	-58,4178	4,47214	-52,1931	4,47214	-52,1931	7,2111	-58,4178
6	5	7,81025	-59,4576	5,38516	-54,6137	3,60555	-49,3869	6,7082	-57,4759
6	6	8,48528	-60,5377	6,32456	-56,7086	2,82843	-46,224	6,32456	-56,7086
5	2	5,38516	-54,6137	3,60555	-49,3869	6,7082	-57,4759	7,81025	-59,4576
5	3	5,83095	-55,6499	4,24264	-51,5068	5,83095	-55,6499	7,07107	-58,1623
5	4	6,40312	-56,8695	5	-53,6468	5	-53,6468	6,40312	-56,8695
5	5	7,07107	-58,1623	4,24264	-55,6499	4,24264	-51,5068	5,83095	-55,6499
5	6	7,81025	-59,4576	6,7082	-57,4759	3,60555	-49,3869	5,38516	-54,6137
4	2	4,47214	-52,1931	4,47214	-52,1931	7,2111	-58,4178	7,2111	-58,4178
4	3	5	-53,6468	5	-53,6468	6,40312	-56,8695	6,40312	-56,8695
4	4	5,65685	-55,2549	5,65685	-55,2549	5,65685	-55,2549	5,65685	-55,2549
4	5	6,40312	-56,8695	6,40312	-56,8695	5	-53,6468	5	-53,6468
4	6	7,2111	-58,4178	7,2111	-58,4178	4,47214	-52,1931	4,47214	-52,1931
3	2	3,60555	-49,3869	5,38516	-54,6137	7,81025	-59,4576	6,7082	-57,4759
3	3	4,24264	-51,5068	5,83095	-55,6499	7,07107	-58,1623	5,83095	-55,6499
3	4	5	-53,6468	6,40312	-56,8695	6,40312	-56,8695	5	-53,6468
3	5	5,83095	-55,6499	7,07107	-58,1623	5,83095	-55,6499	4,24264	-51,5068
3	6	6,7082	-57,4759	7,81025	-59,4576	5,38516	-54,6137	3,60555	-49,3869
2	2	2,82843	-46,224	5,38516	-56,7086	8,48528	-60,5377	6,32456	-56,7086
2	3	4,24264	-49,3869	5,83095	-57,4759	7,07107	-59,4576	5,83095	-54,6137
2	4	4,47214	-52,1931	7,2111	-58,4178	7,2111	-58,4178	4,47214	-52,1931
2	5	5,38516	-54,6137	7,81025	-59,4576	6,7082	-59,4576	3,60555	-49,3869
2	6	6,32456	-56,7086	8,48528	-60,537	6,32456	-56,7086	2,82843	-46,224
1	2	2,23607	-43,1623	7,28011	-58,5418	9,21954	-61,619	6,08276	-61,619
1	3	3,16228	-47,6777	7,61577	-59,1291	8,60233	-60,7162	5,38516	-53,9023
1	4	4,12311	-51,1344	8,06226	-59,8714	8,06226	-59,8714	4,12311	-51,1344
1	5	5,09902	-53,9023	8,60233	-60,7162	7,61577	-59,1291	3,16228	-47,6777
1	6	6,08276	-56,2007	9,21954	-61,619	7,28011	-58,5418	2,23607	-43,1623

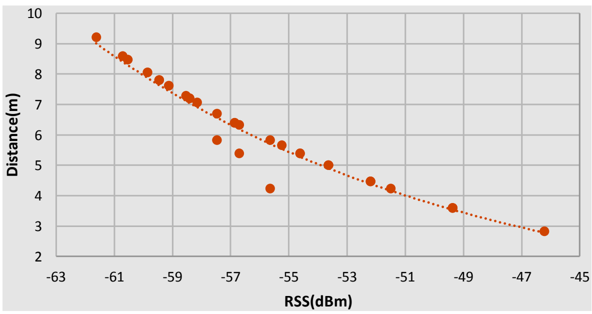
Table III shows the simulation results of measuring RSS values and the distance to each anchor node. Based on the measurement table, it can be seen that in some positions there are similarities in the signal strength values as shown at 5.4 coordinates for anchor node 2 and anchor node 3, coordinates 4.3 against anchor node 1 and anchor node 2 and many coordinates that have the measurement results of the same RSS to several anchor nodes. The similarity of the measurement results occurs because some of the fingerprint positions are at the same distance from the position of the anchor node. The figure showed will explain the relationship between the distance to the strength of the RSS signal.

Figure 7 shows the results of the measurement of RSS values and the distance between the position of the node tracked to all anchor nodes when measuring RSS values. The relationship between RSS and the distance at all anchor shows an exponential function. The overall graph of the measurement results of the RSS value and distance shows the same trend, which shows the same function. The function shows the relationship between the distance of the tracked node to the signal strength received by the anchor node. The farther the distance between the tracked node and the anchor node, the smaller the RSS value obtained. However, in certain positions, the measurement results show a deviation where the RSS value becomes larger at a longer distance and the RSS value is smaller at a closer distance. This deviation is caused by the path loss effect of the indoor environment.

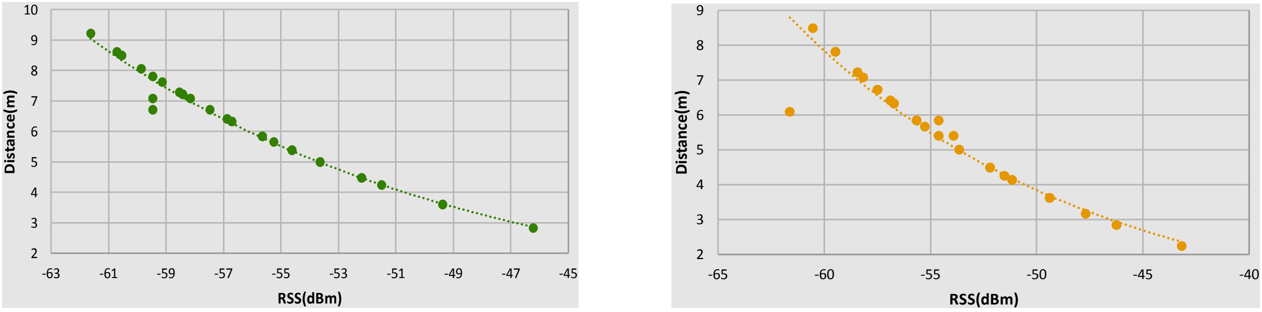
Based on the results of testing using a device, data of RSS values from each measurement position is obtained using 4 LoRa devices. From the measurement results, it is found several data outliers must be filtered first to produce more valid conclusions. The following figure 8 and figure 9 of the measurement results.



A. Comparison of RSSI to distance on anchor node 1



B. Comparison of RSSI to distance on anchor node 2



C. Comparison of RSSI to distance on anchor node 3

D. Comparison of RSSI to distance on anchor node 4

Figure 7. The function of the comparison of RSSI to distance on all anchor node

The testbed results of LoRa device by shifting the interval distance of 1 meter and 2 meters showed the relationship between distance and size of RSS values. The farther the distance between the nodes that are tracked with the anchor node, the smaller the RSS value obtained. However, at certain positions, the measurement results show deviations where the RSS value becomes greater at a longer distance as shown in Figure 8. The magnitude of the measurement results of the RSS value at a distance of 2 meters and 4 meters has increased from the previous distance.

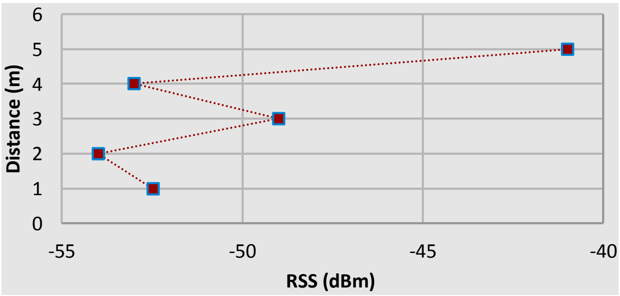


Figure 8. The function of RSSI to the distance (intervals 1 m)

The result testbed of the device by distance interval of 2 meters found deviations at a distance of 10 meters where the RSS value becomes greater than the previous distance as shown in figure 9. Deviations found in both measurements using the device are caused by the effect of path loss from the indoor environment such as also found in a previous simulation.

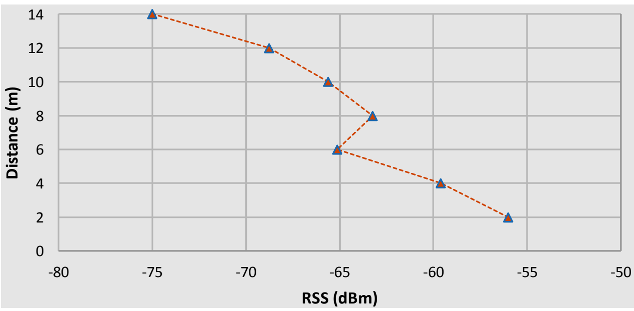


Figure 9. The function of RSSI to the distance (intervals 2 m)

The relationship between distance and signal strength showed in the results of both tests showed the same trend. The occurrence of deviation of the measurement value occurs due to several causes. The characteristics of the LoRa which is intended for long distances giving results that are not suitable for short distances. Signal propagation interference indoor greatly affects the RSS measurement results.

VI. CONCLUSIONS

We generated some function to show the relation between RSS and the distance between nodes. Generally, the overall measurement of the RSS value and distance showed the same trend. The farther the distance between the tracked node and the anchor node, the lower the RSS value obtained. The function shows the relationship between the distance of the tracked node to the signal strength received by the anchor node. The value of signal strength obtained will be a fingerprint database in indoor localization. The database is used as a reference to determine the position of objects at the next implementation stage. However, at certain positions, the measurement results showed deviations where the RSS value becomes larger at longer distances. The deviations show that the use of RSS fingerprinting techniques in indoor localization is strongly influenced by environmental conditions. Position prediction is inaccurate due to differences in reference values in the fingerprinting database against RSS measurement values when tracking positions. This happens because of changes in dynamic room conditions that greatly affect the measurement results. Preliminary steps are needed to determine the characteristics of the indoor environment and the device will be used. These stages help us to find the appropriate technique in the indoor localization system.

The future testing was suggested in a wider indoor area due to excess large coverage on LoRa.

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REFERENCES

[1] A. Mdhaffar, T. Chaari, K. Larbi, M. Jmaiel, and B. Freisleben, "IoT-based health monitoring via LoRaWAN," in IEEE EUROCON 2017 - 17th International Conference on Smart Technologies, 2017, pp. 519-524.

[2] L. Li, J. Ren, and Q. Zhu, "On the application of LoRa LPWAN technology in Sailing Monitoring System," in 2017 13th Annual Conference on Wireless On-demand Network Systems and Services (WONS), 2017, pp. 77-80.

[3] R. F. A. M. Nor, F. H. Zaman, and S. Mubdi, "Smart traffic light for congestion monitoring using LoRaWAN," in Control and System Graduate Research Colloquium (ICSGRC), 2017 IEEE 8th, 2017, pp. 132-137: IEEE.

[4] N. Harris and J. Curry, "Development and Range Testing of a LoRaWAN System in an Urban Environment," World Academy of Science, Engineering and Technology, International Journal of Electronics and Communication Engineering, vol. 5, no. 1, 2018.

[5] K.-H. Ke, Q.-W. Liang, G.-J. Zeng, J.-H. Lin, and H.-C. Lee, "A LoRa wireless mesh networking module for campus-scale monitoring: demo abstract," in Proceedings of the 16th ACM/IEEE International Conference on Information Processing in Sensor Networks, 2017, pp. 259-260: ACM.

[6] A. J. Wixted, P. Kinnaird, H. Larijani, A. Tait, A. Ahmadinia, and N. Strachan, "Evaluation of LoRa and LoRaWAN for wireless sensor networks," in SENSORS, 2016 IEEE, 2016, pp. 1-3: IEEE.

[7] B. C. Fargas and M. N. Petersen, "GPS-free geolocation using LoRa in low-power WANs," in 2017 Global Internet of Things Summit (GIoTS), 2017, pp. 1-6.

[8] B. Islam, M. T. Islam, and S. Nirjon, "Feasibility of LoRa for Indoor Localization," 2017.

[9] K.-H. Lam, C.-C. Cheung, and W.-C. Lee, "LoRa-based localization systems for noisy outdoor environment," in Wireless and Mobile Computing, Networking and Communications (WiMob), 2017, pp. 278-284: IEEE.

[10] R. Quinnell, "Low power wide-area networking alternatives for the IoT," EDN Network, edn. com, 2015.

[11] Semtech. (2015, Access 28, Desember 2017). AN1200.22, LoRa™ Modulation Basics (Revision 2, May 2015 ed.). Available: http://www.semtech.com/images/datasheet/an1200.22.pdf

[12] G. Deak, K. Curran, and J. Condell, "A survey of active and passive indoor localisation systems," Computer Communications, vol. 35, no. 16, pp. 1939-1954, 2012.

[13] P. Bahl and V. N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," in INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE, 2000, vol. 2, pp. 775-784: Ieee.

[14] C. Li, Q. Xu, Z. Gong, and R. Zheng, "TuRF: Fast data collection for fingerprint-based indoor localization," in Indoor Positioning and Indoor Navigation (IPIN), 2017 International Conference on, 2017, pp. 1-8: IEEE.

[15] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 37, no. 6, pp. 1067-1080, 2007.

[16] S. Dayekh, S. Affes, N. Kandil, and C. Nerguizian, "Cooperative localization in mines using fingerprinting and neural networks," in Wireless Communications and Networking Conference (WCNC), 2010 IEEE, 2010, pp. 1-6: IEEE.

[17] L. Xiao, A. Behboodi, and R. Mathar, "A deep learning approach to fingerprinting indoor localization solutions," in 2017 27th International Telecommunication Networks and Applications Conference (ITNAC), 2017, pp. 1-7: IEEE.

[18] K. Lin, M. Chen, J. Deng, M. M. Hassan, and G. Fortino, "Enhanced fingerprinting and trajectory prediction for IoT localization in smart buildings," IEEE Transactions on Automation Science and Engineering, vol. 13, no. 3, pp. 1294-1307, 2016.

[19] C. Luo, L. Cheng, M. C. Chan, Y. Gu, J. Li, and Z. Ming, "Pallas: Self-bootstrapping fine-grained passive indoor localization using WiFi monitors," IEEE Transactions on Mobile Computing, vol. 16, no. 2, pp. 466-481, 2017.

[20] W. Xue et al., "A New Weighted Algorithm Based on the Uneven Spatial Resolution of RSSI for Indoor Localization," IEEE Access, vol. 6, pp. 26588-26595, 2018.

[21] B. Reynders, W. Meert, and S. Pollin, "Range and coexistence analysis of long range unlicensed communication," in Telecommunications (ICT), 2016 23rd International Conference on, 2016, pp. 1-6: IEEE.

[22] M. C. Bor, U. Roedig, T. Voigt, and J. M. Alonso, "Do LoRa low-power wide-area networks scale?," in Proceedings of the 19th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems, 2016, pp. 59-67: ACM.

[23] A.-I. Pop, U. Raza, P. Kulkarni, and M. Sooriyabandara, "Does bidirectional traffic do more harm than good in LoRaWAN based LPWA networks?," in GLOBECOM 2017-2017 IEEE Global Communications Conference, 2017, pp. 1-6: IEEE.

[24] D. Magrin, M. Centenaro, and L. Vangelista, "Performance evaluation of LoRa networks in a smart city scenario," in Communications (ICC), 2017 IEEE International Conference On, 2017, pp. 1-7: IEEE.

[25] R. B. Sørensen, N. Razmi, J. J. Nielsen, and P. Popovski, "Analysis of LoRaWAN uplink with multiple demodulating paths and capture effect," arXiv preprint arXiv:1902.02866, 2019.

[26] T. S. Rappaport, Wireless communications: principles and practice. prentice hall PTR New Jersey, 1996.