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Assessment Of The System Of Monitoring And Tracking Of People In A Confined Space

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Abstract

Nowadays, monitoring and tracking systems are not only important in terms of providing navigation services in the outdoor environment through the most well-known Global Positioning System (GPS) technology, but are also widely used for positioning people and entities in confined spaces, where the implementation of GPS is ineffective due to the limited ability to propagate the signal through the building structure. There are several technologies that can be implemented in confined spaces for the purpose of monitoring and tracking the movement of people and entities. In this research, the authors of this paper discuss the design of a system for monitoring and tracking of people and entities in confined spaces and also the implementation of the system in a healthcare facility. The system of monitoring and tracking of persons and entities can be classified as an alarm system as a part of physical protection. However, the system is also an effective tool for preventing or eliminating the spread of infectious diseases, e.g. COVID-19. The proposed system is based on Bluetooth Low Energy beacons technology. The location of persons and entities is determined by a Fingerprinting algorithm consisting of creating a database of Received Signal Strength Indicator (RSSI) values and then comparing the RSSI values from the database with the RSSI values obtained in real time. The aim of this paper is to propose a system for monitoring and tracking of people and entities in the premises of a healthcare facility and the application of Fingerprinting algorithm for the purpose of determining the location of people and entities.

Keywords: monitoring and tracking system, bluetooth low energy, beacon, fingerprinting

1. Introduction

Location-based systems are used in various areas of people's lives. Monitoring and tracking the movement of people and other entities is widespread within the outdoor environment. Location-based systems can also be used in transport for the purpose of tracking the location of vehicles. Location information is useful for navigating vehicles or people to a desired destination. Over the last few years, emphasis has been placed on the implementation of location systems for people and entities in confined spaces. Confined space positioning systems are gaining importance in terms of person navigation in various types of facilities where there is a high concentration of people during operating hours. Indoor positioning systems are also becoming increasingly significant due to the size and complexity of facilities such as airports, healthcare facilities, educational facilities, shopping centres, etc. Indoor positioning systems are also used to increase security in buildings by tracking the movement of occupants. Among other things, people can receive useful information regarding the location they are in. Based on location and movement information, it is also possible to control, coordinate and manage personnel or other resources in order to increase the efficiency of processes. The issue of monitoring and tracking the movement of people and entities in confined spaces and the design of systems that allow tracking the movement of people is still a challenge today, even in the context of the COVID-19 pandemic, which has greatly affected our daily lives in recent years. Indoor positioning systems are a useful tool for monitoring and tracking the movement and contact of people in healthcare facilities in order to prevent and limit the spread of coronavirus and other respiratory diseases.

1.1 Bluetooh Low Energy beacon

Bluetooth Low Energy Technology, known as Bluetooth Smart, is a short-range wireless technology. It is one of the most suitable technologies for low-power sensors whose power source is a small coin cell b attery. However, the range of their signal can be affected by various environmental factors, resulting in erroneous distances being determined when using the RSSI technique to calculate the distance. The technology can be used for indoor positioning systems, providing accurate positioning and the implementation cost is low. Compared to previous standards, Bluetooth Low Energy technology was developed to simplify the communication over short distances of devices that do not transmit large volumes of data. It is designed for monitoring and control applications such as sending sensor readings or short control messages (Čabarkapa, 2015; Yang, 2019; Posdorfer, 2016). Bluetooth Low Energy version 4.0 reaches speeds of 25 Mbps and operates in the 2.4 GHz frequency band just like Wi-Fi. However, advertising occurs on only 3 channels, which are widely spaced on frequencies 2402, 2426 and 2480 MHz different from the Wi-Fi channels. As a result of the different channels, there is no interference to Wi-Fi network infrastructures (Spachos, 2020; Faragher, 2015).

A Bluetooth beacon is a device that wirelessly transmits signals, including location information, at regular intervals and sends user identifiers and RSSIs as Bluetooth signals. When a smartphone user is within range of the beacon signal, an application installed on the smartphone receives the beacon signal and then sends the user information to a cloud server where the received user information is verified and then the relevant information about the service provided is sent to the user (Jung, 2017). Bluetooth beacons only use the advertisement mode, which is a one-way beacon detection process. They periodically send packets of data that are received by other devices in range. The signal is transmitted at intervals ranging from 20 ms to 10 s. The transmission interval affects the battery life of the beacons. The longer the interval, the faster the battery drains (Spachos, 2020).

RSSI is one of the distance determination techniques. It is based on the measurement of the received radio signal. The RSSI value expresses the relative quality of the received signal in the device. The stronger the signal, the higher the RSSI value. When radio signals are transmitted among sensors, the RSSI value oscillates due to absorption, interference and diffraction effects (Zhang, 2023; Dong, 2011; Maaloul, 2023; Mussina, 2019).

1.2 Positioning techniques and algorithms

There are several algorithms for positioning in confined spaces, including triangulation (Lee, 2014; Turgut, 2016), trilateration (Khanh, 2020; Ainul, 2022), proximity (Alyafawi, 2015; Zafari, 2015), scene analysis (Liu, 2007), fingerprinting (Mohgtadaiee, 2019) and pedestrian dead reckoning (Liu, 2019). The above algorithms are based on techniques such as RSSI (Zhang, 2023), angle of arrival (AoA) (Chen, 2023), channel state information (CSI) (Farahsari, 2022), reference signal reception performance (RSRP), reference signal reception quality (RSRQ) (Poosamani, 2015), time of arrival (ToA) (Mrindoko, 2016), time difference of arrival (TDoA) (Xie, 2022), round trip time (RTT) (Yan, 2019), phase of arrival (PoA) (Poosamani, 2015) and phase difference of arrival (PDoA) (Mrindoko, 2016).

Fingerprinting algorithm was used to determine the location of people and entities in the healthcare facility, which is characterized by high accuracy of indoor positioning. The advantage is the robustness of the algorithm to multipath effects and the measurement does not require direct visibility of access points. Fingerprinting-based localization consists of an offline phase, also called the training phase, and an online phase, which is called the testing phase. In the offline phase, the location is explored to collect RSSI vectors of all the recorded signals from different access points at many reference points of known locations. Within this phase, a database is created where the site survey data is collected and processed. In the online phase, mobile devices record the data in real time. The data is then tested using the database. The output of the test is used to estimate the location of the mobile device in such a way that each training point is searched for the location that most closely matches the location of the target (Subedi, 2017; He, 2015; Wang, 2016).

2. Methodological procedure for the implementation of the monitoring and tracking system

For the purpose of the installation, a monitoring and tracking system architecture was chosen in which the beacon is the transmitter and is operated by a person moving in the space and several receivers are installed on building structures in the space. The devices communicate with each other via Bluetooth Low Energy technology. The transmitter continuously transmits radio signals which are received by the receivers and are then sent to a server and stored in a database.

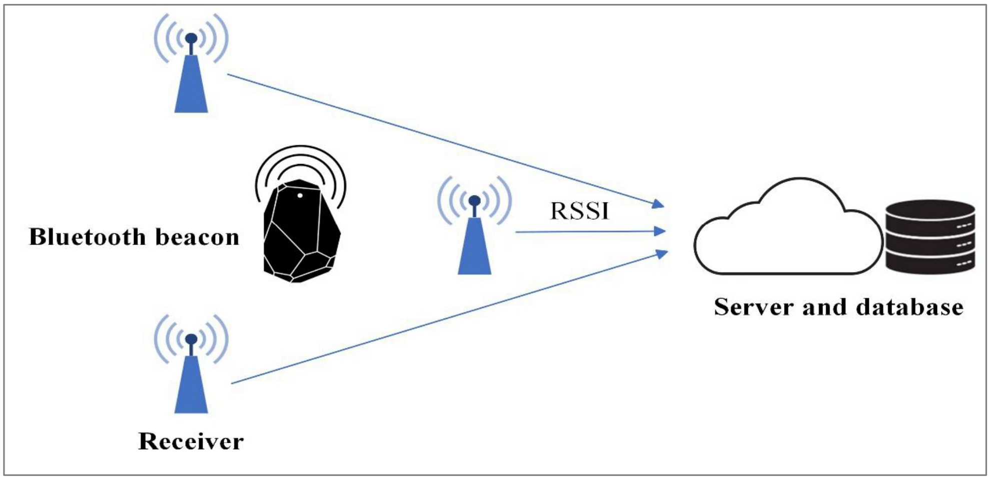

Fig. 1. System based on receivers and Bluetooth beacon.

The monitoring and tracking system implemented in the premises of the healthcare facility consists of transmitting and receiving devices that communicate with each other via Bluetooth Low Energy. The transmitting devices are Gigaset G-Tag Red Bluetooth beacons. The receiving devices are Raspberry Pi Zero microcomputers. The total number of transmitting devices is 25. The transmitting devices are provided by the staff of the healthcare facility, 4 of which are attached to mobile medical devices.

15 receiving devices were installed at a height of 1.6 m in the clinical biology department, atrium and lobby of the healthcare facility. For the purpose of installing the receiving devices, stands were used to which the devices were attached in order to avoid interference with the building structures of the healthcare facility. The power source of the receiving equipment is an external 50 000 mAh Powerbank, which is capable of operating for 5-7 days continuously.

To ensure that the relevant data about the transmitting devices is sent to the server, a Wi-Fi backbone network needs to be created. The procedure for creating a Wi-Fi network consists of the following steps:

- wiring Routerboard MikroTik RB951Ui-2HnD;
- connecting the router to the Internet;
- connecting miniserver Intel NUC via the Ethernet into the Router Mikrotik (Ethernet port 2);
- connecting TP-link Master Mesh marked 01 via the Ethernet into the Router MikroTik (Ethernet port 3);
- sequential connection TP-link Slave 02-05.

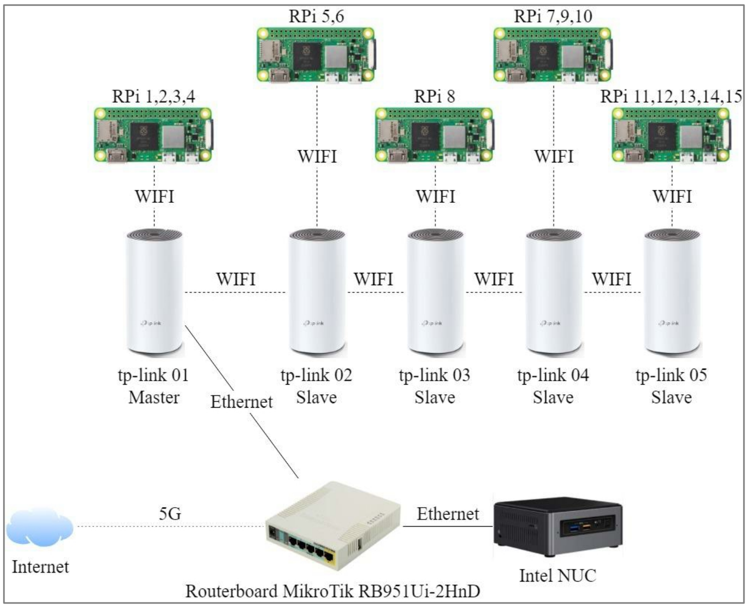

Fig. 2. Diagram of the connection of receiving devices to the Internet network.

The Mikrotik routerboard was connected to the Internet. A server was connected to the Router via cabling, using the Ethernet port and a Master TP-link 01 was also connected to the Router to create and manage the Mesh network. Subsequently, other Slave-TP link Routers labeled 02-05 were connected. Each additional connected Router must be within Wi-Fi range of the previous one. In this way, a backbone Wi-Fi network connected to the server and to the Internet was created.

Once the skeletal Wi-Fi network was established, the microcomputers were connected to external power devices and then attached to racks that were deployed in the given areas of the healthcare facility. Once started, each receiving device logged into the Mesh Wi-Fi network, locating a server on the network and establishing connectivity, automatically sending data about the transmitting devices in range to the server.

Subsequently, the system was calibrated. The monitored area was divided into squares of approximately 2x2 m. The squares represent positions marked with a serial number from 1 to 86.

Fig. 3. Installation of receiving devices.

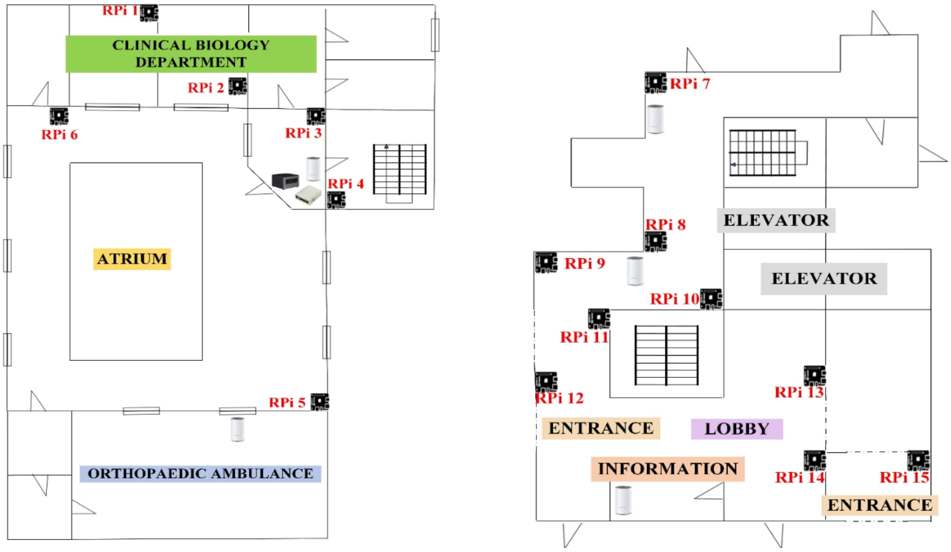

Fig. 4. Installation of components in a healthcare facility.

The person in possession of the transmitting device stood in the center of each square for 30 seconds. The individual squares were named with a serial number. A database of RSSI values was generated during the 30 seconds. RSSI values for each position could be recorded individually at the indicated time intervals via a mobile application. In the app, it was possible to see how many RSSI values were received by each receiving device. A larger number of RSSI values received meant that the receiving devices were in range and closer. Devices that were not in range did not receive any RSSI values. If the number of RSSI values was lower, the receiving device was in range but more distant from the transmitting chip.

The creation of a database of RSSI values is necessary because of the application of the Fingerprinting positioning algorithm. The algorithm consists in comparing the RSSI values in the database with the RSSI values recorded in real time. The actual comparison of RSSI values is performed by means of Pearson's correlation coefficient, which determines the probability with which a person is located at a given position in space.

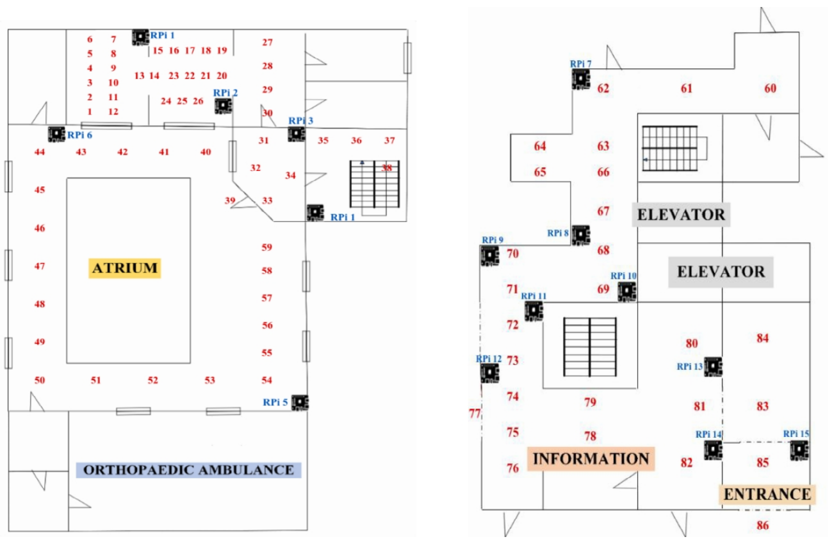

Fig. 5. A map of the location of the calibration points.

3. Creating a calibration matrix

RSSI values for each receiving device in range were obtained by calibration. Subsequently, the data in the database had to be adjusted so that all receiving devices in range with their corresponding RSSIs were associated to each position. As previously stated, the person holding the beacon remained at each position for more than 30 seconds, and therefore multiple RSSI values were obtained for a single receiving device. The average RSSI for the combination of position and receiving device was calculated in the resulting calibration matrix.

Table 1. A calibration matrix.

Position	Reader	RSSI
1	rpi-01	-67
	rpi-02	-66
	rpi-03	-84
	rpi-04	-81
	rpi-05	-85
	rpi-06	-79
2	rpi-01	-59
	rpi-02	-67
	rpi-03	-82
	rpi-05	-95
	rpi-06	-79
3	rpi-01	-59
	rpi-02	-69
	rpi-03	-85
	rpi-05	-91
	rpi-06	-80

Position	Reader	RSSI
73	rpi-07	-95
	rpi-09	-81
	rpi-10	-81
	rpi-11	-63
	rpi-12	-74
	rpi-13	-81
	rpi-14	-73
	rpi-15	-81
83	rpi-09	-86
	rpi-10	-87
	rpi-11	-77
	rpi-12	-70
	rpi-13	-73
	rpi-14	-67
	rpi-15	-62

Table 1 shows some calibration points. For the demonstration, positions 1, 2, 3 on the left and positions 73, 83 on the right were selected. Here it can be seen that the points on the left side have a range to the RPi receiving devices 1-6. The calibration points on the right hand side are at the other end of the building and the range had RPi receiving devices 9-15 located closer to these calibration points.

4. Localization of movement

Once the calibration is complete, the system is put into real operation. It continuously collects RSSI values from all receiving devices. This data is then evaluated using Pearson's correlation coefficient. When locating a route, the data in the database for a particular Beacon tag must be sampled at certain time periods and the recorded values must be compared to all calibration points of the calibration matrix. In this way, a value from -1 to +1 was obtained. The calibration point whose value is closest to +1 is the most likely beacon position.

For the demonstration, a transition was made with the Bluetooth beacon from calibration point 86, located at the entrance to the building, to the transport couch storage located at calibration point 69. The measurement took place from 05/11/2023 13:48:20 to 05/11/2023 13:48:50.

Two types of data evaluation were carried out:

1. Every 1 second, all data for the next 5 seconds were recorded. For each receiving device, averages of these values were taken and the result was evaluated by Pearson's correlation coefficient. The points whose values were closest to +1 were recorded in Table 2.

Table 2. Evaluation of calibration every 1 second.

Date/time	Position	PCC
05.11.2023 13:48:20	86	0.9713255527509856
05.11.2023 13:48:26	80	0.6169909805979569
05.11.2023 13:48:28	81	0.8962581595302719
05.11.2023 13:48:32	76	0.7443164792450041
05.11.2023 13:48:35	73	0.8754316959516941
05.11.2023 13:48:39	72	0.8854004609122829
05.11.2023 13:48:45	70	0.9769339863514583
05.11.2023 13:48:49	69	0.8988397816477322

2. Every 5 seconds, all data for the next 5 seconds were recorded. For each receiving device, averages of these values were taken and the result was evaluated by Pearson's correlation coefficient. The points whose values were closest to +1 were recorded in Table 3.

Table 3. Evaluation of calibration every 5 second.

Date/time	Position	PCC
05.11.2023 13:48:20	86	0.9713255527509856
05.11.2023 13:48:25	86	0.8753432870554492
05.11.2023 13:48:30	62	0.6842105263157895
05.11.2023 13:48:35	73	0.8754316959516941
05.11.2023 13:48:40	72	0.7981089880627689
05.11.2023 13:48:50	69	0.9441476178064289

5. Discussion and conclusion

From the above evaluation, advantages and some disadvantages of both approaches were identified. The first approach is more accurate, due to the fact that there is a lower evaluation interval required for more accurate localization when moving. On the other hand, there are increased demands on the hardware of the evaluation server. The second approach does not have as high hardware requirements as the first, but the 5 second evaluation interval is quite large when people are moving. However, it can be used for localizations of static objects and their occasional movements, or when it is not essential to record a specific movement, but the aim is to detect staying in a place for a certain period of time. This is useful for contact tracking in the spread of viral infection in healthcare facilities.

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References

Ainul, D. R. 2022. An enhanced trilateration algorithm for indoor RSSI based positioning system using zigbee protocol. Journal Infotel 14(4), 301-306.

Alyafawi, I. 2015. Real-time Localization Using Software Defined Radio. Philosophisch-naturwissenschaftliche Fakultät Bern.

Čabarkapa, D., Grujić, I., Pavlović, P. 2015. Comparative analysis of the Bluetooth Low-Energy indoor positioning systems. IEEE Journal.

Dong, Y. et al. 2011. The research and application of indoor location algorithm based on wireless sensor network. IEEE Journal.

Faragher, R., Harle, R. 2015. Location Fingerprinting With Bluetooth Low Energy Beacons. IEEE Journal on Selected Areas in Communications 33(11), 2418 – 2428.

Farahsari, S. P. et al. 2022. A Survey on Indoor Positioning Systems for IoT-Based Applications. IEEE Internet of Things Journal 9(10), 7680 – 7699.

He, S., Chan, G. H. S. 2015. Wi-Fi Fingerprint-Based Indoor Positioning: Recent Advances and Comparisons. IEEE Communications Surveys & Tutorials 18(1), 466–490.

Jung, J., Choi, Y. 2017. Measuring Transport Time of Mine Equipment in an Underground Mine Using a Bluetooth Beacon System. Minerals 7(1), 1-10.

Khanh, T. T. et al. 2020. Wi-Fi indoor positioning and navigation: a cloudlet-based cloud computing approach. Human-centric Computing and Information Sciences 10(32), 1-26.

Lee, B. et al. 2014. Development of self-localizer using collaboration of trilateration and triangulation. 11th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD).

Liu, F. et al. 2019. An Indoor Localization Method for Pedestrians Base on Combined UWB/PDR/Floor Map. Journal of Sensors 19(11), 1-19.

Liu, H. et al. 2007. Survey of Wireless Indoor Positioning Techniques and Systems. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) 37(6), 1067–1080.

Maaloul, K. et al. 2023. Bluetooth beacons based indoor positioning in a shopping malls using machine learning. Bulletin of Electrical Engineering and Informatics 12(1), 911-921.

Moghtadaiee, V., Gharoashi, A. S., Ghavami, M. 2019. New Reconstructed Database for Cost Reduction in Indoor Fingerprinting Localization. IEEE Access 4, 104462 – 104477.

Mrindoko, N., Minga, M. L. 2016. A Comparison Review of Indoor Positioning Techniques. International Journal of Computer (IJC) 21(1), 42-49.

Mussina, A., Aubakirov, S. 2019. Improving Indoor Positioning via Machine Learning. Proceedings of the 8th International Conference on Data Science, Technology and Applications DATA 1, 190-195.

Poosamani, N., Rhee, I. 2015. Towards a practical indoor location matching system using 4G LTE PHY layer information. IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops).

Posdorfer, W., Maalej, W. 2016. Towards Context-aware Surveys Using Bluetooth Beacons. Procedia Computer Science 83, 42-49.

Spachos, P., Plataniotis, N. K. 2020. BLE Beacons for Indoor Positioning at an Interactive IoT-Based Smart Museum. IEEE Systems Journal 14(3), 3483 – 3493.

Subedi, S., Pyun, Y. J. 2017. Practical Fingerprinting Localization for Indoor Positioning System by Using Beacons. Journal of Sensors 2017, 1-16.

Turgut, Z., Aydin, G. Z. G., Sertbas, A. 2016. Indoor Localization Techniques for Smart Building Environment. Procedia Computer Science 83, 1176-1181.

Wang, X. et al. 2016. CSI-Based Fingerprinting for Indoor Localization: A Deep Learning Approach. In IEEE Transactions on Vehicular Technology 66(1), 763–776.

Xie, W. et al. 2022. Time Difference of Arrival Estimation of Stationary Targets Utilizing Deep Neural Network. Journal of Physics: Conference Series 2414, 1-6.

Yan, S. et al. 2019. Wi-Fi RTT based indoor positioning with dynamic weighted multidimensional scaling. International Conference on Indoor Positioning and Indoor Navigation (IPIN).

Yang, J. et al. 2019. Beyond Beaconing: Emerging Applications and Challenges of BLE. Ad Hoc Networks Journal 97, 1-18.

Zafari, F., Papapanagiotou, I., Christidis, K. 2015. Microlocation for Internet-of-Things-Equipped Smart Buildings. IEEE Internet of Things Journal 3(1), 96-112.

Zhang, W., Yang, X. 2023. DV-Hop Location Algorithm Based on RSSI Correction. Electronics 12(5), 1-15.