System design of WiFi-signaling based accurate occupancy detection scheme

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ABSTRACT

Indoor location systems are the key technology to provide the location of a human or a device in indoor space. Since WiFi technology has been spread in various spaces, WiFi is the practical standard to realize the indoor location systems. As a receiver can typically find some WiFi access points (APs), indoor location systems use multiple signals from some APs to estimate a position. Initial systems use Received Signal Strength (RSS) as the measurement of distance because RSS decreases according to the distance between AP and a receiver. Recently, more practical service using indoor location systems has been discussed. This paper proposes an occupancy detection scheme based on a WiFi-based indoor location system. The proposed scheme tracks users' smartphone devices as a human location. The location of a human in a room is useful information to manage human resources efficiently. Therefore, some systems track a beacon tag to estimate the location or typical location systems use WiFi signals from several APs to estimate a location. As a result, the conventional systems require a special beacon tag or special tracking application to realize the human location system. On the contrary, the proposed system uses users' smartphones instead of special devices or applications. In this situation, the proposed system must track all WiFi devices that do not associate with a WiFi access point. Therefore WiFi APs cannot detect all users' devices. The proposed scheme focuses on the WiFi signaling process to detect a user's device and estimates the location of a user's device. The WiFi signal receivers detect a probe request message from a user's device because a probe request message should be transmitted even if the user's device does not associate an AP. We have developed a prototype system to evaluate the performance.

Keywords: Occupancy detection , WiFi signaling, Smartphones

1. INTRODUCTION

Indoor location information is becoming important for various services. Indoor location systems are new technology to provide the location of a human or a device in indoor space. Since GPS signals do not reach indoor space, they use several types of signals such as WiFi signal, BLE signal, ultrasonic sound, etc [1]. WiFi is one of the practical standards to realize the indoor location systems because general WiFi access points broadcast their beacon message periodically. Therefore, a receiver can find some WiFi access points (APs) in practical situations [2]. Additionally, a general WiFi driver provides Received Signal Strength (RSS) of a received packet, and RSS decreased according to the distance between AP and a receiver. As a result, initial systems use RSS as the measurement of distance and predict a position according to RSS of received signals from multiple APs.

Since the RSS usually fluctuates due to multiple wireless waves in real space, several studies have been proposed [3]. Additionally, RSS is affected by obstacles such as a wall, furniture, etc. in a room. Therefore, fingerprinting techniques, where RSS and a position are premeasured as reference data, have been attracted attention to improving the accuracy of localization [4]–[7]. Additionally, some researchers tried to use another discriminant function as a characteristic of the fingerprint [8], [9]. RSS is also fluctuating due to environmental conditions. Therefore, some researchers tried to mitigate the effect due to the fluctuation of RSS [10], [11]. Since the collected fingerprint data is enormous, recent studies use neural networks to learn the characteristics of RSS to realize high accuracy [12]–[14]. Some researchers have tried to estimate a position of an object by channel status, where any wireless device is not required for the estimation [15], [16].

Recently, Indoor location systems are fundamental technology to realize application services such as navigation, monitoring, etc. [17]. Human location tracking is one of the attractive application services because the location of a human in a room is useful information to manage human resources efficiently. The conventional systems use a special beacon tag for tracking a human or introduce a special application into a smartphone. Therefore, the installation cost and usability are issues for practical service.

The authors have proposed an occupancy detection scheme based on WiFi-signaling [18]. Typical location systems use WiFi signals from several APs to estimate a location. Therefore, they require some special device to estimate its location and to inform the system. On the contrary, the proposed system should estimate the location of users' devices because almost all users have some wireless devices such as a smartphone, a smartwatch, etc. In this situation, all WiFi devices do not associate with a WiFi access point. Therefore WiFi APs cannot detect all users' devices, and conventional mechanisms cannot work because they assume that the WiFi device is associated with AP. The proposed scheme focuses on the WiFi signaling process to detect a user's device and estimates the location of a user's device. The WiFi signal receivers detect a probe request message from a user's device because a probe request message should be transmitted even if the user's device does not associate an AP. As a result, the proposed system can detect a user's device without the association process and estimates the position of the device. As the estimation scheme, we use Support Vector Machine (SVM) to learn the characteristics of an indoor wireless environment. We have developed a prototype system to evaluate the performance. The numerical results show that the proposed estimation scheme can identify the location with more than 80% accuracy by onetime measurement.

2. WIFI ASSOCIATION PROCESS

Since WiFi APs provide bridge service to mobile stations, mobile stations must establish an appropriate connection state to the access point. The standard of IEEE 802.11 defines three connection status: Not authenticated or associated, Authenticated but not yet associated, and Authenticated and associated. The mobile station and AP will exchange a series of 802.11 management frames for obtaining an authenticated and associated state. The following is the signaling process shown in Fig. 1.

- A mobile station transmits the probe requests to discover 802.11 networks. The probe requests advertise supported data rates and 802.11 capabilities. Since the status is Not authenticated or associated, the destination address of the probe request is BSSID of ff:ff:ff:ff:ff:ff. Therefore all APs can receive it.
- AP checks is the mobile station has at least one common supported data rate when it receives the probe request. If the mobile station supports compatible 802.11 capabilities, it replies to the mobile station with the probe response advertising the SSID (wireless network name), supported data rates, encryption types if required, and own 802.11 capabilities. The mobile station selects compatible networks from the probe responses after receiving the probe response.
- A mobile station transmits a low-level 802.11 authentication frame to AP to set the authentication to open and the sequence to 0x0001.
- AP receives the authentication frame and responds to the mobile station with the authentication frame set to open, indicating a sequence of 0x0002.
- After reception of the authentication frame, the mobile station will transmit the association request to that AP. The association request contains selected encryption types if required and other compatible 802.11 capabilities. If AP

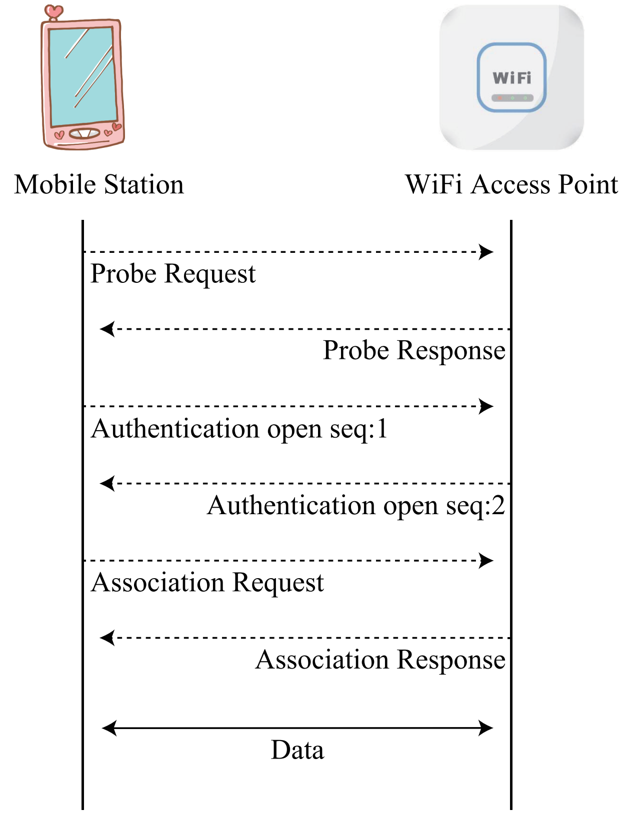

Fig. 1. Overview of WiFi-association process.

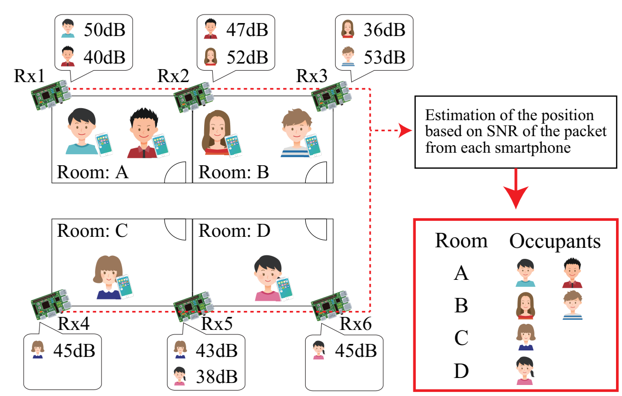

Fig. 2. Overview of WiFi-based occupancy detection system.

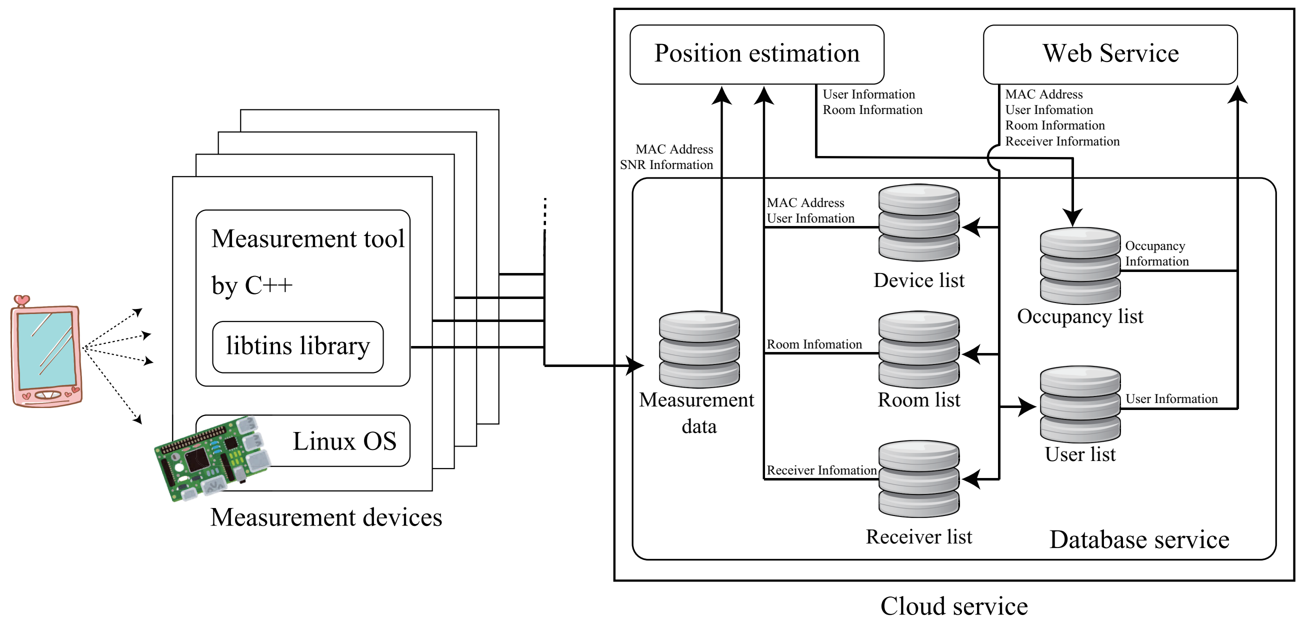

Fig. 3. System model.

receives a frame from a mobile station that is authenticated but not yet associated, it will respond with a disassociation frame to change the mobile station into an authenticated but unassociated state.

- If the association request contains compatible parameters of AP, AP will create an Association ID for the mobile station and respond with an association response with a success message granting network access to the mobile station.
- The mobile station is successfully associated with AP, and the bridge service can start.

3. WIFI-BASED OCCUPANCY DETECTION SYSTEM

3.1. Concept design

Fig. 2 shows the concept design of the proposed WiFi-based occupancy detection system. The system consists of the WiFi receivers that collect a probe request message and the cloud service that stores the measurement data and the position estimation function.

The proposed scheme assumes that some WiFi receivers are implemented in measurement space. It also uses users' devices such as smartphones, smartwatches, etc. for tracking users. These users' devices do not associate with the WiFi receivers of the proposed system. Therefore, typical data communication is not possible because the bridge service does not work before the association process.

As explained in section 2, all WiFi devices usually transmit probe request messages periodically to scan IEEE 802.11 networks. Since the probe request messages are transmitted to the broadcast address in layer-2 address, any WiFi devices can receive the probe request by receiving BSSID of ff:ff:ff:ff:ff:ff address. As a result, each WiFi receiver detects a probe request message from users' devices, and detect the smartphone even if the smartphone does not associate with WiFi AP [19].

Due to the requirement to estimate a distance from each WiFi receiver, the RSS of a probe request is also measured. Since the WiFi receivers have an IP network connection, the detected information is stored in the database on the cloud service. The position estimation function on the cloud service can recognize the position of each smartphone and estimate an occupancy room.

3.2. System Model

Fig. 3 shows the system model of the proposed system. The system consists of users' WiFi devices such as smartphones, measurement devices such as WiFi receivers, and the cloud service with the database, the position estimation, and web service functions. As the tracking object, the system uses users' WiFi devices. Therefore, it does not require any special devices for tracking and is easily installed in a practical environment.

As the tracking signal, the proposed system uses a probe request message from users' WiFi devices because a probe request message is continuously transmitted to scan neighbor IEEE 802.11 networks. The measurement devices scan a neighbor probe request message and measure RSS of the message for estimating the distance between the measurement device and the users' WiFi device. The collected information is transferred to the cloud service to estimate the position of the user's WiFi device because some neighbor measurement devices may receive the same probe request message from the user's WiFi device.

The cloud service has three main functions: the database function, the position estimation function, and the web service function. The database function has three types of tables. The device list table is used for user management and stores a pair of MAC addresses of the user's WiFi device and the user information. The room list table manages the information about the room for occupancy service. The receiver list table

TABLE I
DATABASE FOR USERS' DEVICES LIST.

No.	column	Description	Type
1	id	Index Number	INT
2	address	MAC address	CHAR
3	user_id	Related User ID	INT

TABLE II
DATABASE FOR ROOM LIST.

No.	column	Description	Type
1	id	Index Number	INT
2	room_id	Room ID	INT
3	room_info	Room Information	CHAR

TABLE III
DATABASE FOR RECEIVER LIST.

No.	column	Description	Type
1	id	Index Number	INT
2	receiver_id	Receiver ID	INT
3	room_ids	Room ID list	CHAR
4	location	Location	CHAR

TABLE IV
DATABASE FOR USER LIST.

No.	column	Description	Type
1	id	Index Number	INT
2	user_id	User ID	INT
3	user_info	User Information	CHAR

TABLE V
DATABASE FOR MEASUREMENT DATA.

No.	column	Description	Type
1	id	Index Number	INT
2	receiver_id	Related Receiver ID	INT
3	address	MAC address	CHAR
4	rss	RSS	FLOAT
5	datetime	Date & Time	DATETIME

TABLE VI
DATABASE FOR OCCUPANCY RESULT.

No.	column	Description	Type
1	id	Index Number	INT
2	room_id	Related Room ID	INT
3	user_id_list	User ID list	CHAR
4	datetime	Date & Time	DATETIME

manages the measurement devices. The measurement data table stores collected information about the received probe request messages. The occupancy list table stores the estimated results of the occupancy status of users in each room.

3.3. Database model

As the database service, the proposed system uses a relational database system such as Maria DB, PostgreSQL, etc. It defines six database tables as the initial design of the prototyping shown in Fig. 4.

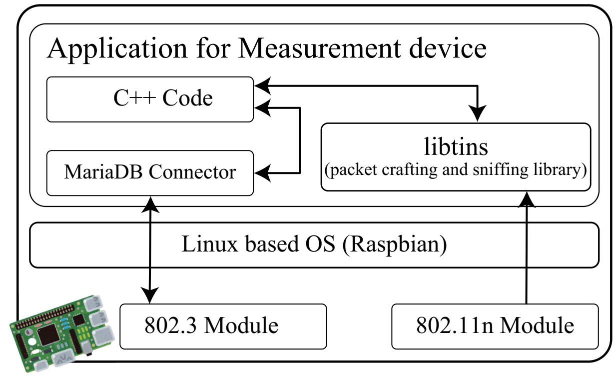

Fig. 4. System model of prototyping measurement device.

Table I is the database table for the users' WiFi devices list. The table is used to manage a MAC address in the layer-2 to track a WiFi device. Table II is the database table for room information. System managers can manage the room information for estimating the occupancy status. Table III is the database table for measurement devices. Since the position estimation function requires the position of each measurement device to estimate the position of tracking WiFi device, the table includes the position of the measurement device and installed room ID. Table IV is the database table for user management. The table includes user information related to the user ID. Table V is the database table to store measurement data from measurement devices. Since the position estimation function collects related RSS values of the tracked WiFi device to estimate the position, the table includes time information and RSS information. Table VI is the database table for the occupancy status of each room.

3.4. Position Estimation

Since multiple measurement devices receive a probe request message from a smartphone, the database has a set of RSS values at different measurement devices and MAC address. The learning process requires a correct location value and a set of RSS values at different measurement devices. Even if we used four measurement devices for the evaluation, the number of measurement devices is not limited in this scheme. The evaluation prototype uses a Support Vector Machine (SVM) as the learning algorithm for making a unique classifier. The classifier can output the grid-based location according to the set of RSS values.

3.5. Prototyping

As the prototyping, we have developed a measurement device with Raspberry Pi 3 Model B+. Since the measurement device must be installed in each room, the size of the device should be small. Fig. 3 shows the system model of the prototyping measurement device. Raspberry Pi 3 Model B+ supporting the 2.4GHz and 5GHz IEEE 802.11.b/g/n/ac wireless LAN function. Therefore, the prototype device can track almost all consumer WiFi devices. Since the Linux OS works on Raspberry Pi, we have developed a measurement application by C++ language for Raspbian OS. General applications do not receive management

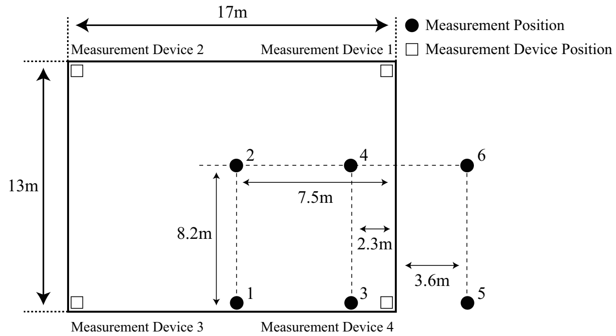

Fig. 5. Measurement environment.

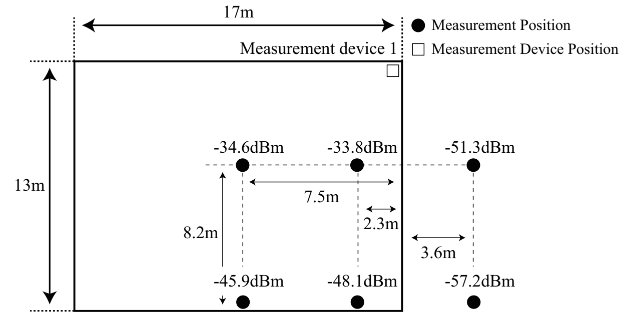

Fig. 6. Measurement example (Receiver 1).

TABLE VII
AVERAGE OF RSS.

Position No.	1	2	3	4	5	6
Receiver1	-45.9	-34.6	-48.1	-33.8	-57.2	-51.3
Receiver2	-40.9	-39.8	-46.1	-45.5	-65.3	-64.2
Receiver3	-48.7	-40.6	-46.3	-47.4	-60.4	-59.9
Receiver4	-54.1	-43.8	-30.4	-34.3	-51.9	-52.2

Unit: dBm

TABLE VIII
VARIANCE OF RSS.

Position No.	1	2	3	4	5	6
Receiver1	3.1	2.4	3.7	3.3	2.5	2.2
Receiver2	2.0	1.7	2.4	2.9	5.1	2.6
Receiver3	3.0	1.7	2.4	2.7	2.1	2.0
Receiver4	2.6	1.8	1.4	3.3	2.5	2.3

Unit: dBm

messages of IEEE 802.11, including probe request messages. Therefore, the developed application uses promiscuous mode to monitor the WiFi interface. Additionally, it also uses libtins library [20] for WiFi message processing. When the measurement device detects a probe message, it also measures RSS of the message. The collected measurement data is stored in the database through the database connector.

Since the device list of users' smartphones is registered beforehand, the position estimation function can recognize the users' smartphone in the measurement data. The result of the recognition is stored in the occupancy list and is shown through the web service.

4. EVALUATION

4.1. Measurement

We have evaluated the essential performance of the proposed scheme in a lecture room. Fig. 5 shows the layout of the lecture room. The square marks are the position of each measurement device. The circle marks are the position of measurements where the transmitter exists. Since the target service should decide which a target device exists in a room or not, the positions 1, 2, 3, and 4 are in the room, and the positions 5 and 6 are out of the room. The height of the devices is 1.2 meters. The transmitter sends a probe request message at channel 1(2.412GHz).

Fig. 6 shows the example measurement result. The values are RSS at each measurement position for the measurement device 1. Table VII is the average values of RSS for each measurement position and measurement device. Table VIII is the variance of Table VII.

4.2. Position estimation

Since our target service should detect which a device exists in a room or not, we have evaluated the room detection ratio based on the SVM which is a well-known learning algorithm. As the validation, we use the k-fold cross-validation with $k = 5$. In k-fold cross-validation, the original sample is randomly partitioned into k equal sized subsamples. A single subsample is used as the validation data for testing the model, and the remaining $k - 1$ subsamples are used as training data. We have evaluated an average of 100 trials for accurate detection ratio. The average accurate detection ratio is 99.9% because the answer is simple patterns: indoor or outdoor. Additionally, Table X shows the results of the grid-based position estimation. Since the SVM requires a correct location for a set of RSS values, we have prepared the learning data based on 50cm-grid. As an evaluation result, the classifier can estimate a correct grid position with more than 80% accuracy by onetime estimation. As smartphone users exist in a room for a while, the system has enough chance to estimate a location during users' stay. Therefore, the accuracy is enough to estimate a position in the target service.

5. CONCLUSION

This paper has proposed an occupancy detection scheme based on WiFi-signaling. The proposed scheme focuses on the WiFi signaling process to detect a user's device and estimates the location of a user's device. The WiFi signal receivers detect a probe request message from a user's device because a probe request message should be transmitted even if the user's device does not associate an AP. We have developed a prototype system to evaluate the performance. The numerical results showed that the system could estimate an indoor location with enough accuracy for the target service.

TABLE IX
PARAMETERS FOR SVM.

Kernel	RBF(Radial Basis function Kernel)
Cost parameter C	100
γ	1000

TABLE X
ESTIMATED GRID POSITION RATIO.

Error Distance [m]	X	Y
0(Correct Grid)	0.816	0.823
0 - 0.5	0.042	0.056
0.5 - 1.5	0.031	0.04
1.5 - 2.5	0.017	0.035
2.5 - 3.5	0.033	0.016
3.5 - 4.5	0.02	0.007
4.5 - 5.5	0.012	0.009
5.5 - 6.5	0.016	0.008
6.5 - 7.5	0.01	0.005
7.5 -	0.004	0.002

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REFERENCES

[1] Y.Yun, J.Lee, D.An, S.Kim and Y.Kim, “Performance Comparison of Indoor Positioning Schemes Exploiting Wi-Fi APs and BLE Beacons,” 2018 5th NAFOSTED Conference on Information and Computer Science (NICS), November 2018.

[2] M.Lin, X.Yubin and Z.Mu, “Accuracy Enhancement for Fingerprint-Based WLAN Indoor Probability Positioning Algorithm,” 2010 First International Conference on Pervasive Computing, Signal Processing and Applications, September 2010.

[3] P.Abhishek, G.Hegde, K.S.Arpitha and N.N.Nagendra, “Performance analysis of received signal strength based Wi-Fi indoor positioning algorithms,” 2017 2nd IEEE International Conference on Recent Trends in Electronics, Information Communication Technology (RTEICT), May 2017.

[4] W Li, D.Wei, H.Yuan and G.Ouyang, “A novel method of WiFi fingerprint positioning using spatial multi-points matching,” 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), October 2016.

[5] H.X.Jian and W.Hao, “WIFI Indoor Location Optimization Method Based on Position Fingerprint Algorithm,” 2017 International Conference on Smart Grid and Electrical Automation (ICSGEA), May 2017.

[6] N.Etemadyrad and J.K.Nelson, “A sequential detection approach to indoor positioning using RSS-based fingerprinting,” 2016 IEEE Global Conference on Signal and Information Processing (GlobalSIP), December 2016.

[7] G.Yang and J.Zhang, “Research on Indoor Positioning Accuracy Based on Wi-Fi Intensity Values,” 2016 International Conference on Network and Information Systems for Computers (ICNISC), April 2016.

[8] M.Fazelinia, M.R.Daliri and S.Ebadollahi, “Wi-Fi RSS-based Indoor Localization Using Reduced Features Second Order Discriminant Function,” 2019 27th Iranian Conference on Electrical Engineering (ICEE), April 2019.

[9] A.Moreira, I.Silva, F.Meneses, M.J.Nicolau, C.Pendao and J.Torres-Sospedra, “Multiple simultaneous Wi-Fi measurements in fingerprinting indoor positioning,” 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN), September 2017.

[10] C.Park and S.H.Rhee, “Indoor positioning using Wi-Fi fingerprint with signal clustering,” 2017 International Conference on Information and Communication Technology Convergence (ICTC), October 2017.

[11] W.Charoenruengkit, S.Saejun, R.Jongfungfeuang and K.Multhonggad, “Position Quantization Approach with Multiclass Classification for Wi-Fi Indoor Positioning System,” 2018 International Conference on Information Technology (InCIT), October 2018.

[12] R.Joseph and S.B.Sasi, “Indoor Positioning Using WiFi Fingerprint,” 2018 International Conference on Circuits and Systems in Digital Enterprise Technology (ICCSDET), December 2018.

[13] K.Wang, X.Yu, Q.Xiong, Q.Zhu, W.Lu, Y.Huang and L.Zhao, “Learning to Improve WLAN Indoor Positioning Accuracy Based on DBSCAN-KRF Algorithm From RSS Fingerprint Data,” IEEE Access, 2019.

[14] S.Cheerla and D.V.Ratnam, “RSS based Wi-Fi positioning method using multi layer neural networks,” 2018 Conference on Signal Processing And Communication Engineering Systems (SPACES), January 2018.

[15] J.Torres-Sospedra, P.Richter, G.Mendoza-Silva, E.S.Lohan and J.Huerta, “Characterising the Alteration in the AP Distribution with the RSS Distance and the Position Estimates,” 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN), September 2018.

[16] R.Y.Chang, S.Liu and Y.Cheng, “Device-Free Indoor Localization Using Wi-Fi Channel State Information for Internet of Things,” 2018 IEEE Global Communications Conference (GLOBECOM), December 2018.

[17] C.Chen, “A Wi-Fi based Pedestrian Navigation System using Kalman Filter and Particle Filter,” 2018 IEEE 4th Information Technology and Mechatronics Engineering Conference (ITOEC), December 2018.

[18] Y. Miwa, A. Ushiyama, H. Komura, and K. Naito, “System design of WiFi-signaling based accurate occupancy detection scheme,” The 11th International Multi-Conference on Complexity, Informatics and Cybernetics: IMCIC 2020, March, 2020.

[19] Julien Freudiger, “How talkative is your mobile device?: an experimental study of Wi-Fi probe requests,” WiSec ’15: Proceedings of the 8th ACM Conference on Security & Privacy in Wireless and Mobile Networks, No. 5, pp. 1–6, June 2015.

[20] Packet crafting and sniffing library, http://libtins.github.io