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# Zone-Based Indoor Positioning System in Faculty Building with Neural Networks

Alvin Ming Song Chong, Boon Chin Yeo*, Way Soong Lim, Sin Yi Lee

***Abstract* – Pervasive Wi-Fi deployment has made Wi-Fi an economically convenient wireless platform for developing an Indoor Positioning System (IPS). This paper presents a zone-based IPS developed on Wi-Fi using fingerprinting technique with Probabilistic Neural Network (PNN) and Radial Basis Function Neural Network (RBFNN) to predict target positions. The zone-based IPS is deployed in an indoor environment (a faculty building) with four Wi-Fi modules separately placed. The indoor environment consists of office rooms and laboratories separated by concrete walls. A two-dimensional coordinate system and zone label are deployed to define each location. After that, data collection is performed on each location. The Wi-Fi Received Signal Strength (RSS) for every Wi-Fi module at each location is discovered, labelled with the location coordinate and zone value to form a fingerprint and finally stored in a database. Fingerprints in the database are then separated into training and testing sets for training and testing of PNN and RBFNN. The testing result shows that the mean positioning error for coordinate prediction of PNN and RBFNN is 3.84m and 6.91m, respectively. Although RBFNN has a large mean positioning error, RBFNN presented a zone positioning accuracy of 78.7%, which is close to the 82.2% accuracy presented by PNN.**

***Keywords: Indoor Positioning System (IPS), Received Signal Strength (RSS), Fingerprinting, Neural Network, Wi-Fi***

## I. Introduction

Recently human life has been dramatically affected by the spread of the covid-19 virus. People have been advised to maintain social distance by avoiding crowded areas, especially in an indoor environment. The reason is that according to [1], a study was carried out by Japanese researchers to study the infection rate of covid-19 in the indoor environment compared with the outdoor environment. The result shows that the rate of infection in the indoor environment is multiple times greater than the rate of infection in the outdoor environment.

This result shows the importance of crowd level information in the indoor environment compared with the outdoor environment during this covid-19 pandemic as it can warn people to stay away from crowded areas. Suppose a person is in an outdoor environment. The person will be able to obtain the crowd level information of an outdoor venue remotely with the help of applications such as Waze and Google Maps, which uses GPS as their fundamental positioning technique. However, in most indoor environments, people are unlikely able to obtain the crowd level of a venue in the indoor environment remotely as this kind of service requires Indoor Positioning System (IPS) as the

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fundamental positioning technique, which is currently still under the growing stage.

IPS can be constructed on different wireless platforms. A popular wireless platform researched by researchers in the past decade is Wi-Fi. This is because Wi-Fi has a ready-to-use infrastructure that benefits developers in terms of low development cost [2]. A wireless platform is just a medium for the construction of IPS. A positioning technique to utilise the medium for target position estimation is required. One of the popular positioning techniques used with Wi-Fi is fingerprinting positioning technique with Received Signal Strength (RSS) as the distance-dependent parameter [3].

Although many researchers had developed different kinds of Wi-Fi RSS fingerprinting based IPS, the method used to measure the performance is mostly in terms of Euclidean distance error (distance between estimated target position with actual target position) [4][5][6]. This means that while those researchers are implementing fingerprinting positioning technique to develop a Wi-Fi RSS based IPS, each location (reference point) in their study area is defined using a coordinate system. Thus, in this paper, a Wi-Fi RSS fingerprinting based IPS using Probabilistic Neural Network (PNN) and Radial Basis Function Neural Network (RBFNN) will be developed. However, the study conducted will measure the performance of the IPS developed in terms of coordinate prediction accuracy (measuring Euclidean distance error) and zone prediction accuracy.

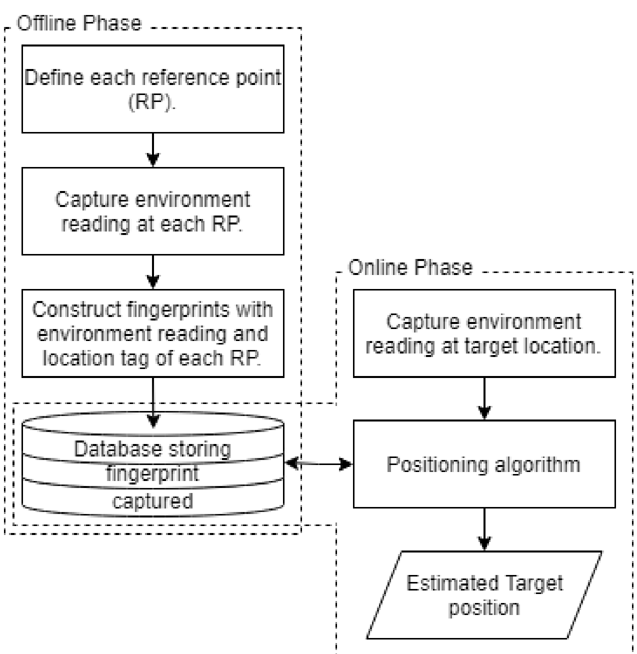


**FIGURE 1. Processes in fingerprinting positioning technique.**

## II. Fingerprinting Positioning Technique

Fingerprinting positioning technique is a popular positioning technique as it does not require Line of Sight (LOS) measurement between nodes, high flexibility and promise performance in complex indoor environments [7][8]. This section will briefly explain fingerprinting positioning technique to provide readers with an understanding in advance. Figure 1 illustrates the processes involve while implementing fingerprinting positioning technique.

As shown in Figure 1, processes involved while implementing fingerprinting positioning technique are categorised into two major phases: offline and online. While implementing fingerprinting positioning technique, processes in the offline phase will be carried out first. All the processes in the offline phase aim to accomplish an objective. The objective is to establish a database (a collection of fingerprints).

Offline phase will start with the process of defining each reference point in a study environment. This process will let each reference point have a unique location tag. A popular way to define each reference point is by adopting a coordinate system. First, defining a reference point as the global origin (with (0,0) for location tag in a 2D situation). Then, the other reference points will have a unique location tag by referring to the global origin. After each reference point has been defined, scanning for environment reading (a collection of distance-dependent parameters, such as RSS value from surrounding wireless anchors) will be carried out on each reference point. These environment readings will then be labelled with the location tag of a reference point where the environment reading is extracted to form a fingerprint. Furthermore, these fingerprints will be kept in a database that later will be used by the positioning algorithm in the online phase.

Online phase is a phase that will utilise the database constructed during the offline phase to estimate the target position. Firstly, the target device will capture the same format of environment reading captured during the offline phase on location in the study environment. Next, the environment reading will then be passed to a positioning algorithm. The positioning algorithm will then look into the database for fingerprint with the value of environment reading that match the environment reading passed to it. If there is a match, the location tag of the fingerprint will be outputted as the estimated target location. Depending on the type of positioning algorithm adopted, the process will be slightly different. For example, when neural networks [9][10][11] are used as the positioning algorithm, neural network training is required to be carried out before starting the online phase. After being trained, during the online phase, when environment reading extracted by a target device is passed to the trained neural network, the neural network can estimate the target position without accessing the database.

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## III. METHODOLOGY

This section will elaborate on works carried out to develop a Wi-Fi RSS fingerprinting based IPS using two different neural networks. Performance study will be conducted from two different aspects: coordinate positioning accuracy (measure in term of Euclidean distance error between estimated and actual target position) and zone prediction accuracy (measure in term of percentage of zone prediction made is same as actual zone value that target is on). This section will begin with a discussion of the required hardware components. As a Wi-Fi RSS fingerprinting based IPS is to be developed, hardware that can serve as Wi-Fi anchors is required. Figure 2 shows the block diagram of hardware that serves as a Wi-Fi anchor in the study environment setup.

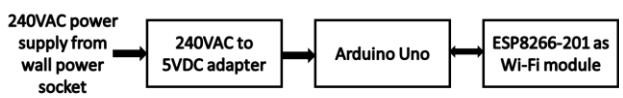


**FIGURE 2. Block diagram of Wi-Fi anchor module.**

As shown in Figure 2, the development of a Wi-Fi anchor involves three different components: a 5V DC adapter, an Arduino Uno board, and an ESP8266-201 Wi-Fi module. ESP8266-201 Wi-Fi module is the core component of the Wi-Fi anchor developed. Low cost and open-source programming platform that can speed up the development progress are reasons that ESP8266-201 Wi-Fi module being chosen to serve as the core component of the Wi-Fi anchor developed. Furthermore, ESP8266-201 can be connected with an external antenna allowing it to have extensive signal coverage that is sufficient to cover the study environment selected for performance study. However, the operating voltage of ESP8266-201 Wi-Fi module is 3.3V. Thus, Arduino Uno has been selected because it consists of an onboard 3.3V regulator that regulates a 3.3V output voltage required by the ESP8266-201 Wi-Fi module. Lastly, a 5V DC adapter has been used to convert the 240V AC power (from the wall power socket) to 5V DC required by Arduino Uno. A total of four Wi-Fi anchors had been developed to be set up in the study environment. Each Wi-Fi anchor is uploaded with firmware that configures them with a unique SSID.

After hardware development is done, a suitable study environment is required to be decided. After a short discussion, the right-wing of the second floor of the Faculty of Engineering and Technology was finally chosen out of a few proposed areas. The study environment chosen is illustrated with a floor plan, as shown in Figure 3. As performance studies on the developed IPS will be carried out from coordinate aspect and zone aspect, each location in the study environment is defined with coordinate value and zone value.

As illustrated in Figure 3, a 2D coordinate system has been implemented to define each location in the study environment with respective x coordinate and y coordinate referring to a global origin. In addition, the study environment is divided into 27 zones to define each location with zone value. Zones are divided according to the rooms, staircases, and corridors and are represented by rectangles, framed by dotted lines, as shown in Figure 3. Furthermore, the four dots in Figure 3 represent the location where the four Wi-Fi anchors developed are being placed. Due to the building constraint for anchors setup, the placement of Wi-Fi anchors ensured that the device that served as the Wi-Fi tag would be able to extract RSS from a minimum of three Wi-Fi anchors, at each location of the whole study environment.


**FIGURE 3. Floorplan of the study environment.**

When each location is defined and Wi-Fi anchors are set up in the study environment, data collection process has been executed to establish a database. The data collection process will be conducted by extracting the Wi-Fi RSS value on 673 different positions in the study environment. Each position is having a spacing size of 1 meter apart in x-direction and y-direction. The hardware used to act as the Wi-Fi tag to scan for RSS value from each Wi-Fi anchor is a mobile phone equipped with Wi-Fi Analyzer application (downloaded from Google Play Store). The Wi-Fi Analyzer application will be able to display the surrounding Wi-Fi RSS in dBm numerically. Besides, the Wi-Fi Analyzer application has a filter function that is useful while conducting data collection. Users can specify the SSID of the Wi-Fi anchors with wireless information to be displayed on the screen into the application. Next, the filter function will filter the list of Wi-Fi signals detected in the environment. Finally, only the Wi-Fi RSS from the Wi-Fi anchors with SSID recorded in the application will be displayed on the screen of the user device.

While conducting data collection at each location, the RSS from each Wi-Fi anchor is collected three times. This is because Wi-Fi signal fluctuates from time to time. Therefore, the averaged RSS value will represent the RSS value extracted from each Wi-Fi anchor and labelled with respective location tag to form a fingerprint ({x, y, zone, RSS1, RSS2, RSS3, RSS4}) and kept in a database. After complete data collection, the next step will be developing a positioning algorithm and conducting a performance study.

## IV. RESULTS AND DISCUSSIONS

In this study, MATLAB R2017b is chosen as software to develop neural network and conduct performance analysis. Its neural network toolbox will be used to develop two different types of neural network. The first type of neural network is Probabilistic Neural Network (PNN). The second type of neural network is Radial Basis Function Neural Network (RBFNN). Before proceeding with training and testing on each neural network, data (fingerprints) in the database constructed is equally separated into three different sets named D1, D2, and D3.

A performance study will be conducted from both the coordinate aspect and zone aspect for each type of neural network. While conducting the study from the coordinate aspect, neural networks will be inputted with RSS from each Wi-Fi anchor, and the output will be coordinate. While conducting the study from the zone aspect, neural networks will be inputted with RSS from each Wi-Fi anchor, but the output will be zone value.

For each performance study, both PNN and RBFNN will be trained and tested three times. The first attempt uses D1 and D2 as training sets, D3 as testing set. The second attempt uses D1 and D3 as training sets, D2 as testing set. The third attempt uses D2 and D3 as training sets, D1 as testing set. Table 1 summarises the training set and testing set used for each attempt.

**TABLE 1. Training set and testing set.**

| Attempt (RBFNN & PNN) | Training set | Testing Set |
|---|---|---|
| 1 | D1, D2 | D3 |

| | | |
|---|---|---|
| 2 | D1, D3 | D2 |
| 3 | D2, D3 | D1 |

The positioning performance of PNN and RBFNN for each attempt is summarised using two tables. Table 2 illustrates the coordinate positioning performance measured using mean Euclidean distance error between the estimated target position and the actual target position. Table 3 illustrates the zone prediction performance measured in the percentage of zone value estimated is the same as the actual zone value.

**TABLE 2. Overall mean Euclidean distance error.**

| Neural network | | Mean Euclidean distance error per test (m) | Mean Euclidean distance error on average(m) | Standard deviation per test (m) | Averaged standard deviation (m) |
|---|---|---|---|---|---|
| PNN | 1 | 3.99 | 3.84 | 4.83 | 4.87 |
| | 2 | 3.76 | | 4.87 | |
| | 3 | 3.77 | | 4.90 | |
| RBFNN | 1 | 6.94 | 6.91 | 5.77 | 5.69 |
| | 2 | 6.74 | | 5.53 | |
| | 3 | 7.06 | | 5.76 | |

**TABLE 3. Overall zone prediction accuracy.**

| Neural network | | Zone accuracy (%) | Averaged Zone Accuracy (%) |
|---|---|---|---|
| PNN | 1 | 80.4 | 80.2 |
| | 2 | 82.2 | |
| | 3 | 78.1 | |
| RBFNN | 1 | 78.8 | 78.7 |
| | 2 | 79.5 | |
| | 3 | 77.7 | |

Based on the test result obtained as shown in Table 2, it can be observed that both PNN and RBFNN presented a minimum mean Euclidean distance error of 3.76m and 6.74m, respectively in the second attempt. On average, both PNN and RBFNN presented a mean Euclidean distance error of 3.84m and 6.91m, respectively. Although both of the neural networks are presenting considerably large coordinate positioning error and the coordinate positioning error of RBFNN is approximately one time larger than PNN. However, based on the zone prediction result shown in Table 3, both neural networks, PNN and RBFNN, managed to achieve a considerably high zone prediction accuracy, i.e., at least 77%, for all three attempts. Among the three attempts, it is observed that training sets of 1 and 3, with testing set 2, produced the highest accuracy for both networks. On the contrary, training sets 2 and 3, with testing set 1, appeared to be the lowest for both networks also. On average, PNN performed slightly better in zone prediction than RBFNN, by achieving 80.2% compared to 78.7% in the latter.

## V. CONCLUSION

In a nutshell, the Wi-Fi RSS fingerprinting based IPS using PNN or RBFNN as positioning algorithm presented limited coordinate positioning performance with mean Euclidean distance error above 3m. However, the Wi-Fi RSS fingerprinting based IPS using these two kinds of neural networks presented their potential in zone prediction. Especially for PNN, the zone prediction accuracy is more than 80%.


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## AUTHOR CONTRIBUTIONS

Alvin Ming Song Chong: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;

Sin Yi Lee: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;

Boon Chin Yeo: Project Administration, Supervision, Writing – Review & Editing;

Way Soong Lim: Project Administration, Supervision, Writing – Review & Editing.

## CONFLICT OF INTERESTS

No conflict of interests were disclosed.

## ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

## REFERENCES


[1] H. Nishiura, H. Oshitani, T. Kobayashi, T. Saito, T. Sunagawa, T. Matsui, T. Wakita, M. Suzuki, and MHLW COVID-19 Response Team, "Closed environments facilitate secondary transmission of coronavirus disease 2019 (COVID-19)," medRxiv, 2020. DOI: https://doi.org/10.1101/2020.02.28.20029272.

[2] N. A. M. Maung and W. Zaw, "Comparative Study of RSS-based Indoor Positioning Techniques on Two Different Wi-Fi Frequency Bands," in Proc. 17th Int. Conf. Electrical Eng./Electronics, Comput., Telecommun. Inf. Technol. (ECTI-CON), 2020, pp. 185–188. DOI: https://doi.org/10.1109/ECTI-CON49241.2020.9158211.

[3] A. M. S. Chong, B. C. Yeo, and W. S. Lim, “Automatic Data Acquisition System for Wi-Fi Fingerprint-Based Indoor Positioning System,” Int. J. Innov. Comput. Inf. Control (IJICIC), vol. 18, no. 1, pp. 231–252, 2022. DOI: https://doi.org/10.24507/ijicic.18.01.231.

[4] W. K. Zegeye, S. B. Amsalu, Y. Astatke, and F. Moazzami, “WiFi RSS fingerprinting indoor localization for mobile devices,” in Proc. 2016 IEEE 7th Annu. Ubiquitous Comput.,

Electron. Mobile Commun. Conf. (UEMCON), 2016, pp. 1–6. DOI: https://doi.org/10.1109/UEMCON.2016.7777834.
[5] S. Yiu, M. Dashti, H. Claussen, and F. Perez-Cruz, "Wireless RSSI fingerprinting localization," Signal Process., vol. 131, pp. 235–244, 2017. DOI: https://doi.org/10.1016/j.sigpro.2016.07.005.
[6] T. A. Z. Rahman, N. Ramli, M. A. A. Rahman, and H. Mohamad, "Hybrid Nearest Neighbour and Feed-forward Neural Networks Algorithm for Indoor Positioning System," in Proc. 2020 IEEE 8th Conf. Syst. Process Control (ICSPC), 2020, pp. 37–40. DOI: https://doi.org/10.1109/ICSPC50992.2020.9305770.
[7] X. Wang, L. Gao, S. Mao, and S. Pandey, "CSI-Based Fingerprinting for Indoor Localization: A Deep Learning Approach," IEEE Trans. Veh. Technol., vol. 66, no. 1, pp. 763–776, 2017. DOI: https://doi.org/10.1109/TVT.2016.2545523.
[8] S. He and S. H. G. Chan, "Wi-Fi fingerprint-based indoor positioning: Recent advances and comparisons," IEEE Commun. Surv. Tutor., vol. 18, no. 1, pp. 466–490, 2016. DOI: https://doi.org/10.1109/COMST.2015.2464084.
[9] C. Chen and Y. Chen, "A modified probability neural network indoor positioning technique," in Proc. 2012 Int. Conf. Inf. Secur. Intell. Control (ISIC), 2012, pp. 317–320. DOI: https://doi.org/10.1109/ISIC.2012.6449770.
[10] H. Mehmood, N. K. Tripathi, and T. Tipdecho, "Indoor Positioning System Using Artificial Neural Network," Comput. Sci., vol. 6, no. 10, pp. 1219–1225, 2010. DOI: https://doi.org/10.3844/jcssp.2010.1219.1225.
[11] H. Dai, H. Liu, X. Xing, and Y. Jin, "Indoor Positioning Algorithm Based on Parallel Multilayer Neural Network," in Proc. 2016 Int. Conf. Inf. Syst. Artif. Intell. (ISAI), 2016, pp. 356–360. DOI: https://doi.org/10.1109/ISAI.2016.0082.