Computers and Electrical Engineering 73 (2019) 46–57

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

Mitigation of multipath fading in indoor radiometric fingerprinting systems☆

Mabruka Mohamed Agel[a], Mohamed Hadi Habaebi[a,*], Md Rafiqul Islam[a]

[a] Dept. of Electrical and Computer Engineering, Faculty of Engineering, International Islamic University Malaysia (IIUM), Kuala Lumpur, Gombak 53100 Malaysia

ARTICLE INFO

Article history:
Received 25 October 2017
Revised 1 November 2018
Accepted 2 November 2018

Keywords:
Multipath fading
Radiometric fingerprinting
Alpha-trimmed filter
Wireless sensor networks
Energy security

ABSTRACT

Wireless sensor network technology offers endless possibilities for innovative solutions for different security and intrusion detection and recognition applications. By distributing multiple clusters of preconfigured wireless sensor network detection nodes, a widely monitored area can be consistently checked for intruders. These systems are simple, easy to install and reliable in detecting intruders automatically. This paper presents the utilization of a wireless sensor network as a non-invasive human identification system for smart homes and security applications. The proposed scheme analyzes the effect of individuals moving into a monitored area, where the 2.4 GHz wireless sensor network has been installed. It is imperative to comprehend the critical impact caused by different human bodies on multiple readings of Received Signal Strength Indicator collected at different levels for individuals at the same recording position. Multiple experiments were performed by utilizing the wireless sensor network nodes on different individuals at different positions. The paper particularly studies the effect of filtration and change of filtering parameters used to mitigate the multipath effect on the accuracy and detection capacity of the presented IEEE802.15.4-based radiometric human identification scheme.

1. Introduction

The rapid progress in the area of wireless and mobile communications have brought attention to wireless-based identification and detection systems. It is the foundation of any recognition systems to be able to precisely identify trespassers in an indoor environment. In the perspective of wireless sensor networks (WSN), the Received Signal Strength Indicator (RSSI), in addition to its intended use of link quality estimation (LQE), has been generally used for localization and positioning, as well as distance evaluation. Previous studies have demonstrated that in indoor environments where motes (i.e. nodes) have been installed, changes in the RSSI value can be used to distinguish people's movement in the area. Additionally, the timely recorded readings of RSSI permit the mapping of the walking paths of a person within the monitored environment.

Multipath fading has been investigated in detail for the utilization in the area of digital communication. Furthermore, studies on the influence of multipath fading on wireless communication and the variation of the level of RSSI in an indoor environment have also been studied in [1–3].

☆ Reviews processed and recommended for publication to the Editor-in-Chief by Area Editor Dr. E. Cabal-Yepez.
* Corresponding author at: ECE Dept. Faculty of Engineering, IIUM.
E-mail addresses: habaebi@iium.edu.my (M.H. Habaebi), rafiq@iium.edu.my (M.R. Islam).

https://doi.org/10.1016/j.compeleceng.2018.11.002
0045-7906/© 2018 Published by Elsevier Ltd.

During any wireless connection, the signal may be corrupted by different changes in the transmission channel. The coverage could be lost due to blockage by surrounding solid objects while the signal's strength could be degraded by further separation of the two ends of the communication link. Furthermore, when a signal traverses different paths between transmitter and receiver in an indoor environment, the received components can add up destructively, causing a noticeable degradation in the wireless communication link's quality.

An LQE for real-time Industrial WSN was introduced in [4]. RSSI information acquired from received packets was utilized in this work. The proposed LQE was successful in representing the combined impact of multipath, noise and magnetic fields interfering with IEEE 802.15.4 radios.

Multiple investigations have highlighted that the RSSI can be used to recognize and track a body within the WSN coverage area. In [5,6], it was demonstrated how a walking individual can generate multipath fading and shadowing effects that influence the level of measured RSSI.

In [7], a filtration technique that utilized Kalman's model was used during the training or offline phase to follow the movements of the subject under testing. In the investigation, the motes produced a mean tracking error of 1.03 m due to data collection and filtration process.

Kalman filtering scheme was simulated for attitude estimation within environments of substantial acceleration and magnetic distortion [8]. The outcomes of this work demonstrate the capability of accurate attitude estimation of the proposed Kalman filter scheme with significantly less time in the computation procedure.

The use of RSSI readings in localization, position estimation, intruder detection, and identification encloses ambiguity and noise. Subsequently, Kalman filter was used in [9] to evaluate and calibrate the system from the surrounding's Gaussian noise, which minimizes the mean squared error of the proposed system.

The use of both ZigBee and WiFi technology for intruder detection was presented in [10] where it is found that large separation distance causes a decline in the sensitivity of the system. The study not only used changes in the RSSI levels for intrusion detection, but also extended the scope to utilize this technique for home automation in a Small Office/Home Office (SOHO) environment. Another finding from this research was that the use of horizontally polarized antennas for the purpose of detection improves the sensitivity of the RSSI levels to the environment, hence improving the overall performance of the system.

This paper introduces a filtering technique based on Alpha-trimmed filters to eliminate the errors of identification process caused by multipath fading. The following section describes related literature to the effect of human movement on the performance of WSN and RSSI levels and the role of Alpha-trimmed filters in mitigating multipath and Gaussian noise. Section 3 introduces the methodology, experimental setups, and the WSN technology used to in the proposed scheme of human identification process based on RSSI fingerprinting. The results and discussion are presented in Section 4 and, lastly, the findings are summarized and concluded in Section 5.

2. Literature review

Wireless communication has introduced new potential applications for use in indoor environments. However, the expansion of wireless and remote communications usage requires more extensive investigations into the behavior of multipath fading in an indoor environment. Hence, to reduce the impacts of multipath, antenna polarization diversity and filtering strategies have been found to be effective solutions. Multipath fading has a crucial effect on the performance of WSN devices and ought to be taken into consideration when installing wireless sensor networks [6,11]. In this work, the mitigation of multipath impacts on an indoor environment was implemented where the RSSI readings were smoothed using the Alpha-trimmed filter.

2.1. Multipath fading in indoor environments

An indoor environment differs significantly from outdoor environment in terms of propagation parameters and factors. Line of Sight (LOS) is hard to establish for long-distance communication due to the existence of barriers such as walls and furniture. A human body is also considered a barrier. Even though environment conditions such as temperature and humidity affect the quality of the signal, they are almost negligible in an indoor environment because those conditions can be easily controlled [12].

These barriers drive the radio frequency signal to diffract, reflect, scatter, and absorb in different ways according to the structure of the indoor environment creating, in the process, a multipath fading effect [10–13].

Due to the existence of barriers, the signal is received from various paths at the end of the communication link. Therefore, multipath fading is dealt with as the most prominent element in the variation of RSSI readings [14].

Past studies that were conducted for the mitigation of multipath fading in the field of wireless communication were still insufficient. Hence, it is important to guarantee the smoothness of the RSSI value for indoor environment applications. Due to the complexity of communication transmission modelling, as well as the presence of barriers and solid objects, RSSI readings in indoor environments are subjected to more drastic fluctuations because of the movements of people and objects such as doors.

The filtration of RSSI signal using median filter, followed by low-pass filter, was utilized as part of the work in [15]. In this research, a tracking method using priori knowledge was presented. The samples were processed with LPF to average the acquired samples and decide the location precisely and a window size of 30 readings was ideal for this study.

The impact of the presence of multiple people on the precision of a localization system was discussed in [16]. The paper introduced a high-performance multi-entity procedure that depends on RSSI readings to estimate location. The Alpha-trimmed filters were then used to overcome noise impact in both training and testing stages. The decision for using these filters, as justified by the authors, was derived from the grounds that Alpha-trimmed filters combine the effects of both mean and median filters. Consequently, the impacts of impulse and Gaussian noises were reduced.

Alpha-trimmed filters were likewise used to remove outliers in [17]. The paper discussed various examples of human intrusion patterns and proposed a new technique to distinguish them. The approach is a joint learning scheme based on grids. RSSI readings were gathered by IEEE 802.15.4 ZigBee motes and then smoothed without compromising the patterns that reflected human intrusion.

A passive system for human detection based on VHF-FM and UHF-TV was proposed by [18]. The paper utilized the standard that the received levels are varied due to multipath fading or shadowing with human presence. To distinguish human presence, a framework that included a receiving antenna in a room was used to reflect radio waves from metal objects and furniture. The paper concluded with the possibility of using both VHF-FM and UHF-TV in human detection system, ideally with the waves having line of sight (LOS) propagation path to increment the detection probability within a monitoring time of just 5 s.

To overcome the latency and power consumption of RSSI-based detection and localization systems, an approach was presented in [19] that minimize such effects by transmitting to the sink node only the warnings related to major events. During tests, the system was able to recognize the intrusion of an individual walking inside the zone of the established communication and effectively tracked his movements during the online phase with an average error of only 0.22 m.

An investigation into human occupancy and movement behavior on signal variation and power degradation in an indoor environment at 2.4 GHz was studied in [20]. The results of this paper demonstrated that the presence of individuals moving in an area where the network was deployed influenced the RSSI considerably, and the attenuation differed according to the number of subjects and their walking speed. This approach was then used in passive human detection systems to automatically control lighting and air-conditioning inside the monitored area.

In this paper, we examined past studies that have been conducted to lessen the impacts of multipath in indoor environments. With this specific end-goal, many filtering methods were tested but resulted in outcomes that did not rise to the expectation. This paper introduces the Alpha-trimmed filter to remove the impacts of multipath in an indoor environment. RSSI readings for multiple individuals at specific locations were collected and then processed with the Alpha-trimmed filters using MATLAB software. The raw and filtered data were analyzed for different filtration parameters. The Alpha-trimmed filter was utilized as a part of this work to eliminate multipath impacts from the RSSI readings collected during experimentation. The motes used are XBee radio mounted on XBee shields in Arduino microcontroller boards. The XBee mote has a 2.4 GHz radio interface compatible with the IEEE 802.15.4 standard, with LE and RSSI feeds, in addition to other features. XBee motes are extensively used in RnD environment for testing and development of new solutions for home/office networking, security and industrial revolution IR4.0 applications by allowing machines to communicate.

2.2. Filtration using Alpha-trimmed filters

To clarify the RSSI readings from the sudden change in levels due to multipath fading, a filtration method was implemented. Alpha-trimmed filters were utilized in view of their straightforwardness and capacity to eliminate sudden extreme data without compromising their uniqueness from one person to another.

Alpha-trimmed mean filter is a nonlinear, windowed-class filter that tends to have a neutral attribute between mean and median filters. The fundamental concept behind this filter is for any components of the signal to be similar to the ones that proceeded and followed it [21].

The essential steps here are to put the elements in a moving window in sequence and then eliminate the components at the beginning and the end. Lastly, the remaining values are averaged and the final value is identified.

This filter calculates the mean of the array by eliminating some parts of the signal instead of averaging the whole set. The outliers in the highest and lowest values are removed. The trimming coefficient 'α' controls the rate of the data, which are then removed from the set.

$$y_n(i;\alpha) = \frac{1}{n-2[an]} \sum_{j=[an]+1}^{n-[an]} x(j) \tag{1}$$

Where αn denotes the ceil of the value αn, and $0 \le \alpha < 0.5$ demonstrates the rate of the trimmed data. Accordingly, the Alpha-trimmed mean filter behaves like a median filter when it approaches 0.5 and a moving average filter when α approaches 0, as shown in Fig. 1 [22]. Thus, multiple values of Alpha were used starting from 0.05 and ending at 0.49 to demonstrate the impact of changing the filtration index (α) on the accuracy of the system.

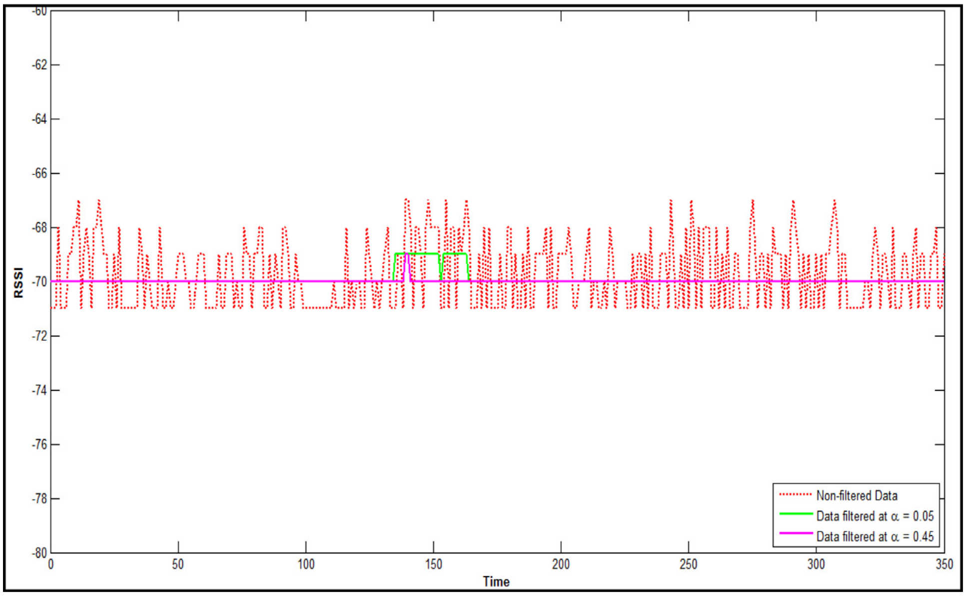

Fig. 1. Effect of changing coefficient of filter on data.

3. Experiment setup

The scheme suggested here used the IEEE 802.15.4 Transceivers, which are light, cheap, and reliable. The IEEE 802.15.4 network will transmit data from the sensing unit (transmitters) to the processing unit, where a comparison process will be performed and a decision will be issued for identification or intrusion purposes.

The testing system was installed using a receiver that acted as the base station. It was placed on a table and connected to a PC to collect RSSI values. On the other side of the Link, there were 8 transmitters operating with the receiver on a multiple point-to-point IEEE 802.15.4 network.

During the experiment, the subject under study was asked to first stand in the direct line of the link between the transmitters and the receiver. The position was 125 cm from the wall where transmitters were mounted. The distance between the standing position and the receiver, where the data is collected, was 375 cm, making the total distance between the transmitters and the receiver 5 m. For the second test, the subjects were asked to sit on chairs at the same spot as the first position.

For the third position, the subject was asked to stand in a specific point that was not in the direct link between the transmitters and the receiver. That point was 150 cm from the direct line. The projection of the point on the direct line was exactly in the middle between the two ends of the connection (250 cm apart from each end). The last position readings involved sitting on a chair at the same place as the third position.

Transmitters were placed aligned to the wall with 50 cm spacing starting from 50 cm height from the floor. The base station was placed connected to a PC on a bench table at 75 cm in height. Fig. 2 shows the schematic view of the placing of the experiment setup.

The transmitters were at 50 cm, 75 cm, 100 cm, 125 cm, 150 cm, 175 cm, 200 cm, and 225 cm on the wall. The idea is to collect data at different heights simultaneously. So the effect of human body on the signal can be used to distinguish between humans with different heights and body sizes. In trials, it is found that larger and taller human bodies, when crossing, perturb more RSSI readings on all links, while smaller short bodies perturb fewer RSSI readings and on lower links only.

3.1. Algorithm of human identification scheme system

The proposed scheme should be able to monitor the indoor environment and distinguish between different people entering the monitored area. For this system, the transmitting nodes send packets to the base station, and from the packets, the processing unit in the base node will extract the RSSI value from the API packet and send it instantly to the connected PC, where the data are immediately stored into the database for further processing. MATLAB software is used for data collection, filtering, and comparison processes.

For the actual identification process, RSSI readings were compared with stored RSSI readings that belong to a pre-specified group of individuals working or residing in the monitored area. During data collection process, when the system starts, the base node receives packets that includes the address of the sending node and the signal strength of the con-

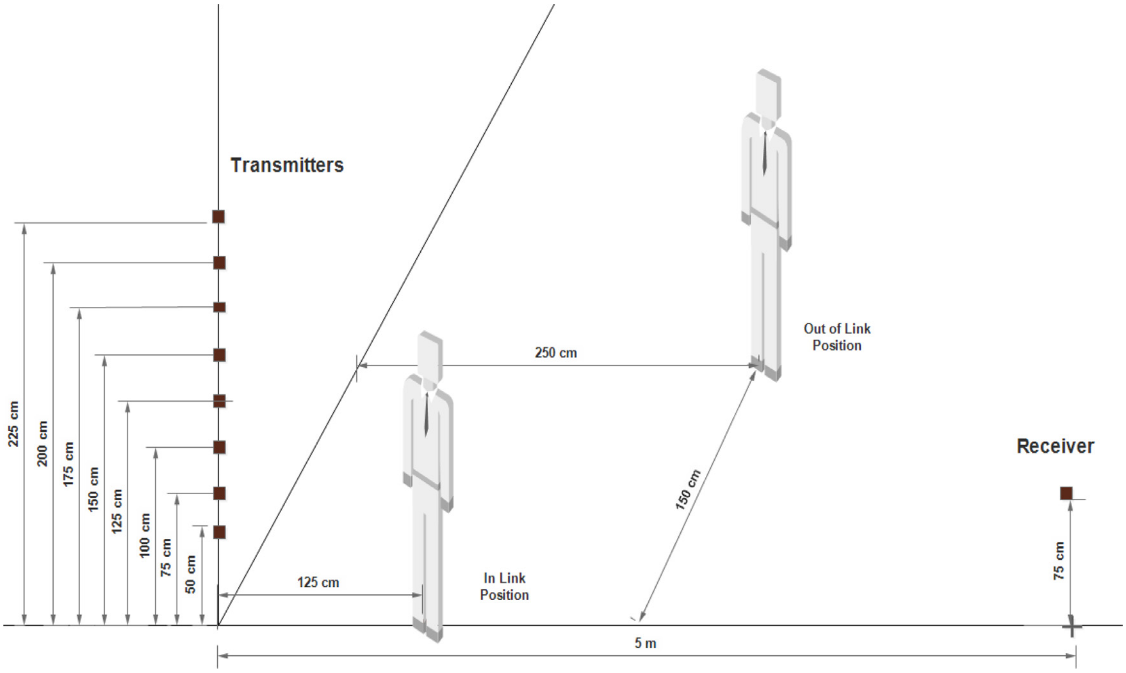

Fig. 2. Schematic view of experiment setup and link placement.

Table 1
Comparison between resolutions for 1 user ($\alpha = 0.3$).

No. of levels	Min.	Max.	Mean	Standard deviation
One level	0	1	0.386239	0.395107
Two levels	0	1	0.459786	0.309351
Three levels	0	1	0.507051	0.242495
Four levels	0	1.25	0.519177	0.260097
Five levels	0.092376	1	0.507197	0.217327
Six levels	0.166667	0.96527	0.500442	0.205461
Seven levels	0.213714	0.924242	0.527259	0.189566
Eight levels	0.187	0.855079	0.528018	0.16901

nection between the transmitter and the receiver. In that case, the processing unit attached to the Receiving IEEE 802.15.4 device will extract the bits that includes the RSSI value as preconfigured. Following that the RSSI values are sent instantly through the serial connection to the PC attached to the base station where the MATLAB software resides to perform the rest of processing, data logging and comparison for decision making process. Data received on the serial port by MATLAB is converted to decimal for usability and to ease the storing of data on the database. MATLAB stores data temporarily into arrays in the workplace which up on the closing of serial connection (disconnection of XBee), it will store these readings in a specific database categorized by each person's profile.

The data were filtered using the same Alpha coefficient for both current collected samples and stored samples in the database. The data were then compared to equal-length samples in order to generate an RMSE index. Root Mean Square Error (RMSE) is a regularly used measure to contrast between predicted qualities by an algorithm and the actual measured values and it is used as a matching parameter in this research work. Based on the predetermined RMSE threshold, if the current readings exceeded that value, a decision for a stranger or intruder within the environment would then be generated. Otherwise, that person is recognized as a member of the pre-specified group, as shown in Fig. 3.

3.2. Statistical profiling

The measurement used as a matching parameter in this paper is the Root Mean Square Error **(RMSE)**. RMSE presents the total averaged differences to measure the validity of the studied algorithm [22].

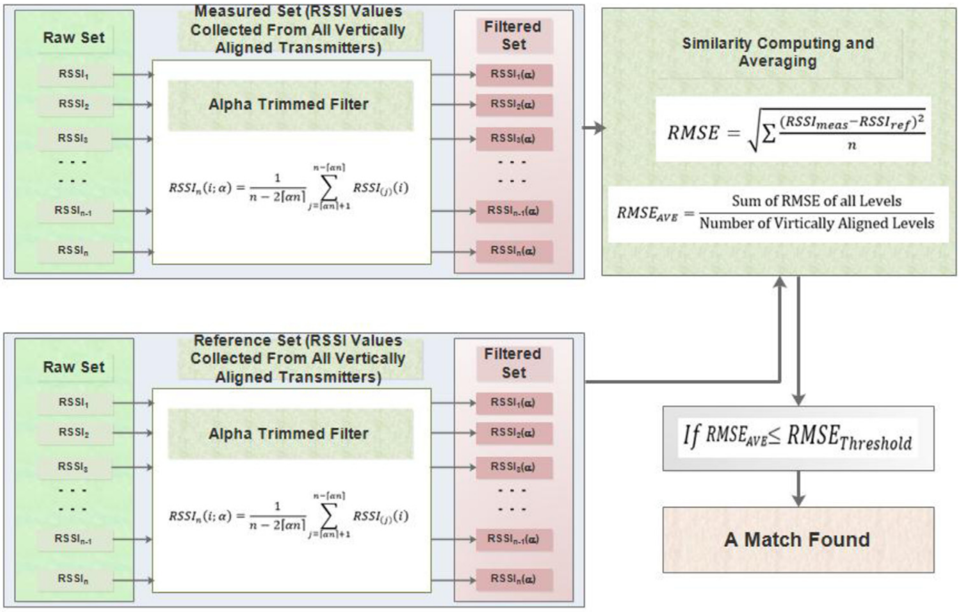

Fig. 3. Fingerprinting process for radiometric human identification scheme.

The RMSE of a model for reference values and the measured values provide a similarity parameter that can be used to make decisions for matching procedures. The RMSE for the case of this paper is calculated using the formula in Eq. (2).

$$RMSE = \sqrt{\sum \frac{\left(RSSI_{meas} - RSSI_{ref}\right)^2}{N}} \tag{2}$$

Where $RSSI_{meas}$ is the observed values and $RSSI_{ref}$ is the modelled values at the offline phase. The key target of any human recognition system is to have the capacity to accomplish an unmistakable separation of intra-class (samples for the same individual at the same position) and inter-class (samples for a person at one position to all other samples, except the samples for the same person at the same position) RMSE distributions [23]. Generally, if the RMSE level is higher than the threshold level, the two samples are then determined to be produced by different individuals [24].

Nonetheless, the separation between the least RMSE value for inter-class matching and the highest RMSE value for intra-class matching cannot be utilized as an accurate measurement to evaluate the difference between different categories, as there will be outliers that make these ranges overlap. A better choice for the metric is 'decidability', which considers other statistical parameters rather than just the minimum and the maximum. It evaluates the separation distance based on the mean and standard deviation of the intra-class and inter-class statistical distributions [24,25].

$$d' = \frac{|\mu_S - \mu_D|}{\sqrt{\frac{\sigma_S^2 - \sigma_D^2}{2}}} \tag{3}$$

Where μ_S: the mean of the intra-class distribution,
μ_D: the mean of the inter-class distribution,
σ_S: the standard deviation of the intra-class distribution, and
σ_D: the standard deviation of the inter-class distribution.
As expressed by Eq. (3), decidability *d'* is a function of the difference between the standard deviation of the two classes. The higher the decidability, the clearer the division between the intra-class and inter-class distributions, which leads to better recognition rate.

3.3. Testing scenarios

To examine the impact of multipath fading on radiometric-based human detection systems, multiple testing scenarios were performed, as presented in the following sub-sections:

3.3.1. Comparison of one subject's data multiple times

The data were collected for a single person multiple times in the span of 10 days without any change in the environment, i.e.: same indoor layout without moving and replacing any object. This test was done to prove the concept of the similarity

Table 2
Effect of filter's window size on performance.

Filtration	Window's size	1 level	2 levels	3 levels	4 levels	5 levels	6 levels	7 levels	8 levels
Alpha 0.1	25	1.3787	1.9103	2.5979	2.7787	2.9217	3.2286	3.5049	3.6619
	50	1.3802	1.9247	2.6232	2.8189	2.9609	3.2693	3.5674	3.7046
	75	1.4348	1.9778	2.6851	2.8692	3.0460	3.3701	3.6729	3.7968
	100	1.4552	1.9875	2.6856	2.8657	3.0452	3.3636	3.6684	3.8214
Alpha 0.2	25	1.3600	1.9136	2.5976	2.7944	2.9340	3.2282	3.5093	3.6601
	50	1.3726	1.9317	2.6201	2.8423	2.9800	3.2947	3.5918	3.7277
	75	1.4684	2.0002	2.6921	2.9023	3.0775	3.3852	3.6969	3.8337
	100	1.4944	2.0072	2.6964	2.9038	3.0841	3.3927	3.7020	3.8562
Alpha 0.3	25	1.3354	1.8901	2.5714	2.8068	2.9399	3.2517	3.5328	3.6818
	50	1.3793	1.9380	2.6147	2.8552	2.9940	3.3008	3.5922	3.7348
	75	1.4652	2.0083	2.6919	2.9167	3.0857	3.3918	3.7057	3.8237
	100	1.7340	2.0704	2.7789	2.9028	3.0355	3.3267	3.6181	3.7333
Alpha 0.4	25	1.3423	1.8905	2.5754	2.8331	2.9589	3.2625	3.5371	3.6935
	50	1.3965	1.9678	2.6391	2.8818	3.0224	3.3286	3.6183	3.7543
	75	1.4906	2.0103	2.6859	2.9119	3.0730	3.3746	3.6836	3.8341
	100	1.4972	2.0127	2.6928	2.9056	3.0836	3.3892	3.6990	3.8300
Alpha 0.49	25	1.3574	1.9202	2.5975	2.8449	2.9724	3.2765	3.5589	3.7099
	50	1.4534	1.9981	2.6808	2.8960	3.0411	3.3452	3.6296	3.7871
	75	1.5151	2.0146	2.6947	2.8981	3.0848	3.3847	3.6699	3.8119
	100	1.5352	1.9961	2.6856	2.8843	3.0751	3.3754	3.6651	3.8051

of RSSI readings for the same environment with the presence of the same obstruction, which in this case, was the subject under test. The reading time was set for 60 s, with a sampling time of 13 samples per second. The acquired data were then analyzed for different filtration coefficients. For this part, the subject under test stood at one position in the direct line of the link (standing in front of the receiver's position). The aim of this test was merely to find the initial range of the RMSE values for the same person in order to define a prime range of threshold to be used for the actual data comparison in the following stages.

The tests performed for readings involved eight levels, in which the data were recorded simultaneously to determine the best resolution (e.g. number of transmitters that needs to be running at the same time).

3.3.2. Cross group matching

Training group analysis was performed on 5 different individuals situated at the before mentioned 4 different positions. Tests were performed in order to identify the best sample size and filter window size.

3.3.2.1. The effect of the window's size of filter on performance. The variation of the system's performance with respect to the moving window size during filtration was based on the change of the decidability of each window size. Filter's window size reflects how many consecutive readings are used as the input for alpha trimmed filter during the filtration process. The decidability reflects the narrowness of the data, so the more the decidability there is, the less overlapping between inter-class and intra-class data will be generated. The tests were performed to determine the window sizes of 25, 50, 75, and 100 readings for different values of Alpha.

3.3.2.2. The effect of sample size on system performance. Equal-length samples were compared to generate the RMSE value used for the matching process. To find the effect of the sample size on that decision, a test was conducted by comparing the performance of the system for different sample sizes. In order to stress-test the system on decidability performance, window size needs to be varied. The sizes were 25, 50, 100, 150, 200, and 250, with 25 representing the smallest number of samples and 250 represents the maximum number of samples supported by the system hardware. In trial, it was found that the system with this setting read 800 samples a minute. Therefore, in order to read 25 samples, the system requires 2 s at the same position. Increasing the sampling rate is possible but requires sending continuous wave (CW) signal using a signal generator instead of IEEE802.15.4 frame beacons from the motes. However, this is not possible in our case due to the large number of transmitters involved in the experiment.

4. Results and analysis

4.1. Intra-Class comparison (Same person multiple times)

The resulting readings were analyzed with a bin size of 50 readings and for different filtration criteria. In analysis, the outcome of the tests was conducted on the same individual. The RMSE value for raw data ranged from 0.5 to 5 with a mean of 2.6127 and a standard deviation of 1.0927, as indicated in Fig. 4 (Top).

An example of the analysis of filtered readings is presented in Fig. 4 (Bottom), where the data were filtered using Alpha-trimmed filters, with an Alpha of 0.05. The effect of filtering was presented in the mean of RMSE value of 0.75284 and

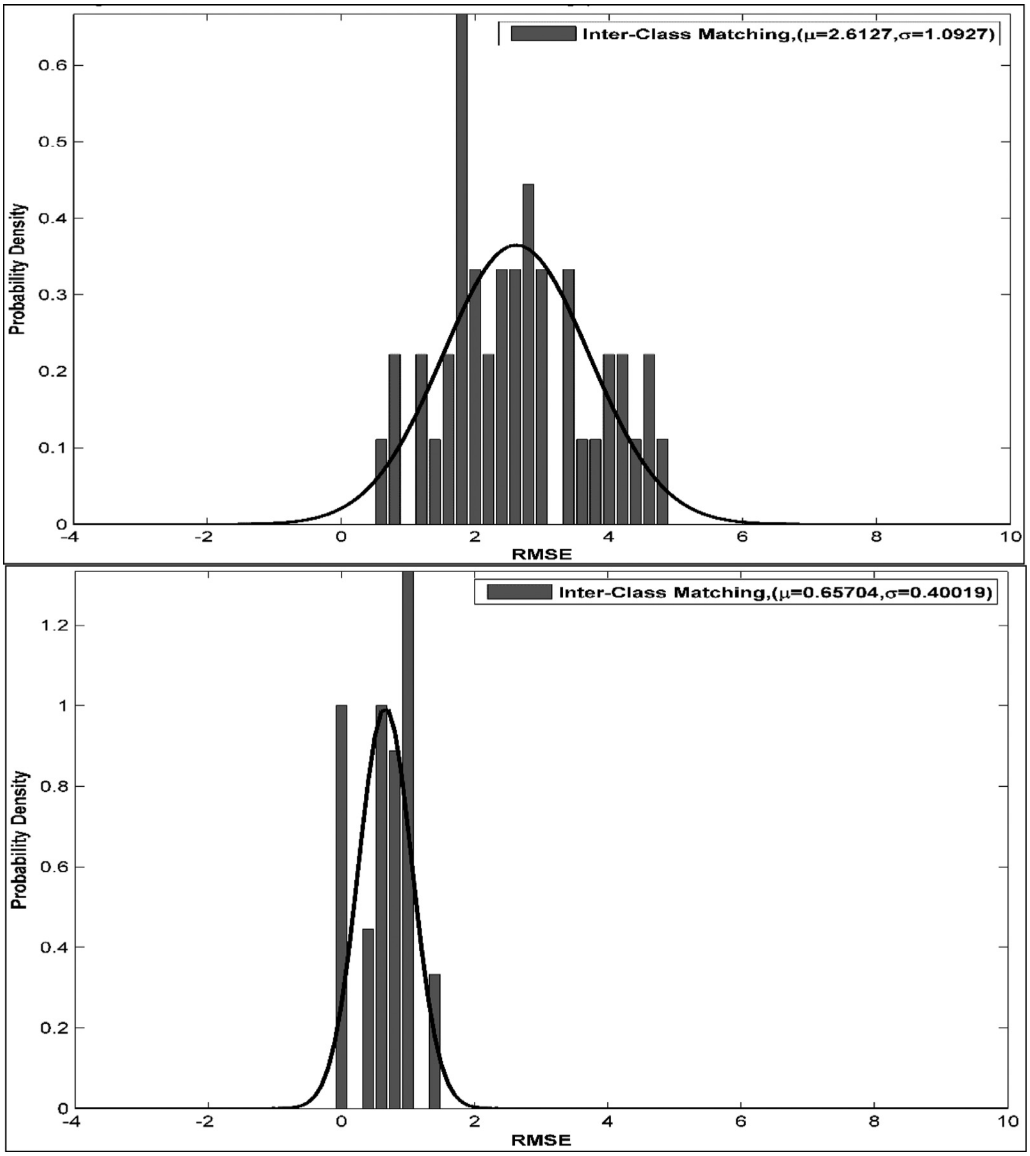

Fig. 4. Intra-Class distribution for 1 user (Top: Raw data, Bottom: Filtered data at $\alpha = 0.05$).

standard deviation of 0.4205. The PDF graph of the RMSE of filtered readings were narrower and more centered in the raw data. This increases the decidability of the filtered readings, which can in turn lead to a better decision for a threshold that lessens the number of false negatives and false positives.

Table 1 presents a comparison of the performance of number of levels used and their corresponding statistics .Increasing the number of levels decreases the standard deviation value or the distribution of RMSE values, which will result in a sharper value of threshold that separates the readings belonging to the same person from readings belonging to different people.

4.2. Cross group matching

Matching the same person's data should almost be the same for the same indoor environment, except for the effects of noise generated by diffraction, reflection, and multipath of signal and resulted in a sudden change in the value of the RSSI reading at a static position.

Fig. 5 shows the outcomes of performing RMSE analysis on data acquired for intra-class matching and inter-class matching. The values presented in the graph are the RMSE analysis for raw data averaged over 4 levels.

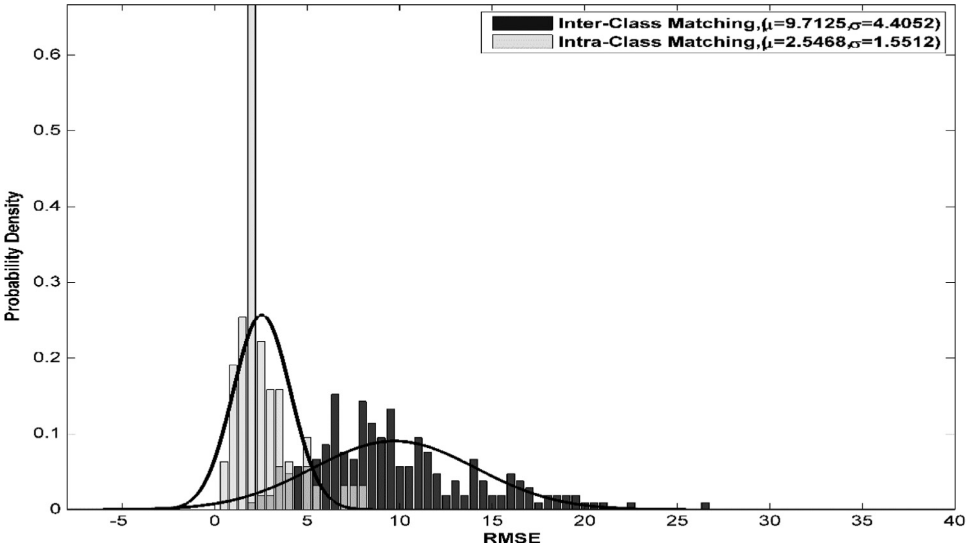

Fig. 5. Training group's matching at four-level resolution (Raw data).

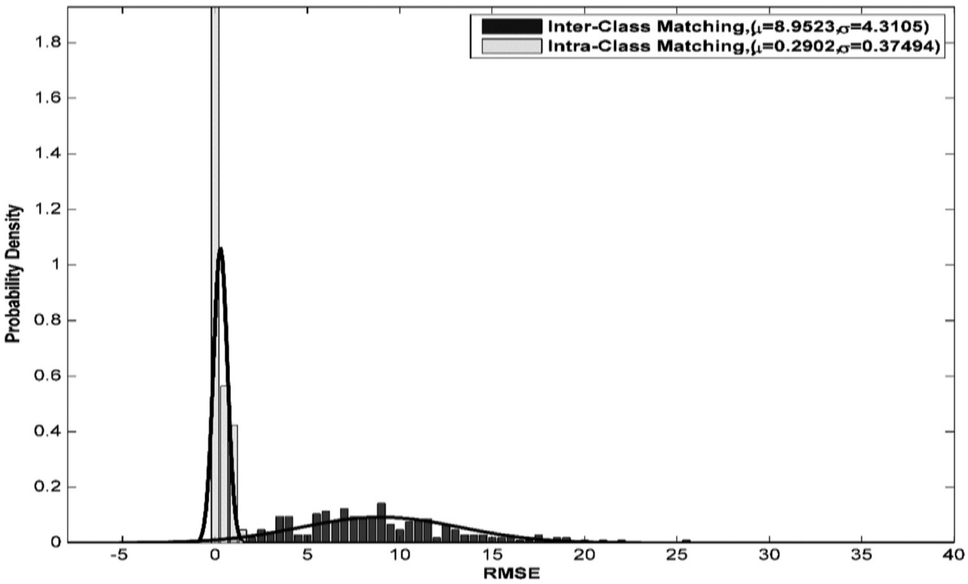

Fig. 6. Training group's matching at four-level resolution (Filtered at $\alpha = 0.3$).

The RMSE values for intra-class matching are centered on the left of Fig. 5, with a mean of 2.5468 and standard deviation of 1.5512, whereas the RMSE values for inter-class matching are more diverted and centered to the right of the graph, with a higher mean value of 9.7125 and standard deviation of 4.4052. Non-filtered data resulted in the overlapping of the PDF graph generated by the RMSE values for intra-class matching and inter-class matching. This overlapping has generated false alarms.

The filtering effect on the data is presented in Fig. 6, where the data is filtered with a 0.3 Alpha-trimmed filter. The impact of filtration on the data was very significant, especially considering the intra-class matching. The RMSE standard variation in intra-class matching filtered data was 0.37494, whereas the non-filtered data for the same category was 1.5512. Meanwhile, the RMSE mean for the same class went from 2.5468 for raw data down to 0.2902. This indicates the importance of filtering data on the process of RSSI-based recognition systems.

4.3. The effect of the window's size of filter on performance

The variation of the system's performance with the change in the moving window size during filtration was based on the change in the decidability of each window size. The decidability reflects the narrowness of the data, so the more the

Table 3
Effect of filter's sample size on performance.

Filtration	Sample size	1 level	2 levels	3 levels	4 levels	5 levels	6 levels	7 levels	8 levels
Raw data	25	0.999	1.417	1.978	2.170	2.317	2.570	2.817	2.952
	50	1.012	1.451	2.013	2.211	2.339	2.592	2.824	2.965
	100	1.003	1.469	2.029	2.250	2.384	2.628	2.873	3.012
	150	1.004	1.481	2.045	2.271	2.403	2.646	2.900	3.042
	200	1.011	1.492	2.059	2.270	2.403	2.644	2.892	3.036
	250	1.008	1.497	2.065	2.257	2.394	2.629	2.879	3.030
Alpha 0.1	25	1.415	1.912	2.606	2.796	2.949	3.259	3.542	3.674
	50	1.395	1.912	2.604	2.796	2.942	3.253	3.538	3.666
	100	1.358	1.901	2.594	2.798	2.937	3.247	3.537	3.670
	150	1.360	1.912	2.608	2.810	2.946	3.256	3.551	3.686
	200	1.380	1.925	2.623	2.819	2.961	3.269	3.567	3.705
	250	1.401	1.935	2.634	2.824	2.965	3.271	3.573	3.711
Alpha 0.2	25	1.421	1.931	2.617	2.821	2.988	3.303	3.580	3.695
	50	1.403	1.935	2.619	2.829	2.986	3.300	3.579	3.695
	100	1.368	1.919	2.603	2.825	2.969	3.284	3.574	3.696
	150	1.360	1.923	2.610	2.832	2.967	3.282	3.577	3.705
	200	1.373	1.932	2.620	2.842	2.980	3.295	3.592	3.728
	250	1.392	1.942	2.632	2.851	2.989	3.303	3.603	3.741
Alpha 0.3	25	1.443	1.927	2.601	2.831	3.006	3.312	3.588	3.709
	50	1.427	1.932	2.606	2.838	3.001	3.308	3.586	3.705
	100	1.393	1.927	2.601	2.840	2.986	3.293	3.583	3.709
	150	1.376	1.930	2.605	2.846	2.984	3.292	3.583	3.718
	200	1.379	1.938	2.615	2.855	2.994	3.301	3.592	3.735
	250	1.396	1.950	2.628	2.864	3.002	3.308	3.603	3.749
Alpha 0.4	25	1.447	1.928	2.604	2.829	3.008	3.313	3.601	3.730
	50	1.447	1.944	2.619	2.848	3.016	3.324	3.612	3.733
	100	1.418	1.951	2.624	2.861	3.013	3.320	3.611	3.736
	150	1.401	1.960	2.632	2.873	3.016	3.324	3.613	3.744
	200	1.396	1.968	2.639	2.882	3.022	3.329	3.618	3.754
	250	1.411	1.982	2.654	2.893	3.029	3.335	3.629	3.766
Alpha 0.49	25	1.472	1.945	2.634	2.847	3.024	3.322	3.601	3.757
	50	1.478	1.956	2.642	2.855	3.025	3.324	3.601	3.754
	100	1.461	1.970	2.654	2.868	3.024	3.327	3.608	3.764
	150	1.453	1.985	2.668	2.883	3.032	3.336	3.620	3.777
	200	1.453	1.998	2.681	2.896	3.041	3.345	3.630	3.787
	250	1.465	2.012	2.694	2.907	3.048	3.353	3.641	3.797

decidability there is, the less overlapping between inter-class and intra-class data will be generated. Table 2 shows the effect of the window's sizes at 25, 50, 75, and 100 readings for different Alpha values.

The increase in the window size caused the data to be smoother and decreased the effect of sudden change in the RSSI readings due to multipath. Another finding showed that the increase in the value of Alpha or the trimmed readings from the filtering window produced a narrower data, and an easier differentiation between the different classes could be made. This finding was based on the increase of decidability which consequently produces a narrower data with clearer cutoff threshold between inter-class and intra-class data as sown in Table 2.

4.4. The effect of sample size on system performance

Table 3 shows the results of this testing. Generally, the increase in sampling size only showed a marginal increase of data decidability. This is because the RSSI value for a single person at the same position is not a constant value at discrete levels. In contrary, RSSI reading normally fluctuates at its mean by ± 1. Increasing the sampling size will increase the averaging window and further eliminate changes to the signal due to the environment. This effect can clearly be noticed in the raw data, as there were no filtration and trimming to eliminate changes due to the multipath of the signal experienced in the environment.

The analysis of these results showed that increasing the number of samples did not provide a big increase in the performance of the system, but required more time for a subject at the same position instead. For example, the highest difference for the samples' decidability for filtered data was 0.067, which is less than 3.5% increase between the sample sizes of 25 and 250 readings. This very small increase in decidability, however, required an increase of time from approximately 2 s (25 readings a sample) to 20 s (250 readings a sample).

Although the length of a 20 s sample was performed for testing purposes, it is not practical for the daily-life application of this system. The analysis of sampling size and the filtering's window size specified that the increase of these two variables subsequently increases the performance of the system. For both tests, the increase in filtration coefficient (α), in turn, increases the performance of the system in terms of decidability. In addition, increasing the resolution or the levels that are compared lowers the significance of the change in these variables.

5. Conclusion and recommendations

This study focused on achieving an optimum performance radiometric identification scheme for indoor environments by utilizing one of the properties of radio frequency-based networks. The scheme's installation cost and accuracy were a trade-off, but there are other factors that contribute to the performance:

- While filtered data achieved high decidability and clearer cut-off threshold, raw data achieved much less decidability, leading the system to generate multiple false alarms in distinguishing different individuals.
- Increasing the number of sensing levels, e.g. achieving higher resolution, leads to an increase in decidability or a clearer cut-off between intra-class and inter-class RMSE readings.
- The window size of the filter plays a marginal role in increasing decidability for filtered data. However, increasing the size of filtering window requires the data to be recorded for a longer time, which is impractical for daily-life applications. Therefore, a small window size of 50 readings was used in the experiment.
- The size of the compared samples does not play a significant role in the results of the decidability of the filtered data. Testing showed only a 3.5% increase in decidability with increasing sampling time from 2 s to 20 s.

The universality of this proposed scheme and obtained conclusions require more data to be collected for a larger number of subjects. The accomplished results of the proposed scheme were acquired under basic and restrictive conditions. To specify, the compared groups were relatively small in number, the comparison on all subjects were done in settled positions, and the outcomes were altogether performed at a single place in an indoor environment with only a single person present in the room. These points will be addressed in future works in addition to the effect of changing receiver's height on the experiment's outcomes. The ability of the scheme to differentiate multiple subjects simultaneously present in the monitored environment ought to be inve stigated further.

Acknowledgment

This work is conducted at and supported by IoT & Wireless Communication Protocols Lab, faculty of Engineering, International Islamic University Malaysia (IIUM).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.compeleceng.2018.11.002.

References

[1] Shakhparonov V, Adán EM, Vivas EV. Multipath fading analysis of telemetry signals power fluctuations from Universitetsky microsatellite. Acta Astronautica 2012;72:38–46.
[2] Lavanya V, Rao GS, Bidikar B. Fast fading mobile channel modeling for wireless communication. Procedia Comput Sci 2016;85:777–81.
[3] Eskola M, Heikkilä T. Classification of radio channel disturbances for industrial wireless sensor networks. Ad Hoc Networks 2016;42:19–33.
[4] Gomes RD, Queiroz DV, Lima Filho AC, Fonseca IE, Alencar MS. Real-time link quality estimation for industrial wireless sensor networks using dedicated nodes. Ad Hoc Networks 2017;59:116–33.
[5] Zhang D, Ni LM. Dynamic clustering for tracking multiple transceiver-free objects. In: Pervasive computing and communications, 2009. PerCom 2009. IEEE international conference on. IEEE; 2009. p. 1–8. March.
[6] Kaltiokallio O, Bocca M. Real-time intrusion detection and tracking in indoor environment through distributed RSSI processing. In: Embedded and Real-Time Computing Systems and Applications (RTCSA), 2011 IEEE 17th international conference on, 1. IEEE; 2011. p. 61–70. August.
[7] Wilson J, Patwari N. See-through walls: motion tracking using variance-based radio tomography networks. IEEE Trans Mobile Comput 2011;10(5):612–21.
[8] Shan S, Hou Z, Wu J. Linear Kalman filter for attitude estimation from angular rate and a single vector measurement. J Sens 2017;2017.
[9] Ligorio G, Sabatini AM. A novel Kalman filter for human motion tracking with an inertial-based dynamic inclinometer. IEEE Trans Biomed Eng 2015;62(8):2033–43.
[10] Habaebi MH, Ali MM, Hassan MM, Shoib MS, Zahrudin AA, Kamarulzaman AA, Islam MR. Development of physical intrusion detection system using Wi-Fi/ZigBee RF signals. Procedia Comput Sci 2015;76:547–52.
[11] Kuriakose J, Joshi S, Raju RV, Kilaru A. A review on localization in wireless sensor networks. In *SIRS* 2014:599–610.
[12] Xiao J, Zhou Z, Yi Y, Ni LM. A survey on wireless indoor localization from the device perspective. ACM Comput Surv (CSUR) 2016;49(2):25.
[13] Hong T, Yan D, D'Oca S, Chen CF. Ten questions concerning occupant behavior in buildings: the big picture. Build Environ 2017;114:518–30.
[14] Kaltiokallio, O., Bocca, M., Patwari, N. A Multi-Scale Spatial Model for RSS-based Device-Free Localization. 2013, *CoRR, abs/1302.5914*.
[15] Blumrosen G, Hod B, Anker T, Dolev D, Rubinsky B. Enhancing RSSI-based tracking accuracy in wireless sensor networks. ACM Trans Sens Networks (TOSN) 2013;9(3):29.
[16] Sabek I, Youssef M, Vasilakos AV. ACE: An accurate and efficient multi-entity device-free WLAN localization system. IEEE Trans Mobile Comput 2015;14(2):261–73.
[17] Yang J, Ge Y, Xiong H, Chen Y, Liu H. Performing joint learning for passive intrusion detection in pervasive wireless environments. In: INFOCOM, 2010 proceedings IEEE. IEEE; 2010. p. 1–9. March.
[18] Nishi M, Takahashi S, Yoshida T. Indoor human detection systems using VHF-FM and UHF-TV broadcasting waves. In: Personal, indoor and mobile radio communications, 2006 IEEE 17th international symposium on. IEEE; 2006. p. 1–5. September.
[19] Kaltiokallio O, Bocca M. Real-time intrusion detection and tracking in indoor environment through distributed RSSI processing. In: Embedded and Real-Time Computing Systems and Applications (RTCSA), 2011 IEEE 17th international conference on, 1. IEEE; 2011. p. 61–70. August.
[20] Turner JS, Ramli MF, Kamarudin LM, Zakaria A, Shakaff AYM, Ndzi DL, Mamduh SM. The study of human movement effect on signal strength for indoor WSN deployment. In: Wireless Sensor (ICWISE), 2013 IEEE conference on. IEEE; 2013. p. 30–5. December.
[21] Nayan NPMY, Hassan MF, Subhan F. Filters for device-free indoor localization system based on RSSI measurement. In: Computer and Information Sciences (ICCOINS), 2014 international conference on. IEEE; 2014. p. 1–5. June.

[22] Chai T, Draxler RR. Root mean square error (RMSE) or mean absolute error (MAE)?–Arguments against avoiding RMSE in the literature. Geosci Model Dev 2014;7(3):1247–50.
[23] Masek, L. Recognition of human iris patterns for biometric identification. 2013.
[24] Dinca LM, Hancke G. The fall of one, the rise of many: a survey on multi-biometric fusion methods. IEEE Access 2017.
[25] Daugman J. Biometric decision landscapes (No.UCAM-CL-TR-482). University of Cambridge, Computer Laboratory; 2000.

Mabruka Mohamed Agel received the Bachelor of Science in Communication Engineering in 2014 and her Master of Science in Communication Engineering in 2017 from the department of Electrical and Computer Engineering, International Islamic University Malaysia. Her current research interests are in Wireless Sensor Networks and Internet of Things.

Mohamed Hadi Habaebi, (PhD) is with the department of Electrical and Computer Engineering, International Islamic University Malaysia. He is the head of ECE department and IoT and wireless communication protocols laboratory. His research interests are in wireless communications, Cognitive Radios, computer networks and Internet of things.

Md Rafiqul Islam (PhD) is with the department of Electrical and Computer Engineering, International Islamic University Malaysia. His research interests are wireless channel modelling, radio link design, RF propagation measurement and modelling in tropical and desert areas, RF design, smart antennas and array antenna design, and FSO propagation and modelling.