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A System for Detection and Tracking of Human Movements Using RSSI Signals

Apidet Booranawong, Nattha Jindapetch, *Member, IEEE*, and Hiroshi Saito, *Member, IEEE*

***Abstract*—A device-free human detection and tracking system using a received signal strength indicator (RSSI) for an indoor environment is presented in this paper. The proposed system has two major functions: a wireless communication system and a human detection and tracking system. The first function is developed for measuring and collecting RSSI signals affected by human presence and movement, while the second function is developed for detecting and tracking the human using a predefined threshold and a zone selection method. The novelty of our proposed system is that the communication protocol can avoid signal interference and packet loss in the network, and the detection and tracking method can specify an actual zone that the human is present by taking an optimal predefined threshold and a level of RSSI variation in each zone into consideration. The proposed system is verified by experiments, and various human movement patterns with different directions and speeds are tested. The experimental results show that the proposed communication protocol can significantly provide communication reliability, and the proposed method can properly detect and track human movements. The packet delivery ratio indicating communication reliability is almost 100%. Detection and tracking accuracy measured by the number of times the method can detect and track the human with the correct zone is almost 100% in all cases of one man movements.**

***Index Terms*—Device-free detection and tracking systems, human movements, RSSI, protocols, indoor, wireless networks**

I. Introduction

CURRENTLY, human detection and tracking using radio signal strength in indoor wireless networks has attracted a great deal of interest from the research community, because this technology can be applied in many applications including intrusion detection and tracking in buildings [1], [2], elderly and patient monitoring [3], human monitoring and tracking in emergency situations (i.e., during dark periods, smoke events, and fires etc.) [4], and human monitoring for controlling automated devices [5]. In many scenarios, the humans to be monitored cannot be expected to carry any radio device. Consequently, a device-free human detection and tracking system, that works by monitoring and analyzing the changes in received signal strength patterns, is used to fulfill such a requirement [1], [6].

To detect and track human movements, RSSI information is widely used because most wireless devices have RSSI circuits built into them. Thus, no additional or extra hardware is required. This helps reduce the hardware cost and power consumption of the system [7]. The major challenge in the use of RSSI is that the measured RSSI is time-varying and unreliable in general. It often fluctuates over time due to multi-path effects caused by reflection, diffraction, and scattering of radio signals in a physical environment [6]. High variation of the RSSI can cause significantly high levels of detection and tracking errors, and inaccurate results can lead to poor decisions in the overall system.

Due to the RSSI variation problem, an acceptance level for the detection and tracking accuracies is required (depending on the application). The issue of the balance between the detection and tracking accuracy and the complexity of the method should also be considered [8]. In addition, from a wireless communication perspective, for RSSI measurement and collection, the signaling overhead generated by communication protocols, the power consumption of wireless devices, and communication reliability are also major concerns [2]. Therefore, in the design and development of a human detection and tracking system using RSSI, the mentioned requirements are very challenging and need investigation.

In this paper, a human detection and tracking system using RSSI for an indoor environment is presented. The major contributions of our paper are threefold.

- First, a simple and efficient communication protocol is developed for measuring and collecting the RSSI. By controlling the sending and receiving sequences of packets that are exchanged among nodes, the signal interference and the packet loss in the network can be reduced (packet retransmission is then reduced). Also, the signaling overhead generated in the network and the power consumption of the system are minimized.
- Second, we develop an autonomous human detection and tracking method that can accurately detect and track the human and consume low complexity processing. The novelty of such a proposed method is that the actual zone that the human is present is determined by taking an appropriate threshold and a level of RSSI variation measured in each zone into consideration.
- Third, various human movement patterns with different movement directions and speeds are tested to investigate the performance of the proposed system.

Experimental results show that the proposed communication protocol can provide communication reliability; packet delivery ratio in all tested scenarios is almost 100%. Also, the proposed

A. Booranawong is with the Department of Electrical Engineering, Faculty of Engineering, Prince of Songkla University, Songkhla, 90112 Thailand (e-mail: apidet.boo@gmail.com).

N. Jindapetch is with the Department of Electrical Engineering, Faculty of Engineering, Prince of Songkla University, Songkhla, 90112 Thailand (e-mail: nattha.s@psu.ac.th).

H. Saito is with the University of Aizu, Aizu-Wakamatsu, 965-8580 Japan (e-mail: hiroshis@u-aizu.ac.jp).

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method can properly detect and track human movements; the detection and tracking accuracies are almost 100% in all cases of one man movements.

The structure of this paper is as follows. Section II gives a summary of prior related work. Section III describes details of the proposed system including the proposed communication protocol and the proposed human detection and tracking method. Description of experiments and their results with discussion are presented in Section. IV. Finally, we conclude the paper in Section V.

II. Related Work

Based on prior studies in the literature, the study of human movement effects on RSSI behavior and the presence of human detection and tracking systems using RSSI are summarized here.

In [9]–[11], evaluations of RSSI behavior under various scenarios were performed by experiments. The authors summarized that when the line-of-sight (LOS) from transmitter to receiver was broken by a walking human, the RSSI was significantly fluctuated. The work in [12] reported that human activities significantly influenced the performance of wireless communications both in LOS and in non line-of-sight (NLOS) conditions. In [13], [14], experiments revealed that human blocking of the radio signal path significantly affected both the mean and the standard deviation of the RSSI. In [15], human movement effects on 2.4 GHz networks were assessed by experiments, and the results showed that the RSSI variation levels depended on the number of people and the people's movement speeds. In [16], the authors claimed that human presence between an access point and a mobile device in WLAN significantly decreased the received signal strength by approximately –2 to –5 dBm. However, although the RSSI behaviors with human movement effects were studied in [9]–[16], the detection and tracking of human was not included in the scope of those studies.

In [17], a method to detect an intruder using RSSI was proposed. An RSSI mean and its standard deviation, which were computed over a predefined number of samples, were processed and used for detecting the RSSI changes caused by an intruder. The experimental results in the case of using only one transmitter and one receiver showed that the method in [17] could properly detect an intruder. In [18], the authors proposed a simple method to detect human motion by processing the standard deviation of the RSSI time series at each moving time window. Human motion was detected, if the standard deviation was larger than a threshold which was determined by measurement in a test field. The authors verified their proposed method by experiments using one transmitter and one receiver. In [19] and [13] (extending the work in [19]), a study of motion detection using radio irregularity for automated people counting was presented. People were detected by considering the probability of an RSSI fluctuation. The probabilities of RSSI fluctuation in cases of the human presence and no human presence were classified using a threshold level. The experimental results in the case of one transmitter and one receiver demonstrated that the proposed methods in [19] and [13] could suitably count people. In [5], an RSSI-based human detection method for residential smart energy systems was presented. The authors showed the efficiency of their proposed method to detect the human and control the smart power outlets and light switches. The walking human was detected by comparing the RSSI variation with an optimal threshold, and four transmitter-receiver pairs were deployed in the test. Although the methods in [17]–[19], [13], and [5] provided accurate detection and low complexity to run the algorithms, they were not intently designed for tracking different movement patterns of the humans, and no communication protocol was proposed for communication improvement.

In [2], real-time intrusion detection and tracking through distributed RSSI processing was introduced. The idea enabling detection was that when an intruder crossed several wireless links in a network, the attenuation of RSSI was automatically detected, and the intruder was located. A Kalman filter was also applied to improve the tracking accuracy. To minimize the communication overhead and to save the power consumption of the system, only alerts related to significant events were transmitted to a base station for processing, and a time division multiple access (TDMA) communication protocol was implemented. The system in [2] was tested in indoor environments using sixteen nodes deployed in the network. The experimental results showed the efficiency of such a system to detect and track the human. Although the work in [2] was the pioneer work which designed and developed the system by integrating the communication and the detection/tracking functions, it still has limitations. The Kalman filter technique suffers from high computational complexity [22], and dense deployment may not be suitable for covering a large region due to high communication cost and the equipment investment [20].

In [21], radio tomographic imaging (RTI) for imaging the attenuation caused by moving persons in wireless networks was presented. In such a method, each node in the network broadcasted packets and stored the received signal strength of the packets which were received from all other nodes. The attenuations of the received signal strength from all nodes were used to locate the human. The experimental results in an unobstructed environment with twenty-eight nodes deployed showed that the system was capable of detecting and tracking humans in a dense wireless network. In [4], the method of [21] was extended for tracking humans behind walls. The signal strength variance caused by moving humans was used as the detection criterion, and the Kalman filter was applied to track the human location. An experiment with thirty-four nodes illustrated the performance in detection and tracking. However, the main drawbacks in [4] and [21] were that they used a high number of nodes (i.e. twenty-eight and thirty-four nodes) in a small test field to obtain high detection accuracy, and also the Kalman filter required high processing for tracking [22]. Thus, they may not be suitable in large-scale networks and in resource-constrained applications [8].

The works in [1], [23], and [24] relied on a fingerprint-based method. This method worked in two phases: the off-line and the on-line phases. In the off-line phase, RSSI data were collected to a database by asking a person to stand in different locations throughout the area of interest, while in the on-line phase, the location of a person was determined by mapping the measured RSSI to the RSSI in the database. However, the limitations of

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such fingerprint-based method were that it required accurate and up-to-date RSSI data in the database, and a typical construction of the radio map involved measurements and calibrations making it tedious and time-consuming [25].

A summary comparison between the systems presented in this work and the systems introduced in prior research is given in Table I.

TABLE I
COMPARISON BETWEEN THE PROPOSED SYSTEM AND THE RELATED SYSTEMS INTRODUCED IN PRIOR LITERATURE

Ref	Type of study	Wireless technology	Metric	Test field	Considered issue	Human movement behavior	Complexity
[9]	Experiment	IEEE 802.11 b and g 2.4 GHz	RSSI	Indoor	HME	Simple	-
[10]	Experiment	IEEE 802.15.4/ ZigBee 2.4 GHz	RSSI	Indoor	HME	Simple	-
[11]	Experiment	IEEE 802.11 b/g/n 2.4 GHz	RSSI	Indoor	HME	Simple	-
[12]	- Simulation - Experiment	CC1100 RF transceiver 868 MHz	RSSI	Indoor	HME	Simple	-
[13][19]	Experiment	IEEE 802.15.4/ ZigBee 2.4 GHz	RSSI	- Indoor - Outdoor - Semi-outdoor	- HME - People counting	Simple	Low (i.e. the people counting method)
[14]	Experiment	IEEE 802.11 b 2.4 GHz	RSSI	Indoor	HME	Simple	-
[15]	Experiment	IEEE 802.15.4/ ZigBee 2.4 GHz	RSSI	Indoor	HME	Different numbers of people and movement patterns are tested.	-
[16]	Experiment	IEEE 802.11 2.4 GHz	RSSI	Indoor	HME	Simple	-
[17]	Experiment	IEEE 802.11 2.4 GHz	- RSSI - LQI	Indoor	- HME - HDT	Simple	Low (i.e. the HDT method)
[18]	Experiment	IEEE 802.11 b/g/n 2.4 GHz	RSSI	Indoor	- HME - HDT	Simple	Low (i.e. the HDT method)
[5]	Experiment	IEEE 802.15.4 2.4 GHz	RSSI	Indoor	- HME - HDT	Simple	Low (i.e. the HDT method)
[2]	Experiment	IEEE 802.15.4 2.4 GHz	RSSI	Indoor	- HME - WCP (i.e. the TDMA protocol) - HDT	Different movement patterns are tested.	High (i.e. Kalman filter for HDT and dense deployment)
[4][21]	Experiment	IEEE 802.15.4 2.4 GHz	RSSI	- Indoor - Outdoor	- HME - WCP (i.e. the simple token passing protocol) - HDT	Different numbers of people and movement patterns are tested.	High (i.e. Kalman filter for HDT and dense deployment)
[1]	Experiment	IEEE 802.11 b 2.4 GHz	RSSI	Indoor	- HME - HDT	Different movement patterns are tested.	High (i.e. Fingerprint-based method for HDT)
[23]	Experiment	CC1100 RF transceiver 868 MHz	RSSI	Indoor	-HME -HDT	Different movement patterns are tested.	High (i.e. Fingerprint-based method for HDT and dense deployment)
[24]	Experiment	IEEE 802.11 b 2.4 GHz	RSSI	Indoor	- HME - HDT	Different movement patterns are tested.	High (i.e. Fingerprint-based method for HDT)
Proposed system	Experiment	CC2500 RF transceiver 2.4 GHz	RSSI	Indoor	- HME - WCP (i.e. the proposed method) - HDT	Different numbers of people and movement patterns (i.e. directions and speeds) are tested.	Low (i.e. the HDT method)

LQI: Link quality indicator, HME: Human moving effects on RSSI behavior, WCP: wireless communication protocol, HDT: Human detection and tracking

III. HUMAN DETECTION AND TRACKING SYSTEMS

The human detection and tracking system proposed in this work has two major functions: the RSSI measurement and collection in the network by the proposed communication protocol and the human detection and tracking using the predefined threshold with the zone selection method. These are now described in detail.

A. A Proposed Wireless Communication Protocol

The wireless network presented in this work is illustrated in Fig. 1. There is one base station node connected to a central computer (the processing center), one receiver node (Rx node 0) and three transmitter nodes (Tx nodes 1, 2 and 3). All nodes are placed at predefined positions to cover the expected detection and tracking area. We note that the illustration in Fig. 1 is also corresponding to test fields which are tested in Section IV, and the LPC2103F microcontroller interfacing with the CC2500 radio module is used as the wireless node. These are described in Section IV.

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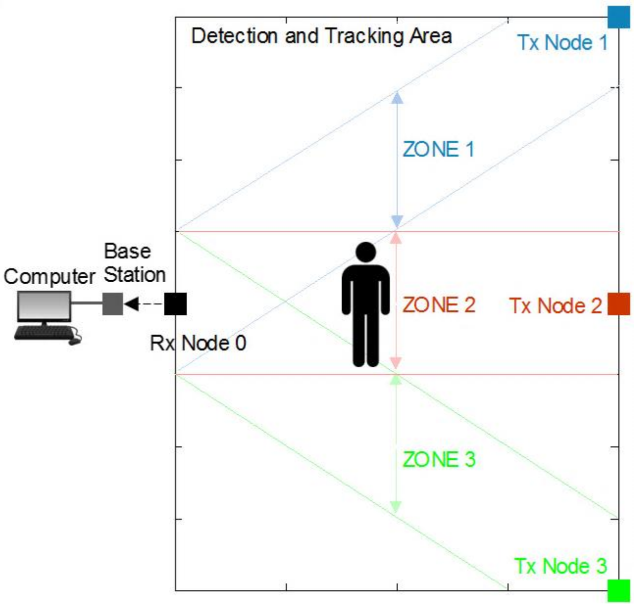

Fig. 1 The wireless network presented in this work.

To detect and track the human, the process begins with the RSSI measurement and collection described by the proposed communication protocol in Algorithm 1 and Fig. 2. When the central computer (CC) connected to the base station node (BSN) wants to detect and track the human, it first notifies the base station node to generate and send a command packet (CP) to each transmitter node (Tx-N) separately (beginning with transmitter node 1). This command packet consists of the base station node ID, the receiver node ID (Rx-N ID), and the transmitter node ID. The corresponding transmitter node then generates a beacon packet (BP) which consists of its ID and the receiver node ID, and sends this beacon packet to the receiver node. Upon receiving the beacon packet, the receiver node immediately reads the RSSI value from the RSSI status register provided by its radio circuit and collects the RSSI in its available buffer. Also, the receiver node continuously creates a data packet (DP) that consists of its ID, the base station node ID, the transmitter node ID, the RSSI value and the packet number (PN), and forwards the data packet to the base station node. Finally, at the central computer, the transmitter node ID, the RSSI value and the packet number received from the base station node are inserted to the human detection and tracking process.

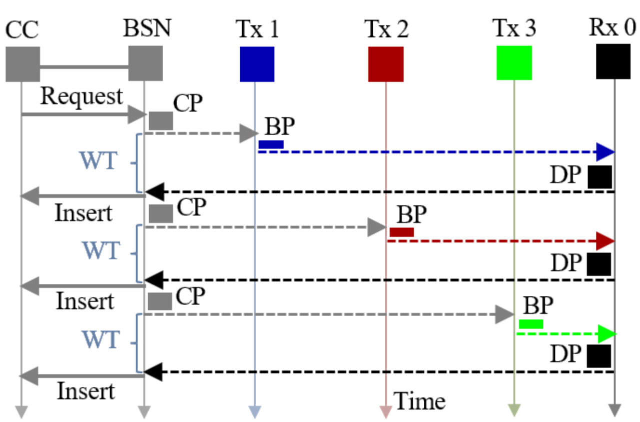

Fig. 2 The proposed communication sequence.

Algorithm 1 The proposed communication protocol.

BEGIN
01: //FOR THE BASE STATION NODE
02: **IF**BSN wants to detect and track the human in the wireless network **THEN**
03: Generate CP including BSN ID, Rx-N ID and Tx-N ID *n* (*n* begins with 1)
04: Send CP to Tx-N ID *n*
05: Wait with a predefined waiting time for receiving DP
06: **END IF**
07: **IF** BSN receives DP from Rx-N **THEN**
08: Read Rx-N ID, Tx-N ID *n*, RSSI, and PN in the data packet fields
09: Send them to CC
10:**END IF**
11: Repeat the line (02) with Tx-N ID (n + 1)
12: **IF** n > Maximum ID of Tx-N **THEN**
13: Repeat the line (02) with Tx-N ID 1
14: **END IF**
15: //FOR EACH TRANSMITTER NODE
16: **IF** Tx-N receives CP from BSN **THEN**
17: Generate BP including Tx-N ID *n* and Rx-N ID
18: Send BP to Rx-N
19: **END IF**
20: //FOR THE RECEIVER NODE
21: **IF** Rx-N receives BP from Tx-N *n* **THEN**
22: Gather RSSI from the RSSI status register
23: Generate DP including Rx-N ID, BSN ID, Tx-N ID *n*, RSSI and PN
24: Send DP to BSN
25: **END IF**
END

CC, BSN, Rx-N, Tx-N, CP, BP, DP and PN are the central computer, the base station node, the receiver node, the transmitter node, the command packet, the beacon packet, the data packet, and the packet number, respectively.

To save the amount of power consumed by the wireless nodes, and to reduce signal interference in the network that would cause packet losses, we intend to control the base station node, so that it communicates with each transmitter node sequentially. As illustrated in Algorithm 1 (lines 1-14), the base station node is programmed to sequentially send the command packet to the transmitter nodes 1, 2, and 3. After sending the command packet to the corresponding transmitter node, the base station node waits for a small period of time (a predefined waiting time, WT) to receive the data packet from the receiver node, and then transmits the next command packet to the next transmitter node. This procedure is repeated in every iteration. In addition, in the current version of our communication protocol, there is no retransmission mechanism for the command packet sending to reduce communication latency which is occurred due to a sequential transmission manner. Consequently, this may cause a tradeoff between communication latency and communication reliability when there are more transmitter and receiver nodes, especially in large-scale networks. Thus, this issue should be taken into consideration in further studies. Nevertheless, as mentioned above, the proposed communication protocol can reduce the signal interference and the packet loss. This can directly improve communication reliability.

B. A Proposed Human Detection and Tracking Method

After the central computer receives the transmitter node ID, the RSSI value, and the packet number forwarded by the base station node, the human detection and tracking process begins. The major concept in how the proposed method detects and tracks the human is now introduced.

Generally, without the human in the communication area between the transmitter and the receiver nodes, RSSI values observed by the receiver node often fluctuate around their means.

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On the other hand, when the human is in the communication area, blocking the radio signal path, the measured RSSI during such a situation will significantly fluctuate [11], [14], [15]. Therefore, the changes in the measured RSSI values can indicate presence and movements of the human [13], [14]. Based on this physical understanding, in this work we use a different level between a mean RSSI value determined during no human presence in the test field and a measured RSSI value collected during the test to compare with a predefined threshold (i.e. an appropriate level of RSSI variation that indicates human presence in the test field) for detecting the human. Then, the detection results from all communication pairs (i.e. Tx 1 and Rx 0 in zone 1, Tx 2 and Rx 0 in zone 2, and Tx 3 and Rx 0 in zone 3, as shown in Fig. 1) are further processed to determine which zone the human actually is in. The actual zone is specified by taking the detection results and the levels of RSSI variation in all zones into account. The procedure of the proposed method is as follows.

1) Noise Reduction: After the central computer successfully receives the RSSI values from the base station node, such raw RSSI input values are first filtered to reduce their noise and variation using the weighted moving average technique [26]. The weighted moving average is expressed by (1), where $RSSI\_input_{i,j}$ is the smoothed RSSI input value at the sample number i gathered from the zone j (i.e. j = 1, 2 and 3), $RSSI_{i,j}$ is the raw RSSI input value, W is the weighting factor, and n is the number of RSSI samples to be averaged. Since the weighted moving average assigns higher weight to more recent data than the past, it quickly reacts to RSSI changes during human presence and movement. In this work, n is set to 5, and W_1 to W_5 are set to 5, 4, 3, 2 and 1, respectively. The smoothed RSSI signals are prepared for the next step of our proposed method.

$$RSSI\_input_{i,j} = \frac{(RSSI_{i,j} \times W_1) + (RSSI_{i-1,j} \times W_2) + \ldots (RSSI_{i-n+1,j} \times W_n)}{W_1 + W_2 + \ldots W_n} \quad (1)$$

2) Threshold Consideration: During no human presence in the test field, the receiver node is assigned to collect the RSSI values (received from each transmitter node) with a predefined number of samples. This set of RSSI data is used to determine the mean RSSI value ($RSSI\_mean_j$) as shown in (2), where N is the number of RSSI samples set to 50 in this study. During the test, this mean RSSI value is compared to the new RSSI input value ($RSSI\_input_{i,j}$, where $i > N$). If the subtraction result ($\Delta RSSI_{i,j}$) between these values is smaller than the predefined threshold ($Threshold_j$) of the zone, this indicates that there is no human blocking the radio signal path in the zone. On the other hand, if the subtraction result is equal to or greater than the threshold, the human is in the zone. $\Delta RSSI_{i,j}$, $Decision_j$ and $Threshold_j$ are expressed by (3) to (5), respectively.

$$RSSI\_mean_j = \frac{1}{N}\sum_{i=1}^{N} RSSI\_input_{i,j} \quad (2)$$

$$\Delta RSSI_{i,j} = RSSI\_mean_j - RSSI\_input_{i,j}, \text{ where } i > N \quad (3)$$

$$Decision_j = \begin{cases} 0\,(no\ presence); if\ \ \Delta RSSI_{i,j} < Threshold_j \\ 1\,(presence)\quad ; if\ \ \Delta RSSI_{i,j} \geq Threshold_j \end{cases}, \text{ where } i > N \quad (4)$$

$$Threshold_j = \left(RSSI\_mean_{j(obs)} - RSSI\_min_{j(obs)}\right) \times \left(\frac{C}{100}\right) \quad (5)$$

The predefined threshold in (5) represents the size of RSSI variation. In this work, it equals the percentage of the different levels between the mean RSSI value and the minimum RSSI value ($RSSI\_mean_{j(obs)}$ and $RSSI\_min_{j(obs)}$). They are determined from the observed RSSI signal which is measured in the off-line phase when the human continuously walks passing each communication pair. This will be further explained in Section IV. Therefore, there are three different predefined thresholds for the zones 1, 2 and 3 to be used. To find the appropriate threshold for each zone, the constant C is varied within nine levels: 0, 12.50, 25.00, 37.50, 50.00, 62.50, 75.00, 87.50 and 100 which are corresponding to 0 to 100% of the different level between the mean RSSI value and the minimum RSSI value. In our experiment, we found that C at 25.00 and 37.50 gave optimal accuracy and sensitivity to detect the human; using the smaller value of C cannot classify the difference between human presence and no presence, while using the higher value, the human can be detected after the time the man comes to the zone. We note that in our experiment, the optimal C is determined by trial and error. The proposed method with C at 50.00 (the middle value between 0 and 100) is first applied to the observed RSSI signal to obtain the detection result. If the result shows that such a value cannot be used to distinguish between human presence and no presence (the C is still a small value), then C at 75 (the middle value between 50.00 and 100) is selected and tested. On the other hand, if the human can be detected, then C at 25.00 (the middle value between 0 and 50.00) is applied instead. This process is repeated and continued until the optimal C is determined. Since there are three zones in the given wireless network as presented in Fig. 1, the possible detection results by the threshold consideration can be categorized into eight cases as listed in Table II. For each zone, if $\Delta RSSI_{i,j}$ is equal to or greater than $Threshold_j$, the detection result ($Decision_j$) is expressed by 1 (human presence). Otherwise, it is 0 (no human presence).

TABLE II
POSSIBLE DETECTION RESULTS BY THE THRESHOLD CONSIDERATION AND THE SELECTED ZONE BY THE RSSI VARIATION CONSIDERATION

Case	Possible detection results by the threshold consideration			The selected zone by the RSSI variation consideration
	Zone1	Zone2	Zone3	
1	0	0	0	No
2	1	0	0	1
3	0	1	0	2
4	0	0	1	3
5	1	1	0	max ($\Delta variation_1$, $\Delta variation_2$)
6	1	0	1	max ($\Delta variation_1$, $\Delta variation_3$)
7	0	1	1	max ($\Delta variation_2$, $\Delta variation_3$)
8	1	1	1	max ($\Delta variation_1$, $\Delta variation_2$, $\Delta variation_3$)

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3) Zone Selection by the RSSI Variation Consideration: To specify which zone the human actually is in, zone selection is presented here. For the case 1 (in Table 1), if the detection results of zones 1, 2, and 3 are 0, 0, and 0, respectively, the proposed method identifies that the man is not yet detected. If the detection results are (1, 0, and 0) for the case 2, (0, 1, and 0) for the case 3, and (0, 0, and 1) for the case 4, the proposed method identifies that the man is in zones 1, 2, and 3, respectively (i.e. selected zones). For the cases 5, 6, 7, and 8, because multiple zones are detected simultaneously, the selected zone is further determined by considering the maximum value of the different level ($\Delta variation_j$) between the RSSI threshold of the zone ($RSSI\_Threshold_j$) and the measured RSSI value from the zone ($RSSI\_input_{i,j}$). The maximum value of $\Delta variation_j$ represents the zone that it has the highest possibility of the man presence (i.e. more RSSI variation). $\Delta variation_j$, $RSSI\_threshold_j$ and the selected zone (*Selected zone*) are expressed by (6) to (8).

$$\Delta variation_j = RSSI\_threshold_j - RSSI\_input_{i,j} \tag{6}$$

$$RSSI\_threshold_j = RSSI\_mean_j - Threshold_j \tag{7}$$

$$Selected\ zone: max.of\left(\Delta variation_j\right),\ j = 1, 2 \text{ and } 3 \tag{8}$$

We note that the proposed method described above can be efficiently used in the case of only one man present in the wireless network. For the detection and tracking of multiple persons, the proposed method should be further developed. We also show our limitations by the experiments.

IV. Experiments

A. Experiment Description

1) Experimental Setup: Two sets of experiments have been carried out in a laboratory at the Department of Electrical Engineering, Prince of Songkla University, as shown in Figs. 3 and 4 (i.e. the test fields 1 and 2). Test scenarios of these two experiments will be described in detail in 2). The layout of the test field is also illustrated in Fig. 5. The dimension of the test field is 2.00 m × 4.00 m. We note that since the received signal strength depends on the distance between the transmitter and the receiver, to keep the efficiency of the proposed method, $RSSI\_mean_j$ and $Threshold_j$ in (2) and (5) should be re-determined when the dimensions of the test field are changed. Three transmitter nodes are fixed at the positions (x_1 = 2.00 m, y_1 = 4.00 m), (x_2 = 2.00 m, y_2 = 2.00 m) and (x_3 = 2.00 m, y_3 = 0.00 m), while the receiver node connected to the base station node and the central computer is fixed at the position (x_4 = 0.00 m, y_4 = 2.00 m). Both the transmitter and the receiver nodes are kept at the same altitude from the ground level, at one meter height. In the test fields, the receiver node transfers data to the base station node via one-hop communications. The base station node communicates with the central computer via an RS232 serial port interface, and real-time RSSI signals are displayed on the central computer. The human detection and tracking method proposed in Section III is implemented on MATLAB Simulink as illustrated by examples in Fig. 6, where the mathematical model which represents the proposed method is developed by drawing block diagrams, and the measured RSSI signals are inserted to the model as input data streams. The detection and tracking results are also immediately reported by MATLAB Simulink. We note that the environments of experiments 1 and 2 are not similar. In experiment 1, there is only one man in the room, while in experiment 2, there are five people (a group of two and three people) and obstacles in the room, such as chairs, desks, and boxes. Additionally, the testing in these experiments was done on different days.

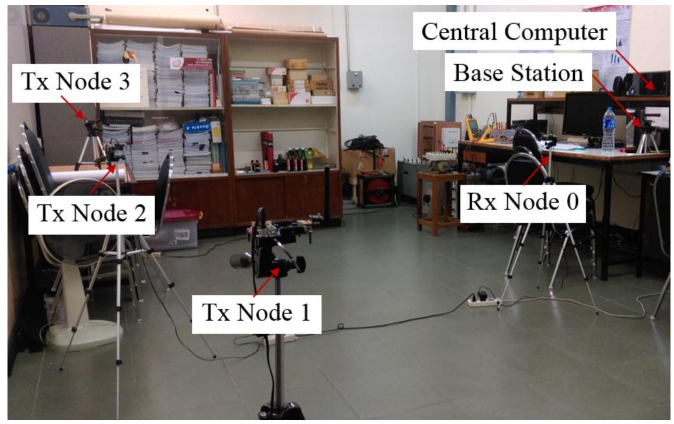

Fig. 3 The test field for experiment 1.

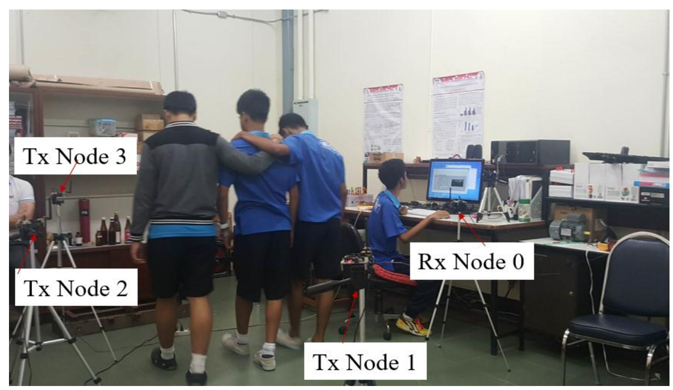

Fig. 4 The test field for experiment 2.

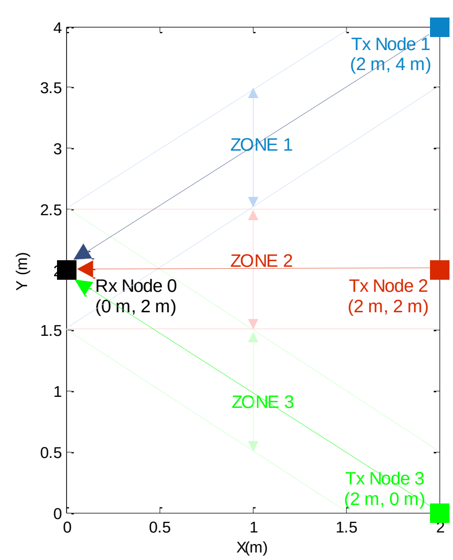

Fig. 5 The layout of test fields #1 and #2.

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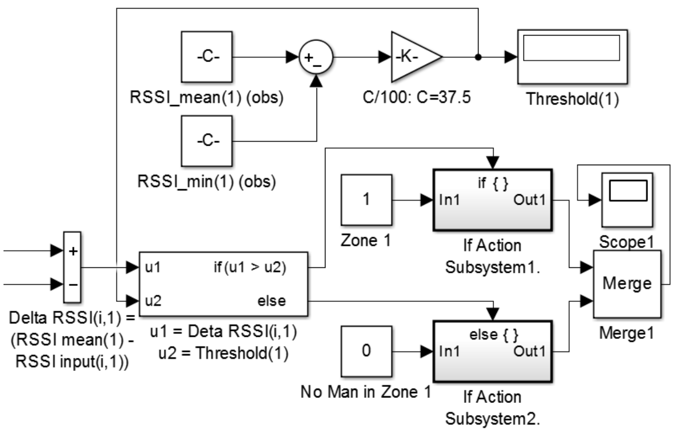
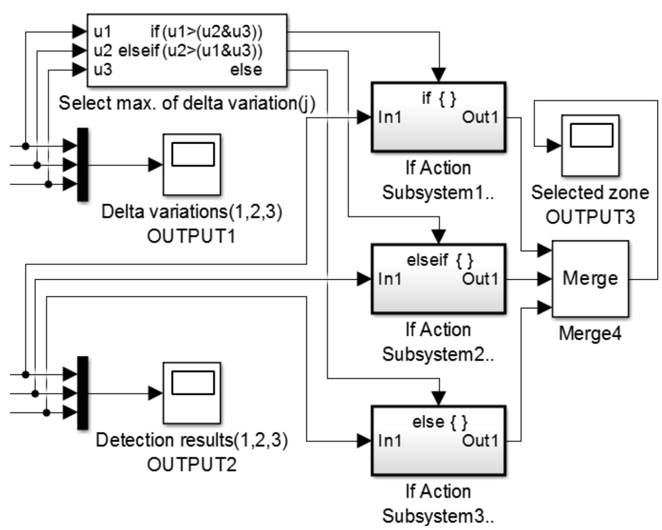
We also note that, to maintain a level of detection and tracking accuracy, the transmitter nodes and the receiver node are intently placed at the defined positions to cover the detection and tracking area. Although there are some small spaces among the zones as seen in Fig. 5, in our tests the movement of human in such spaces can also be detected and tracked. This is because the RSSI signals received by the receiver node still fluctuate due to multi-path propagation effects caused by radio reflection, diffraction, and scattering in the indoor environment [6], [15], [31]; the radio signals arrive at the receiver from transmitter via a variety of paths.



a) Threshold consideration (as in Section III), where u1 and u2 are $\Delta RSSI_{i,j}$ and $Threshold_j$, respectively. Scope 1 reports the detection result.



b) Zone selection (as in Section III), where u1, u2, and u3 are $\Delta variation_j$ of the zones 1, 2, and 3, respectively. The max. value is determined, and the corresponding zone is chosen as the selected zone.

Fig. 6 Examples of the human detection and tracking method implemented on MATLAB/Simulink: a) threshold consideration and b) zone selection.

The LPC2103F microcontroller interfacing with the CC2500 radio module developed by our research team is used as the wireless node [27], as shown in Fig. 7. The CC2500 is a low-cost 2.4 GHz radio module designed for very low power wireless applications. The CC2500 can support multiple radio channels operating in the frequency range 2.4−2.4835 GHz, and it can have up to 256 carrier frequencies based on a starting frequency and a channel spacing. Therefore, the desired radio channel can be freely assigned by the user. Since most IEEE 802.11 wireless local area network (WLAN) devices operate on channels 1, 6, and 11, which correspond to the center frequencies 2.412, 2.437, and 2.462 GHz, respectively, in our experiments we intend to configure the radio channels of the wireless nodes differently from the radio channels of any WLAN devices that are available in the EE Department, to avoid signal interference and packet loss. The SmartRF Studio software provided by Texas Instruments is utilized to automatically determine the optimum parameters for the channel settings. The CC2500 reads the RSSI value for the selected channel using (9), where $RSSI_{dBm}$ is the RSSI value in dBm units, $RSSI_{dec}$ is the RSSI value as a decimal number, and the $RSSI_{offset}$ is the offset corresponding to the data rate. The $RSSI_{offset}$ is 72 in this work, since the data rate is set at 500 kbps. Finally, the CC2500 communicates with the LPC2103F via a serial peripheral interface (SPI), which has four input/output pins, namely master out slave in, master in slave out, slave select, and serial clock, where the LPC2103F is the master and the CC2500 is the slave. Implementation details of the SPI are further described in [28], [29].

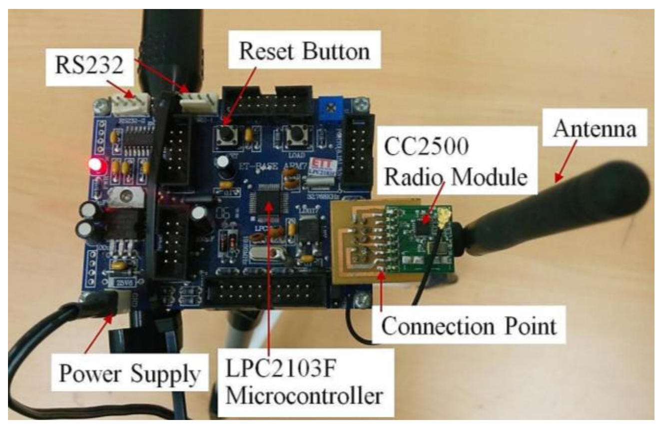


Fig. 7 The wireless node; the LPC2103F microcontroller interfacing with the CCC2500 radio module.

$$RSSI_{dBm} = \begin{cases} \left[\dfrac{RSSI_{dec} - 256}{2}\right] - RSSI_{offset}, RSSI_{dec} \geq 128 \\ \left[\dfrac{RSSI_{dec}}{2}\right] - RSSI_{offset}, RSSI_{dec} < 128 \end{cases} \quad (9)$$

According to the CC2500 configuration, the CC2500 packet format consists of preamble (32 bits), synchronization word (32 bits), packet length (8 bits), address field (8 bits), data payload (n bits, dependent on packet types), and finally an optional cyclic redundancy check (CRC) field (16 bits). Where the packet's maximum size by the CC2500 is 256 bytes. The CC2500 packet format is illustrated in Fig. 8. As described in Section III, the command, the beacon, and the data packets are presented in Algorithm 1. They are only the small packet sizes. The data payload size of the command packet is 24 bits, containing the base station node ID (8 bits), the receiver node ID (8 bits) and the

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transmitter node ID (8 bits). The data payload size of the beacon packet is 16 bits, containing the transmitter node ID (8 bits) and the receiver node ID (8 bits). For the data payload size of the data packet, it is 72 bits containing the receiver node ID (8 bits), the base station node ID (8 bits), the transmitter node ID (8 bits), the RSSI data (40 bits) and the data packet number (8 bits). The data packet number is run from 0 to 9, and it is repeated when the number is exceeded. Using small sized packets can also help reduce the communication overhead in the network, contributing to energy savings [30].

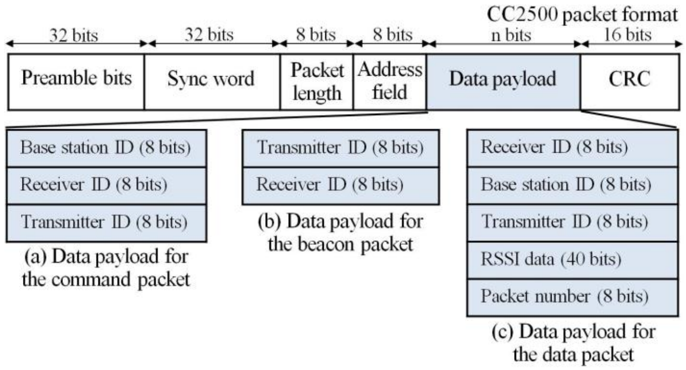

Fig. 8 The CCC2500 packet format and the data payloads of the command, the beacon and the data packets.

2) Test Scenarios: In experiment 1, there are six different test scenarios of human movement patterns to be tested. The details of each movement pattern are described in Table III. We define that the movement pattern #1 is for determining the predefined thresholds in (5) setting for the zones 1, 2, and 3. The RSSI signals from this case are the observed RSSI signals measured in the off-line phase.

TABLE III
MOVEMENT PATTERNS OF EXPERIMENT 1

Movement pattern	Details of the movement pattern
#1	The man walks in the test field passing the zones 3, 2, and 1, respectively.
#2	The man walks passing the zones 3, 2, and 1, respectively, and during walking he also stops at each zone for a period of time.
#3	The man walks passing the zones 3, 2, and 1, respectively. Then, he returns back to the starting point (i.e. walking passing the zones 1, 2, and 3, respectively).
#4	The man runs, with speed higher than walking, passing the zones 3, 2 and 1, respectively. Then, he returns back to the starting point (i.e. running passing the zones 1, 2, and 3, respectively).
#5(a)	The man freely walks and sometimes stops in each zone; he walks passing the zones 3, 3, 3, 2, 2, 2, 1, 1, 1, 2, and 3, respectively
#5(b)	The man freely walks and sometimes stops in each zone; he walks passing the zones 3, 3, 2, 2, 1, 1, 2, 3, 2, 1, 2, and 3, respectively (see an example of walking directions indicated by numbers (1) to (9), shown in Fig. 9.

Walking and running speeds are 1 m/s and 3 m/s approximately.

In experiment 2, seven movement patterns with more than one walking man are tested. The details of each movement pattern are described in Table IV. We define that the movement pattern #1 is for determining the predefined thresholds in (5) setting for the zones 1, 2, and 3.

TABLE IV
MOVEMENT PATTERNS OF EXPERIMENT 2

Movement pattern	Details of the movement pattern
#1	One man walks in the test field passing the zones 1, 2, and 3, respectively.
#2	One man walks passing the zones 1, 2 and 3, respectively, and during walking he also stops in zone 3 for a period of time.
#3	One man freely walks passing the zones 1, 2, 1, 1, 2, 3, 2, and 1, respectively.
#4	One man runs, with speed higher than walking, passing the zones 1, 2, and 3, respectively.
#5	Two people walk passing the zones 1, 2, and 3, respectively (i.e. single file movement).
#6	Two people walk passing the zones 1, 2, and 3, respectively (i.e. parallel walking).
#7	Three people continuously walk passing the zones 1, 2, and 3, respectively (i.e. parallel walking).

Walking and running speeds are 1 m/s and 3 m/s approximately.

We note that although the movement patterns described in Tables III and IV are regular, such movement patterns can be seen in many applications. For examples, people walk across corridors inside buildings, and elderly people move from one room to another room in their houses. In addition, based on the related work presented in Section II, our proposed system should be compared with the system in [2], which was developed considering both the wireless communication protocol and the detection and tracking method. Also, the proposed system should be compared with the device-free detection and tracking systems using RSSI signals presented in [1], [4], [21], [23], [24], [32], and [33]. However, implementing the systems in [1], [2], [4], [21], [23], [24], [32], and [33] by ourselves is not a good choice due to complexity and unfairness, and the experimental setups and test scenarios from both works are totally different. By this reason, we do not include them in our study.

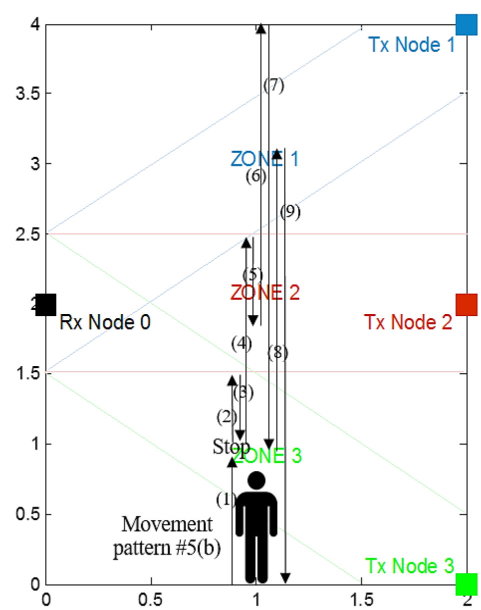

Fig. 9 An example of the movement pattern #5(b) in experiment 1.

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B. Experimental Results and Discussion

1) Experiment 1: The smoothed RSSI signals of the movement pattern #1 by the weighted moving average technique are shown in Fig. 10. It can be seen that the smoothed RSSI values immediately and significantly fluctuate when the man walks passing the zones 3, 2, and 1, respectively. As mentioned before, these signals are used for determining $Threshold_j$ in (5). Table V shows $RSSI\_mean_{(obs)}$ and $RSSI\_min_{(obs)}$ of the smoothed RSSI signals. To find the appropriate threshold for each zone, we vary the constant C within nine levels corresponding to the nine threshold levels listed in Table VI. Therefore, there are three sets of predefined thresholds to be tested for the zones 1, 2, and 3.

TABLE V
MEAN AND MINIMUM RSSI VALUES OF THE OBSERVED SIGNALS IN EXPERIMENT 1

Statics	Value of each zone		
	Zone 1	Zone 2	Zone 3
$RSSI\_mean_{(obs)}$	-52.723	-45.741	-50.449
$RSSI\_min_{(obs)}$	-60.933	-60.233	-60.500

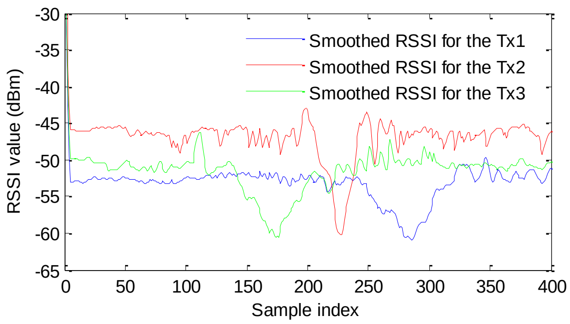

Fig. 10 The smoothed RSSI signal from the movement pattern #1 in experiment 1; the first 50 RSSI samples are collected during no man presence and used for determining the RSSI mean values, and the rest are collected when the man walks.

TABLE VI
PREDEFINED THRESHOLD LEVELS FOR EACH ZONE IN EXPERIMENT 1

Threshold	Threshold value for each zone		
Level	1	2	3
1 (i.e. 0%)	0.000	0.000	0.000
2 (i.e. 12.5%)	1.026	1.812	1.256
3 (i.e. 25.0%)	2.053	3.623	2.513
4 (i.e. 37.5%)	3.079	5.435	3.769
5 (i.e. 50.0%)	4.105	7.246	5.025
6 (i.e. 62.5%)	5.132	9.058	6.282
7 (i.e. 75.0%)	6.158	10.870	7.538
8 (i.e. 87.5%)	7.185	12.681	8.794
9 (i.e. 100%)	8.211	14.493	10.051

On applying the proposed method with the threshold levels listed in Table VI to the signals in Fig. 10, we found that using the small thresholds the proposed method quickly gives detection results, but it cannot precisely specify the actual zone that the man presence. On the other hand, on using high thresholds the proposed method slowly provides detection results. From our test, using the threshold level 4 (i.e. C = 37.5) can properly provide both the detection accuracy and the response time to detect the man. On using the threshold level 4, Fig. 11 shows the detection and tracking results without applying the zone selection method proposed in the right column of Table II (or in Section III). Fig. 12 shows $\Delta variation_j$ of the zones 1, 2, and 3, and Fig. 13 shows the results after applying the zone selection method. These results indicate that the proposed method can correctly detect and track the man with the actual zone. We note that for the RSSI signals in Fig. 10, the detection and tracking results are corresponding to the cases 1 to 4 as presented in Table II. This means that (6) to (8) are not considered.

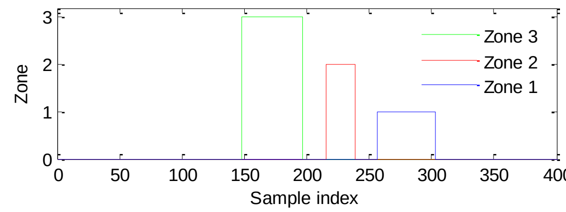

Fig. 11 The detection and tracking results of the movement pattern #1 in experiment 1 without applying the zone selection method; the zone number is displayed when the detection result by the threshold consideration is 1 as presented in the left column of Table II.

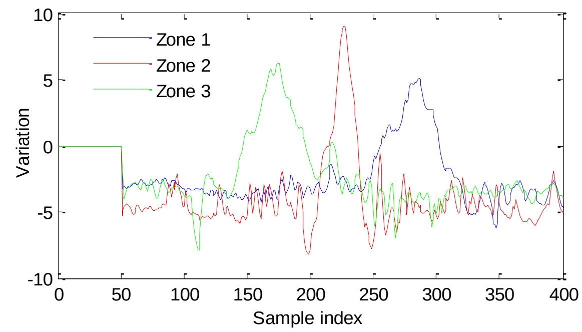

Fig. 12 The Δ$variation_j$ of the signals from the movement pattern #1 in experiment 1.

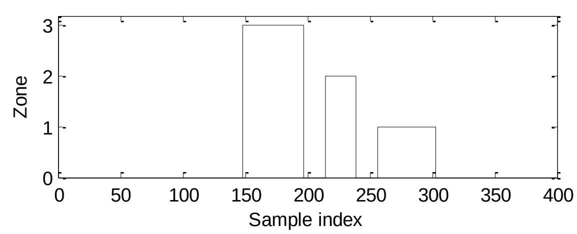

Fig. 13 The detection and tracking results of the movement pattern #1 in experiment 1 after applying the zone selection method.

Table VII shows the actual number of times that the man is in a zone for each movement pattern as presented in Table III, and Table VIII shows the number of times the proposed method can detect the man in the zone. We note that to detect and track the man for the movement patterns #2 to #5(b), the mean RSSI values (i.e. in (2)) of the signals from each movement pattern are first determined (i.e., the first 50 RSSI samples during no man presence), and the predefined thresholds are set to 3.079, 5.435, and 3.769 for the zones 1, 2, and 3, respectively. Table VIII reveals that the detection and tracking accuracy is 100% for the movement patterns #2, #3, #4, and #5(a). Only the movement pattern #5(b), there is over estimation; the proposed method specifies that the man is in the zone 1 four times during the sample indexes 941 to 978, 1002 to 1020, 1246 to 1308, and 1777 to 1793. In fact, the man is in this zone only three times, during

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the sample indexes 941 to 1020, 1246 to 1308, and 1777 to 1793 (see Figs. 14 and 15). However, this is a minor problem for this application.

TABLE VII
ACTUAL NUMBER OF TIMES THE MAN IS IN THE ZONE IN EXPERIMENT 1

Zone	Movement Pattern					
	#1	#2	#3	#4	#5(a)	#5(b)
1	1	1	2	2	3	3
2	1	1	2	2	3	5
3	1	1	2	2	4	4

TABLE VIII
DETECTION AND TRACKING RESULTS BY THE PROPOSED METHOD IN EXPERIMENT 1

Zone	Movement Pattern					
	#1	#2	#3	#4	#5(a)	#5(b)
1	1	1	2	2	3	**4**
2	1	1	2	2	3	5
3	1	1	2	2	4	4

Figs. 14, 15, 16, and 17 illustrate the smoothed RSSI signals of the movement pattern #5(b), the detection and tracking results without applying the zone selection method of Section III, the $\Delta variation_j$ of the zones 1, 2, and 3, and the detection and tracking results with the zone selection method, respectively. These results show that, using the zone selection method, at the RSSI sample indexes 578, 779 to 780, and 1415 to 1433, the proposed method selects the zone 2 as the selected zone that the man is in (not the zones 1, 1, and 3, respectively). These experimental results show the efficiency of the zone selection method to correctly classify and specify the actual zone; the maximum value of $\Delta variation_j$ can be used to indicate the zone that it has the highest possibility of the man presence. We note that for the RSSI signals in Fig. 14, the detection and tracking results are corresponding to the cases 1, 2, 3, 4, 5, and 7, as presented in Table II.

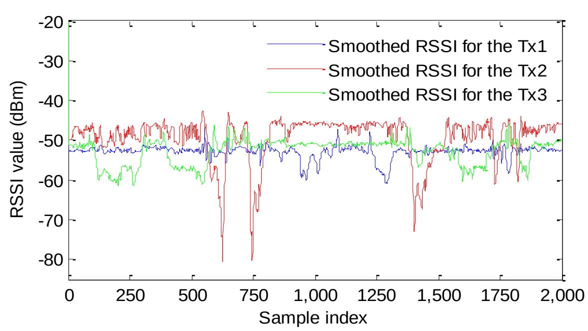

Fig. 14 The smoothed RSSI signals from the movement patterns #5(b) in experiment 1.

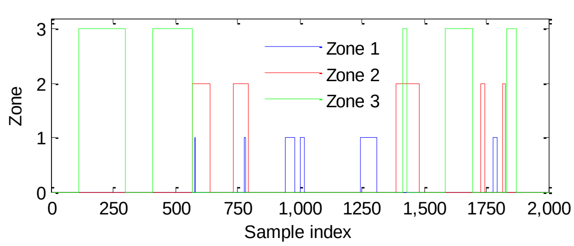

Fig. 15.The detection and tracking results of the movement pattern #5(b) in experiment 1 without applying the zone selection method.

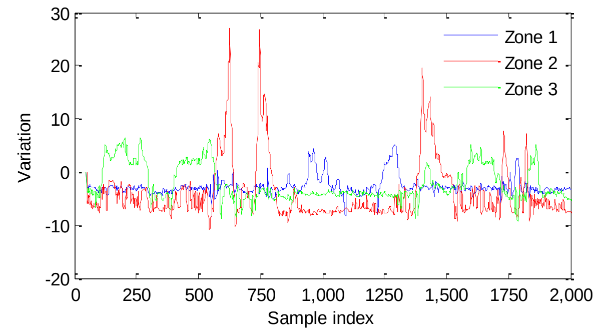

Fig. 16 The $\Delta variation_j$ of the signals from the movement pattern #5(b) in experiment 1.

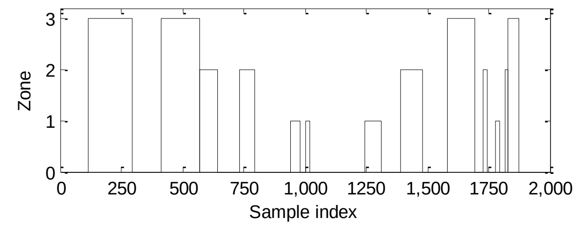

Fig. 17 The detection and tracking results of the movement pattern #5(b) in experiment 1 after applying the zone selection method. Note that as the real-time RSSI signals in Fig. 14 are received and displayed on the central computer, the detection and tracking results are immediately reported by MATLAB Simulink.

Table IX shows the delivery ratio of data packets. The delivery ratio is defined as the ratio of the total number of data packets received at the base station node to the total number of data packets sent by the receiver node. It indicates the success rate of data transmission. Note that as explained in Section III, the data packet contains the RSSI value that the receiver node reads from its radio circuit during communications with the transmitter node. Table IX indicates that the communication protocol proposed in Algorithm 1 provides successful data transmission; the delivery ratio is nearly 100% in all cases.

TABLE IX
DELIVERY RATIO OF THE DATA PACKETS IN EXPERIMENT 1

Movement Pattern	% Packet Delivery Ratio (from the Transmitter Node ID)		
	1	2	3
#1	99.750	100.00	100.00
#2	99.500	99.750	99.750
#3	99.830	99.830	99.830
#4	99.500	100.00	100.00
#5(a)	99.750	99.830	99.750
#5(b)	99.750	99.850	99.900

2) Experiment 2: For experiment 2, the smoothed RSSI signals of the movement pattern #1 are shown in Fig. 18. Table X also shows $RSSI\_mean_{(obs)}$ and $RSSI\_min_{(obs)}$ of these signals. In this test, we found that the threshold level $C = 25.0$ provides the best detection of the man. Fig. 19 shows the detection and tracking results after applying the zone selection method. We note that the threshold level $C = 25.0$ corresponds to the predefined thresholds 4.887, 6.955, and 3.840 for the zones 1, 2, and 3, respectively. They will be also used for other movement patterns.

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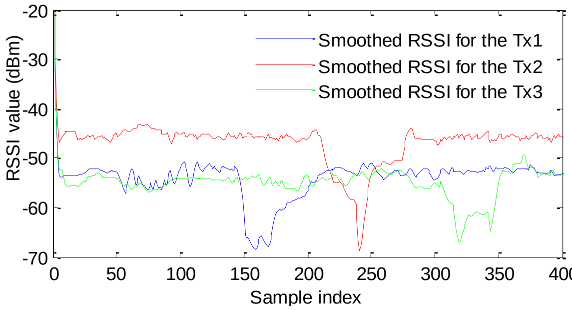

Fig. 18 The smoothed RSSI signal from the movement pattern #1 in experiment 2.

TABLE X
MEAN AND MINIMUM RSSI VALUES OF THE OBSERVED SIGNALS IN EXPERIMENT 2

Statistic	Value of each zone		
	Zone 1	Zone 2	Zone 3
$RSSI\_mean_{(obs)}$	-52.950	-45.680	-54.140
$RSSI\_min_{(obs)}$	-72.500	-73.500	-69.500

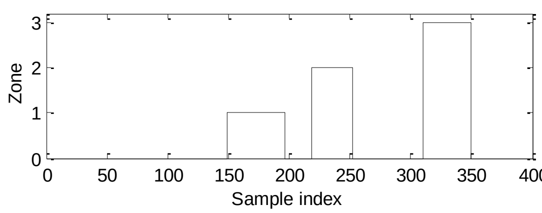

Fig. 19 The detection and tracking results of the movement pattern #1 in experiment 2 after applying the zone selection method.

Tables XI and XII show the actual numbers of times the man is in the zone of each movement pattern presented in Table IV, and the numbers of times the proposed method can detect the man in the zone. The results demonstrate that, for the movement patterns #2 to #4 (i.e. only one walking man), the detection and tracking accuracy is 100%. However, the performance of the proposed method decreases in the case of the movement pattern #5 (i.e. two walking people with single file movement). Also, the proposed method cannot specify the zone for two or more people when they are in the same zone, as in the cases of the movement patterns #6 and #7 (i.e. two and three people with parallel walking). We note that (1, 1) in Tables XI and XII refers to the actual number of times the first man and the second man are in the zone in the cases of the movement patterns #5 and #6. (1, 1, 1) in Tables XI refers to the actual number of times the first man, the second man, and the third man are in the zone in the case of the movement pattern #7. (-) means the proposed method cannot specify the zone for each man.

TABLE XI
ACTUAL NUMBER OF TIMES THE MAN IS IN THE ZONE IN EXPERIMENT 2

Zone	Movement Pattern						
	#1	#2	#3	#4	#5	#6	#7
1	1	1	4	1	1, 1	1, 1	1, 1, 1
2	1	1	3	1	1, 1	1, 1	1, 1, 1
3	1	1	1	1	1, 1	1, 1	1, 1, 1

TABLE XII
DETECTION AND TRACKING RESULTS BY THE PROPOSED METHOD IN EXPERIMENT 2

Zone	Movement Pattern						
	#1	#2	#3	#4	#5	#6	#7
1	1	1	4	1	1, 1	-	-
2	1	1	3	1	**1, 0**	-	-
3	1	1	1	1	1, 1	-	-

Figs. 20 to 22 show the smoothed RSSI signals, the $\Delta variation_j$ of the zones, and the detection and tracking results of the movement pattern #5. We can see that, during the RSSI sample indexes 201 to 212, the first man is in the zone 3, and, at the same time, the second man is in the zone 2. By considering the maximum value of $\Delta variation_j$ in (8), the proposed method specifies that the man is in the zone 3. This refers to the first man, while the second man in the zone 2 is ignored. The result in this case indicates that the proposed method cannot classify the zone for two or more people who are in different zones at the same time.

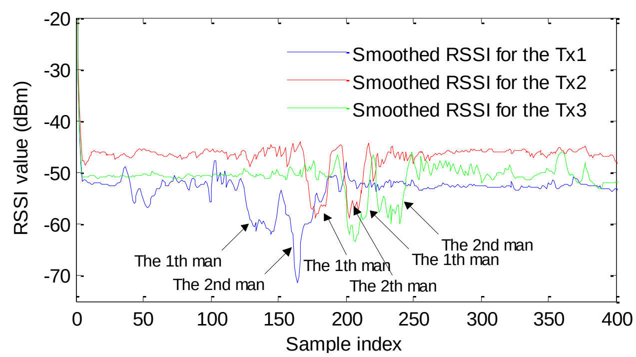

Fig. 20 The smoothed RSSI signal from the movement pattern #1 in experiment 2.

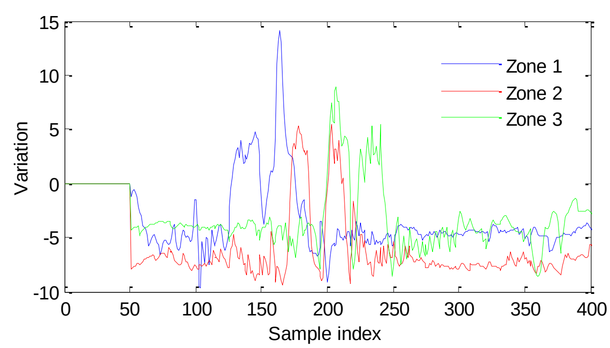

Fig. 21 The $\Delta variation_j$ of the signals from the movement pattern #5 in experiment 2.

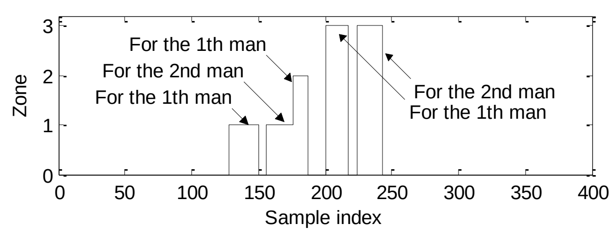

Fig. 22 The detection and tracking results of the movement pattern #5 in experiment 2 after applying the zone selection method.

Examples of the smoothed RSSI signals and the detection results of the movement pattern #7 are illustrated in Figs. 23 and 24. These results show that the proposed method cannot specify the zone for three people, when they are in the same zone at the

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same time. For the movement pattern #6, the proposed method cannot also specify the zone for two people.

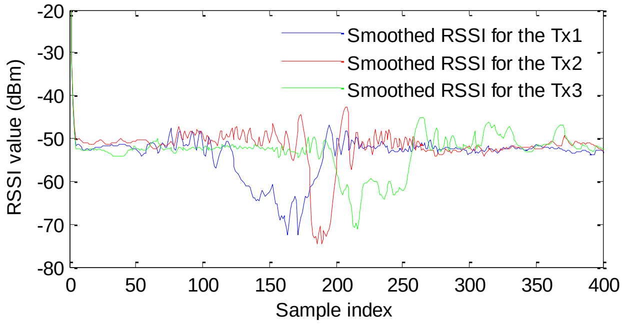

Fig. 23 The smoothed RSSI signal from the movement pattern #7 in experiment 2.

In Table XIII, the delivery ratio of data packets is nearly 100% in all cases tested. These results again confirm that the communication protocol proposed in Algorithm 1 can provide communication reliability.

We note that, as introduced in Section III, in the current version of our proposed communication protocol, a sequential transmission manner is presented to avoid signal interference. This can cause a tradeoff between communication latency and communication reliability when there are more transmitter and receiver nodes in a large-scale network. Also, if human presence in several zones needs to be identified, the processing time will increase. This issue should be considered in further studies; each receiver node may work as the leader for collecting and processing the RSSI information sent by transmitter nodes in a group, and then cooperates with the base station. In addition, due to this sequential transmission manner, time synchronization problems for all transmitter nodes can be occurred, especially in large-scale networks. Therefore, methods for handling this problem should also be developed. However, in this current work, at the beginning of the process, the base station broadcasts a notification message to all nodes in the network. Such a message contains a start time, which is used for all nodes to start the process. Thus, time synchronization problems can be alleviated.

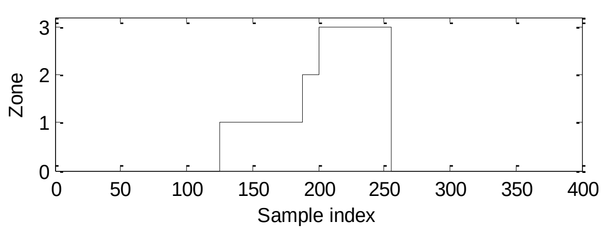

Fig. 24 The detection and tracking results of the movement pattern #7 in experiment 2 after applying the zone selection method.

TABLE XIII
DELIVERY RATIO OF THE DATA PACKETS IN EXPERIMENT 2

Movement Pattern	% Packet Delivery Ratio (from the Transmitter Node ID) 1	2	3
#1	99.750	100.00	99.750
#2	100.00	99.750	99.500
#3	99.500	99.670	99.830
#4	100.00	99.500	100.00
#5	100.00	99.750	100.00
#6	99.500	99.500	99.750
#7	99.750	99.250	99.500

V. CONCLUSIONS

In this paper, a device-free human detection and tracking system using RSSI for an indoor environment is proposed. The proposed wireless communication protocol is developed for measuring and collecting the RSSI signals affected by human movements. The human detection and tracking method is developed for specifying the actual zone that the man is in. The experimental results confirm that the proposed communication protocol can significantly provide communication reliability, and the human detection and tracking method can correctly specify the actual zone in all cases of one man movements.

In future work, adaptively setting the optimal threshold should be further investigated. More complex human movement patterns in various environments (including LOS and NLOS conditions) should be tested. Also, developing communication protocols to support multiple wireless links in large-scale wireless networks, and developing detection and tracking methods to support multiple human movements are required.

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Apidet Booranawong received the B.Eng. degree in Electrical Engineering from Walailak University, Thailand, in 2007, and the M.Eng. and the Ph.D. degrees in Electrical Engineering from Prince of Songkla University, Thailand, in 2009 and 2015, respectively. He was a postdoctoral research fellow at Prince of Songkla University, and he now is a visiting researcher at the University of Aizu, Fukushima, Japan. His research interests include wireless sensor and actuator networks and RSSI-based indoor localization.

Nattha Jindapetch received the B.Eng. degree in Electrical Engineering from Prince of Songkla University, Thailand, in 1993 and the Ph.D. degree in Information Technology from the University of Tokyo, Japan, in 2004. She now is an Associate Professor in the Department of Electrical Engineering, Prince of Songkla University. Her research interests are FPGAs, embedded systems, and sensor networks.

Hiroshi Saito received his B.S. and M.S. degrees in Computer Science and Engineering from the University of Aizu in 1998 and 2000, respectively. In 2003, he received his Ph.D. degree in Electronic Engineering from the University of Tokyo. He is a Senior Associate Professor of the University of Aizu. His research interests include asynchronous circuit design, multi-core system design, and wireless sensor network system design.