Low-Cost Indoor Human Tracking by Utilizing Fluctuation of Received Radio Signal Strength

Huang-Chen Lee*, Tzu-Ting Lin

***Abstract*—Existing indoor positioning technologies aim at providing location information of extremely high accuracy, but are limited by the requirement for infrastructure with high installation and maintenance costs. Thus, for indoor human tracking applications, a suitable indoor positioning technique should be selected by taking into account practical considerations of adequate accuracy as well as cost-effectiveness. Based on this observation, an indoor, room-level tracking method is presented, which is characterized by an infrastructure that is cost-effective to build and maintain with no need to deal with calibration issues of the fingerprint map caused by hardware heterogeneity. A mobile device tracks variations in the radio signal strength from nearby Bluetooth beacons to determine the entry and exit of the user's device from a given room or hallway. Therefore, by determining the sequence of users' movements, their moving path can be recorded for indoor tracking or navigation. Experiments revealed that the proposed method attains an average hit rate, false alarm rate, and miss rate of 94.2%, 3.6%, and 5.8%, respectively.**

Keywords—indoor, map, tracking, positioning, radio signal strength, RSS, Bluetooth, smartphone, heterogeneous hardware.

I. Introduction

The aim of indoor positioning is to provide a subject's location and directions to a desired destination in an indoor environment where Global Positioning System (GPS) is unavailable. In previous studies, researchers investigated radio received signal strength (RSS) approaches with RFID[1]; WiFi [2][3][4]; Bluetooth [5][6][7][8]; IEEE 802.15.4/ZigBee[9]; FM radio[10]; and a geomagnetic field [11] by using distance estimation or fingerprint-based techniques to achieve indoor positioning.

The proximity approach [5] determines the radio receiver's location according to the beacon with the strongest RSS from a Bluetooth beacon (i.e., Apple's iBeacon) or WiFi AP. This approach is simple and intuitive, but different types of receivers (i.e., different smartphone models) may receive different RSS levels from the same groups of beacons at the same location. Other approaches, such as a light-sensor-based positioning system [12][13] and an ultrasonic time-of-flight [14] approach, a camera system [15], and a 3D laser scanner approach [16], are useful, but these approaches may necessitate additional infrastructure and a handheld device support, i.e., modification of lamps to provide location information or installation of cameras on the ceiling. In addition, a suitable sensor (i.e., a special light sensor, an ultrasonic sensor, a 3D laser scanner) also may be unavailable in commercial off-the-shelf smartphones; thus, specially designed handheld equipment is required to use this system.

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Several indoor positioning technologies aim at providing high location accuracy. However, currently, no technique can provide extremely high location accuracy (i.e., error < 1 cm), high reliability, and a low response time while simultaneously considering the costs of infrastructure, handheld equipment (no need for specially designed smartphones), and maintenance (no need for building and updating radio fingerprint maps). The radio fingerprinting approach can provide good positioning accuracy by using RSS from WiFi[3][4], Bluetooth[6][7][8], IEEE 802.15.4/ZigBee[9], FM radio[10], a geomagnetic field [11], and WiMAX [22]. However, a radio fingerprint map may be outdated if the environment changes after the radio fingerprint map is built. For example, changes in the location of the WiFi access point or furniture can lead to an incorrect map and may require building the radio fingerprint map again. In addition, different radio receivers may record different levels of RSS at the same location, which must be calibrated for matching to a radio fingerprint map. Consequently, researchers developed several algorithms to perform RSS calibration for handling heterogeneous hardware problems [17][18]. The maintenance of an up to date, accurate radio fingerprint map is labor-intensive, expensive, and possibly impractical in real life. Meanwhile, this approach typically requires a large number of beacons (i.e., WiFi access points or RFID), leading to high costs for the installation and maintenance of the necessary infrastructure.

Nevertheless, in most real-world applications (such as indoor human tracking or navigation), the selection of a suitable indoor positioning technique might depend on finding an economical option that provides just sufficient accuracy for specific applications. This study is extended from our previous study [19]. This study presents a more comprehensive introduction of the design and implementation of the proposed indoor human tracking system for room-level navigation. Fig. 1 shows a diagram describing the method. A Bluetooth beacon is installed on the doorframe in the middle of the hallway and in a room designated as #202. When a user carrying a mobile device enters the room from the hallway, the mobile device receives the RSS ramp-up and ramp-down period (as depicted in the upper-right inset in Fig. 1), indicating that the mobile device is currently moving toward (approaching)/leaving from the beacon. Hence, the greater the distance between the user and beacon, the lower the RSS. The beacon message comprises the beacon's ID, indicating its corresponding room number and the entry or exit directions in a range of degrees (i.e., 5° to 85° for entry and −95° to −175° for exit); all information is programmed in the beacon. In this design, the building owner provides the building's floor plan to create an indoor map for users, e.g., Google Maps allowing building owners to upload their floor plans for indoor tracking [20]. The indoor map defines the location of each room corresponding to the beacon's ID. Therefore, the proposed method determines the users' movement and then indicates their location on the off-line indoor map.

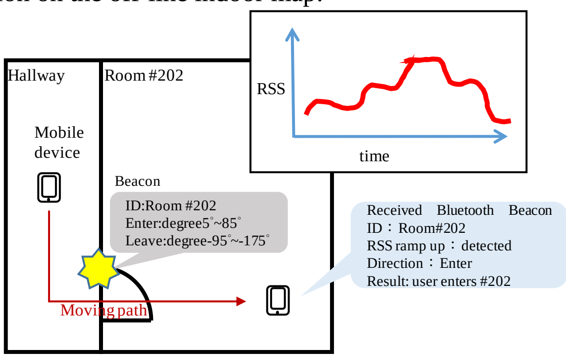


Fig. 1 Use of RSS variation to estimate the location of a mobile device.

The mobile device can determine that the user is entering or exiting the room according to its own moving direction, provided by its compass sensor. By installing beacons at the intersections of hallways and rooms, the mobile device can determine whether the user is entering or exiting a specific room for the purpose of determining the user's moving path on the indoor map. This proposed method, which determines the user's movement by the variations in the received radio signal strength (RSS) of his/her mobile device, avoids the inconvenience of having to build and maintain radio fingerprint maps and performing sophisticated RSS calibration. In summary, the contributions of this study are as follows:

1) A novel method that uses RSS variations in a mobile device to determine the moving event, which can improve the performance of indoor tracking and navigation and avoid heterogeneous hardware problems, is proposed.
2) The proposed method utilizes Bluetooth Low Energy (BLE) as the beacon, which consumes less energy than WiFi or other wireless interfaces in a smartphone and does not significantly shorten a smartphone's battery life.
3) The installation and deployment of beacons are easy and cost-effective and can operate for several years with a battery pack.
4) This approach does not need a radio fingerprint map for location estimation, considerably reducing the cost of building and maintaining infrastructure given that the indoor environment and interference can change.

II. Proof-of-Concept Experiment

In this section, a proof-of-concept experiment was designed and executed to examine whether the above-described idea was feasible and practical in the real world. An Android app was designed to run on an Android smartphone that would record the date, time, RSS of the beacon, acceleration, and azimuth. The azimuth value reported by a smartphone's compass indicates the angle between the magnetic North direction. For example, azimuth values of 0, 90, 180, and 270 indicate that the smartphone is aimed to the North, East, South, and West. The Bluetooth beacon (hereafter called the Beacon) used in this experiment is based on Nordic nRF51822. Its advertisement's broadcast frequency is set to 10 Hz.

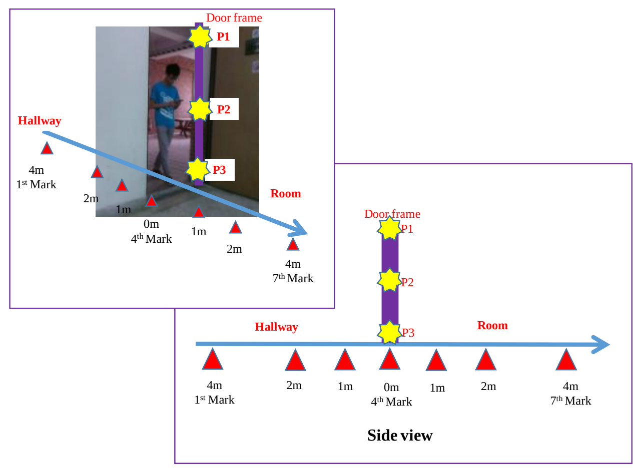


Fig. 2 Scenario 1: Entering/exiting a room/hallway.

Fig. 3 Two beacons installed on the walls of a staircase.

A. *Testing Scenarios*

Two scenarios were examined: (1) enter/exit a room (designated as room #318 in this example), as depicted in the lateral view shown in Fig. 2; and (2) walk up/down a staircase, as shown in Fig. 3. In the proof-of-concept experiment, the data-collecting program was designed to make the subject/user intentionally push a button on the screen of the mobile device to mark his/her present location. These locations were marked on the ground with colored sticks for reference. Referring to the Fig. 2, the 1st mark indicates the location (in the hallway), and its distance to the doorframe is 4 m. The user marked his/her location at 0 m, 1 m, 2 m, and 4 m from the doorframe (indicated by the red triangles in Fig. 2) and at the intersection where the floor meets the stairs. These location marks correlate log information to the corresponding physical location information during later analysis.

To examine the manner in which the beacon's height can affect the mobile device's ability to receive a clear RSS ramp-up/ramp-down period, the beacons also were deployed at three locations, identified as P1 (at the top of door frame), P2 (at the height of the door knob), and P3 (on the ground), respectively, in Fig. 2. The experimental results indicated that location P2 gives the most significant and clear RSS ramp up/down period for passing mobile devices as this location is the nearest to the device in the user's hand.

In scenario 1, the time when a user enters/exits a room was determined. In Scenario 2, to determine when a person walks up/down a stairway, two beacons were used to improve the accuracy of detection, based on the first scenario. As illustrated in Fig. 3, two beacons designated Stair_L and Stair_R were installed on the walls of a staircase. By determining the sequence of movement with respect to these two beacons, whether the user is walking up or down the staircase can be determined.

B. *Scenario 1: Entering/Exiting a Room*

Two android mobile devices Asus Zenfone and Asus Memopad, respectively, were used in this proof-of-concept experiment. Fig. 4 shows the test results of the Asus Zenfone in Scenario 1. In Fig. 4–Fig. 8, Received Signal Strength Indicator of a smartphone is abbreviated as RSSI, which is reported by the user carrying the smartphone.

As the user carries the smartphone and walks from one side to another across the doorframe (refer to Fig. 2), the distance between the user and beacon changes, and the smartphone's RSSI varies, following an intuitive rule: the shorter the distance (between the radio transmitter and receiver), the higher the RSS. The RSS ramp-up period (refer to Fig. 4, from −87 dBm to −45 dBm, from the 1st mark to the 4th mark, for which the mark indicates the time the user is at this location) is clear as the subject is moving closer to the beacon, with some fluctuations in the RSS ramp-down period (from the 4th mark to the 7th mark) as the subject moves farther from the beacon. Fig. 5 shows the same RSS features for the Asus Memopad; the RSS ramp-up and ramp-down periods are clear, indicated by orange dotted arrows. Even at the same location, the peak RSSs (at the 4th mark in Fig. 4 and Fig. 5) of the two devices are different (−45 dBm and −62 dBm, respectively), caused by the known heterogeneous hardware problems [17][18]. As two mobile devices receive the same RSS trend line, which the proposed method uses for determining whether a user enters or leaves the room, the performance of our method is not affected by different mobile devices. Thus, in the following paragraphs, only the results for the Asus Zenfone are presented, while those for other mobile devices exhibit the same RSS trend line.

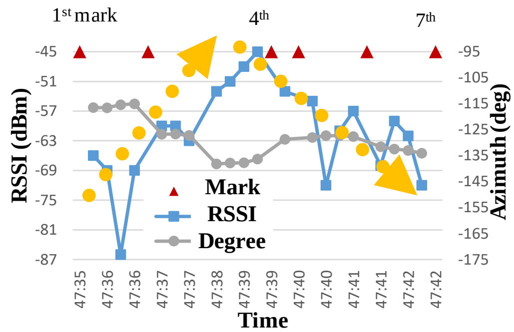


Fig. 4 Entering room #318 (Asus Zenphone).

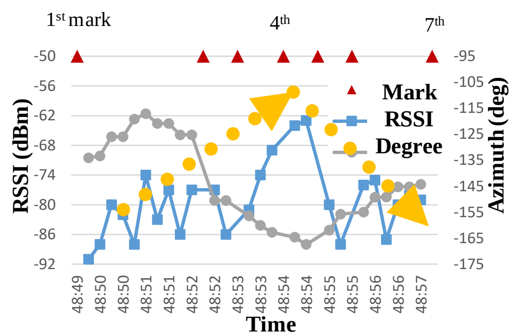


Fig. 5 Entering room #318 (Asus Memopad).

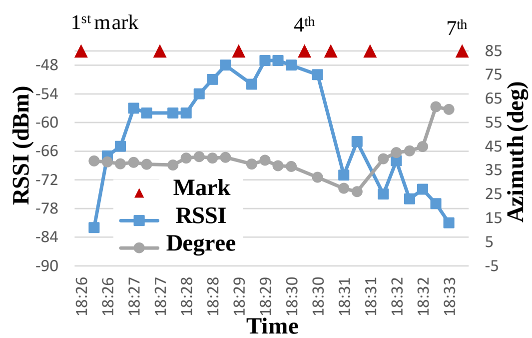


Fig. 6 Exiting room #318.

In addition, in Fig. 4 and Fig. 5, the azimuth moving direction read from the smartphone's compass is approximately −135 degrees, indicating that it is entering the room—in this case, room #318. These figures show a clear moving direction that can help users to determine when they are entering a specific room.

Fig. 6 shows the results when a user carries the smartphone while exiting room #318. The trends in the RSS ramp-up and ramp-down periods are clear, from the 1st to the 4th mark and from the 4th to the 7th mark (in Fig. 6, the RSS is from −83 dBm to −48 dBm and −48 dBm to −80 dBm), although some fluctuations are still observed. The moving direction in the figure is in the range of 25–60 degrees (the direction of exiting room #318), indicating that the user is exiting the room.

C. *Scenario 2: Walking up/down a stairway*

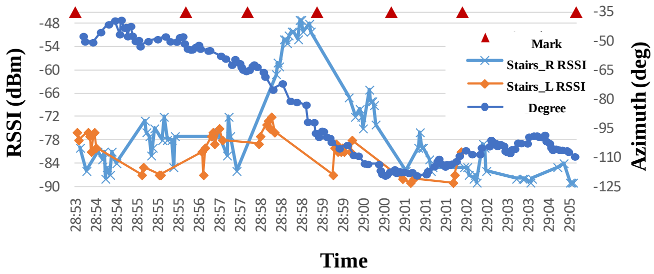


Fig. 7 Walking down the stairs.

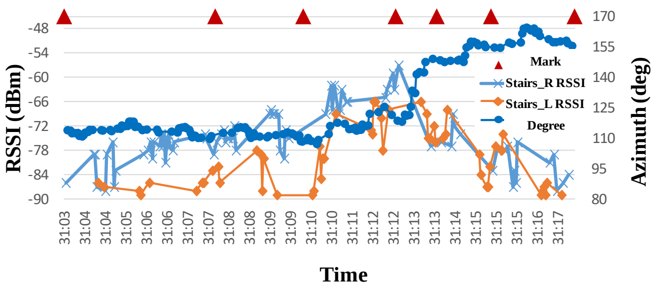


Fig. 8 Walking up the stairs.

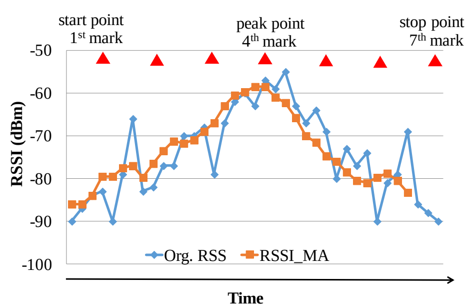


Fig. 9 Example of interpolated and moving average RSS curves.

For this scenario, beacons were installed on walls close to the staircase (as shown in Fig. 3), and the user walked up and down the stairs carrying a smartphone. As in the previous scenario, the data-collecting program required the subject to push a button on the screen of the mobile device, marking their location at 0 m, 1 m, 2 m, and 4 m from the intersection of a floor in the building and stairs.

Fig. 7 shows data from the user's walk down the stairs. The user walks on the right side of the stairway, near beacon Stair_R, and that beacon's RSS ramp-up and ramp-down periods are significant in comparison with the RSS of Stair_L. The direction of movement is toward the West as it fluctuates between −40 and −115 degrees, indicating that the user is walking down the stairs.

Fig. 8 shows the user's walk up the stairs on the right side, which is near beacon Stair_R. The RSS of Stair_R is greater than the RSS of Stair_L as the user is nearer to Stair_R. The moving direction is in the range of 110–160 degrees, indicating that the user is walking up the stairs.

By this experiment, the proposed idea is feasible, and this method can be utilized to determine the location of a mobile device user for indoor navigation. In the next section, issues of the algorithm's design are discussed.

III. SYSTEM DESIGN

A. *Design Issues*

Before discussing the algorithm, it is useful to review some lessons learned in the experiment and propose countermeasures to address them (see Fig. 9):

1) The received beacon samples can be used to determine the moving path of the user, but some beacon samples are missing, and RSS is often unstable. Data pre-processing is mandatory to produce a smooth RSS curve before movement detection. Therefore, interpolation and moving average are applied to the received samples to generate an RSS curve with a clear trend line, as shown in RSSI_MA in Fig. 9.
2) The moving direction changes while the user is moving. The peak point of RSSI_MA indicates the closest distance between the user and beacon, which is installed on a doorframe or entrance to a stairway. The moving direction in this moment can be seen as the user's major moving direction.

The algorithm shown in Fig. 10 illustrates the procedure of the method. During the experiment, the subject logs the date, time, RSS of the beacon, and moving direction, as in the previous proof-of-concept experiment. In addition, the user records the time and location at which they pass the beacon as the ground truth.

B. *The Proposed Moving Event Detection Algorithm*

A moving event detection (MED) algorithm was designed for determining when and where users change their location based on the concept described in the previous section. In the beginning, the algorithm starts to read the log data and tries to find the start point of an event (user entering or exiting a room, etc.). In Fig. 9, the start point of this event is at the 1st mark. In our current design, the criterion for determining the start point of the event is where the RSS of all three consecutive samples is greater than the predefined RSS threshold (RSSth = −85 dBm in the current design). Next, the algorithm continues to seek the stop point (i.e., the 7th mark in Fig. 9), where the RSS of all three consecutive samples is less than RSSth.

After the stop point is decided, the samples between the start point and stop point are copied to the temporary data array Temp_log. If the direction is valid (i.e., equal to the direction of entering or exiting the room), the algorithm generates another temporary data array Temp_a_log. It stores the interpolated and moving averaged (averaged with the last four samples in this experiment) RSS/moving direction of Temp_log in Temp_a_log to find the RSS peak point (i.e., the 4th mark in Fig. 9) between the start and stop points and uses this information to determine the major moving direction Sp.

Subsequently, the algorithm tries to find the RSS descending phase in the Temp_a_log. If the descending phase (i.e., between the 4th mark and 7th mark) is found and the moving direction Sp is valid, then, the algorithm can use this RSS ramp-down period to determine the subject's movement and output a message that an entering/exiting event is detected. Then, the algorithm goes back to its start to find the next movement event until the log ends.

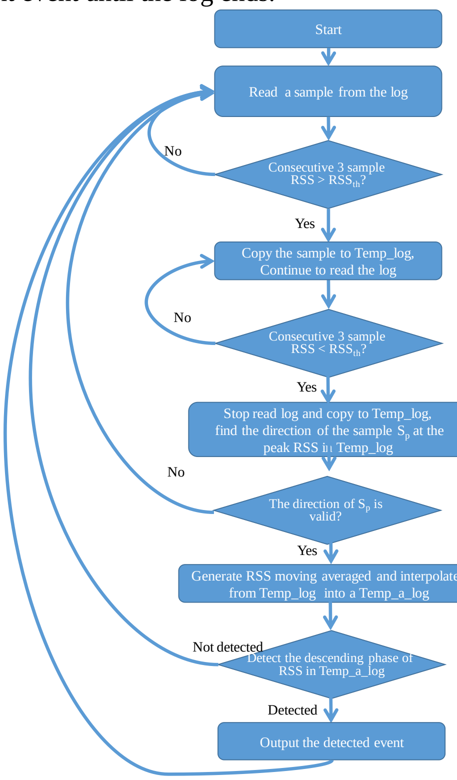


Fig. 10 MED algorithm.

C. Reconstructing Undetected Events

After users tested our proposed algorithm, still some moving events went undetected. Fig. 12 shows an example of the moving path, which is based on the floor plan in Fig. 11. In the study, all beacons were installed at location P2 of a hallway of a room (refer to Fig.2) and at locations Stair_L and Stair_R of a staircase (refer to Fig.3). The left portion of Fig. 12 shows the ground truth, while the right portion shows the algorithm-generated moving paths. Two events (indicated by the red arrows) with the timestamp "xx:xx:xx:xxx" indicate undetected moving events, which can be reconstructed automatically. Some samples are lost and causes the RSS feature of the user's movement to appear insignificant; hence, they are not recognized. Interpolated and moving average RSS data offer some improvement, but they still cannot detect all moving events due to the loss of some beacon samples.

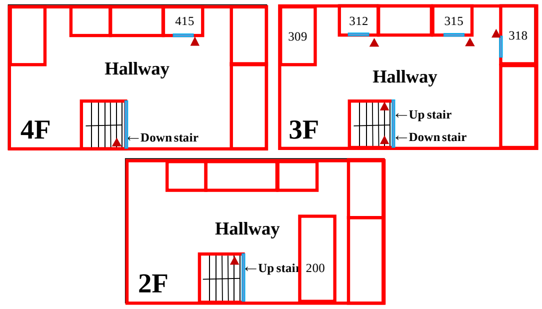


Fig. 11 Floor plan of the test site.

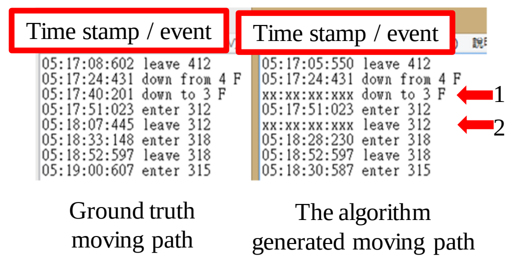


Fig. 12 Comparison of the moving path from ground truth and the path generated by the algorithm.

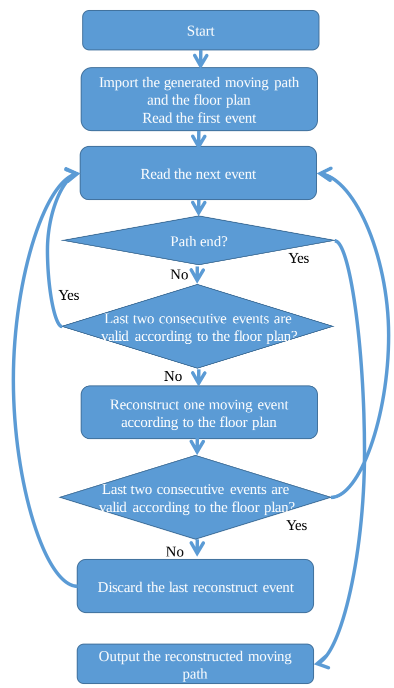


Fig. 13 RUE algorithm.

Nevertheless, some undetected moving events still can be automatically reconstructed by referring to the last and next moving event using the floor plan. For example, the first undetected event, "down to 3F" (indicated by red arrow 1 in Fig. 12), can be reconstructed by referring to "down from 4F" and "enter 312," because the user must walk down the stairs from 4F to 3F and can then enter room #312. In addition, the user must leave room #312 (red arrow 2 in Fig. 12) before they can enter another room #318. In the proposed method, using the floor plan, the reconstruct undetected event (RUE) algorithm (shown in Fig. 13) can be applied to generate a more complete moving path. In the example, the two undetected events are reconstructed using RUE. However, RUE is still limited by the inability to reconstruct two or more consecutive undetected events. The following section presents the experiment for verifying the proposed algorithm and its evaluation.

IV. Experiment and Evaluation

A. Performance Indexes

In this section, an experiment was conducted to evaluate the performance of the proposed method. Three performance indexes were evaluated: hit, miss, and false alarm. Hit indicates that the user's moving event, which exists in the ground truth, is correctly detected by the proposed algorithm. Miss indicates that the moving event is in the ground truth, but it is not detected by the algorithm. False alarm indicates that the moving event does not appear in the ground truth, but the algorithm reports this non-exist moving event. These performance indexes are evaluated as the subjects move along the predefined paths listed in Table I, and the results are calculated on the basis of a per-moving-path basis, not per-moving-event (in the paths) basis. Therefore, the results can help to understand the manner in which the performance of the proposed method can be utilized to track subjects in indoor environments, as well as use for indoor navigation applications. An example calculation of the performance indexes for a specific moving path is shown as follows:

1) Ground truth moving path: **Leave #318 → Enter #315 → Leave #315 → Enter #318**
2) The MED and RUE algorithm-generated moving path: **Leave #318 (*hit*) → Enter #312 (*false alarm*) → Leave #312 (*false alarm*) → Enter #315 (*hit*) → Leave #315 (*hit*)**

In this example, the performance indexes of this path are as follows:

- hit rate = 3/4 = 75%
- miss rate = 1/4 = 25%
- false alarm rate = 2/4 = 50%

B. Experiment Configuration

The experiment was conducted in the building in our university, and the floor plan was preset in Fig. 11. Table I summarizes four test moving paths. Ten subjects were assigned to walk these predefined four paths 10 times each. The generated moving paths evaluated the performance of the proposed MED and RUE algorithms. The ground truth during the experiments was collected for later analysis. Table I shows the predefined test moving paths.

TABLE I. Test Moving Paths

Path #1	Leave #318 → Enter #315 → Leave #315 → Walk down stair from 3F → Walk to 2F → Enter #200 → Leave #200 → Walk up stair from 2F → Walk to 3F → Enter #312 → Leave #312 → Walk up stair from 3F → Walk to 4F → Enter #412 → Leave #412 → Walk down stair from 4F→ Walk to 3F → Enter #309 → Leave #309 → Enter #318
Path #2	Leave #318 → Enter #312 → Leave #312 → Enter #309→ Leave #309→ Walk down from 3F → Walk to 2F → Enter #200 → Leave #200 → Walk up stair from 2F→ Walk to 3F → Enter #309→ Leave #309→ Enter #318
Path #3	Leave #318 → Enter #309→ Leave #309→ Walk up stair from 3F → Walk to 4F → Enter #412 → Leave #412 → Walk down stair from 4F→ Walk to 3F → Enter #315 → Leave #315 → Enter #318
Path #4	Leave #318 → Walk down from 3F → Walk to 2F → Enter #200 → Leave #200 → Walk up stair from 2F → Walk to 3F → Enter #309→ Leave #309→ Walk up stair from 3F → Walk to 4F → Enter #412 → Leave #412 → Walk down stair from 4F→ Walk to 3F → Enter #318

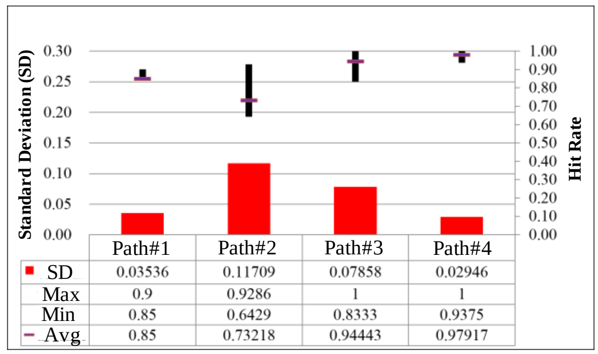


Fig. 14 Hit rate in the first experiment.

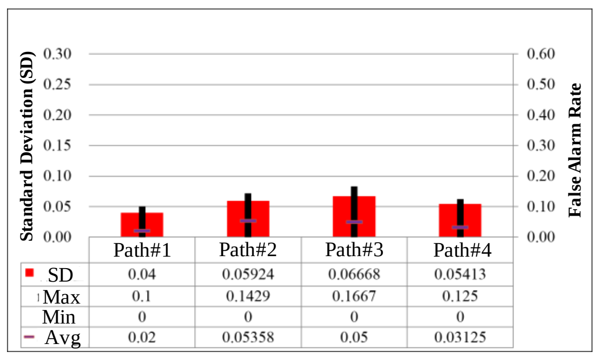


Fig. 15 False alarm rate in the first experiment.

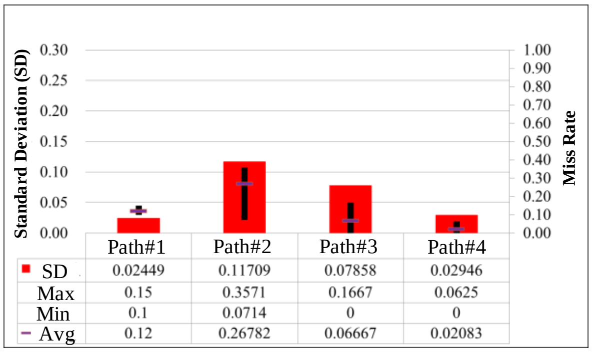
C. First Experiment

Fig. 14 shows the hit rate of the experiment over different predefined paths. Path #4 exhibits the highest average hit rate, 94.4%, while path #2 exhibits the lowest average hit rate and the highest standard deviation (SD) of 73.2% and 11.7%, respectively.

As shown in Fig. 15, the average false alarm rate over four paths is in the range of 2–5.3%, although in some cases, the false alarm rate is 0%. The SD of the false alarm rate varies from 4% to 6.6%. The false alarm rates of the four paths are similar.

Fig. 16 shows the miss rate. Again, the average miss rate of path #2, 26.7%, is greater than those of other paths. Path #2 exhibits the highest miss rate of 35% and the highest SD of 11.7%. It is assumed that there must be some reason for the unusual performance of path #2 compared to the other paths.

The root cause was further examined, and the beacon at room #309 was found to be faulty and did not reliably broadcast beacons. Therefore, some beacon samples for room #309 are lost, and the RSS features are changed, implying that the algorithm cannot detect the entry/exit events for room #309. The average hit rate of path #2 is low as it contains four moving events related to room #309, while other paths each contain two room #309 moving events. This result demonstrates another merit of our method, i.e., a faulty beacon in the system can be easily located if all subjects fail to register the moving event for the same room. We can simply check the corresponding beacon and determine whether it is the root cause of the problem.



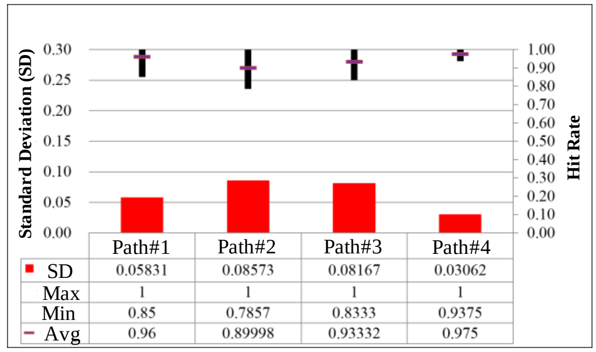
	Path#1	Path#2	Path#3	Path#4
SD	0.02449	0.11709	0.07858	0.02946
Max	0.15	0.3571	0.1667	0.0625
Min	0.1	0.0714	0	0
Avg	0.12	0.26782	0.06667	0.02083

Fig. 16 Miss rate in the first experiment.

D. Second Experiment After Fixing the Room #309 Beacon

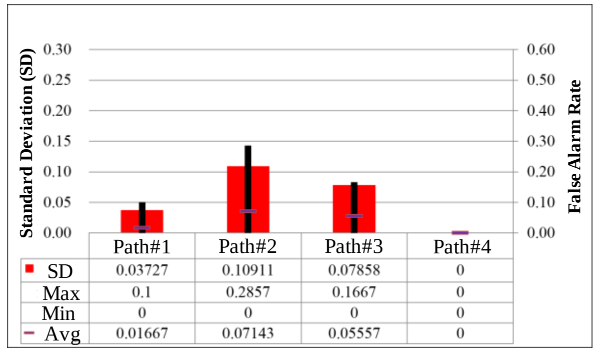
After the faulty beacon in room #309 was replaced with a working one, a new experiment was performed under the same configuration. Fig. 17 shows the hit rate of the second experiment. The hit rate of path #2 increases from 73.2% to 89.9%, and the SD decreases from 11.7% to 8.5% compared to the data shown in Fig. 14. The average hit rate of the four moving paths is 94.2%. The highest hit rate is 100% for all four paths, and the lowest SD decreases to 3%. The results demonstrated that our proposed method could provide adequate performance for indoor tracking and navigation with an extremely cost-effective infrastructure support as each room merely requires a beacon.

Fig. 18 shows the false alarm rate of the experiment: The algorithm generates a moving event, but the event is incorrect and does not exist in the ground truth. In the results, the lowest false alarm rate is 0%, and the highest rate is 28%. As shown in the figure, the average false alarm rates for all four paths are in the range of 0–7.1%, which is reasonably low and acceptable for this type of application. Fig. 19 shows the miss rate of the four paths. The average miss rate is 2.5–10%, and the SD is 3–8.5%. In all four paths, the minimal miss rate is 0%, and the maximum miss rate is 21.4%. The result indicated that, with the proposed method, the miss rate for detecting moving events is acceptable, and the generated moving path is sufficient for tracking or navigation applications. Even though some moving events are missed, the subject still can be tracked by the remaining moving paths.



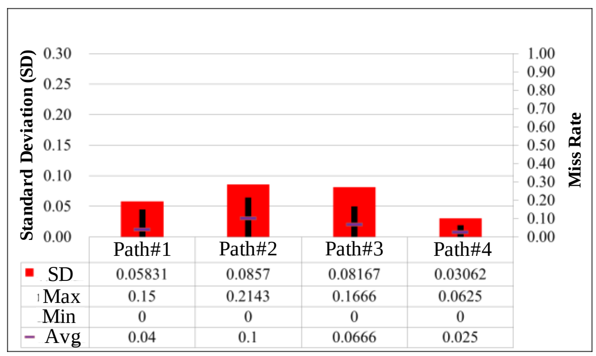
	Path#1	Path#2	Path#3	Path#4
SD	0.05831	0.08573	0.08167	0.03062
Max	1	1	1	1
Min	0.85	0.7857	0.8333	0.9375
Avg	0.96	0.89998	0.93332	0.975

Fig. 17 Hit rate after fixing the room #309 beacon.



	Path#1	Path#2	Path#3	Path#4
SD	0.03727	0.10911	0.07858	0
Max	0.1	0.2857	0.1667	0
Min	0	0	0	0
Avg	0.01667	0.07143	0.05557	0

Fig. 18 False alarm rate after fixing the room #309 beacon.



	Path#1	Path#2	Path#3	Path#4
SD	0.05831	0.0857	0.08167	0.03062
Max	0.15	0.2143	0.1666	0.0625
Min	0	0	0	0
Avg	0.04	0.1	0.0666	0.025

Fig. 19 Miss rate after fixing the room #309 beacon.

V. Discussion and Conclusions

In this paper, the design and performance evaluation of a smartphone-based indoor tracking method are described. Experiments revealed that the proposed method exhibits an average hit rate, false alarm rate, and miss rate of 94.2%, 3.6%, and 5.8%, respectively. The results support the idea that the proposed method is useful and provides satisfactory performance for indoor navigation and tracking applications while considering practical issues, including the costs of building and maintaining infrastructure and hardware heterogeneous problems, among others. The idea of using RSS temporal variations to track a subject's indoor movement is novel. If higher accuracy is needed, additional beacons can be added on the path to allow devices to collect more RSS samples from different beacons to help in determine the user's movement with higher confidence.

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References

[1] Q. Ma, X. Li, G. Li, B. Ning, M. Bai, and X. Wang, "MRLIHT: Mobile RFID-Based Localization for Indoor Human Tracking,"in Sensors, vol. 20, no. 6, p. 1711, Mar. 2020.

[2] Z. Zhang, S. He, Y. Shu and Z. Shi, "A Self-Evolving WiFi-based Indoor Navigation System Using Smartphones," in IEEE Transactions on Mobile Computing, May. 2019.

[3] Z. Yin and C. Wu and Z. Yang and Y. Liu, "Peer-to-Peer indoor navigation using smartphones," IEEE J. Selec. Areas Commun., vol. 35, no. 5, pp. 1141-1153, May 2017.

[4] W. Xue, W. Qiu, X. Hua and K. Yu, "Improved Wi-Fi RSSI Measurement for Indoor Localization," in IEEE Sensors Journal, vol. 17, no. 7, pp. 2224-2230, 1 April1, 2017,

[5] J. Rezazadeh, R. Subramanian, K. Sandrasegaran, X. Kong, M. Moradi and F. Khodamoradi, "Novel iBeacon Placement for Indoor Positioning in IoT," in IEEE Sensors Journal, vol. 18, no. 24, pp. 10240-10247, 15 Dec.15, 2018.

[6] C. Ke, M. Wu, Y. Chan, and K. Lu, "Developing a BLE Beacon-Based Location System Using Location Fingerprint Positioning for Smart Home Power Management," Energies, vol. 11, no. 12, p. 3464, Dec. 2018.

[7] R. Faragher and R. Harle, "Location fingerprinting with Bluetooth low energy beacons," IEEE J. Sel. Areas Commun., vol. 33, no. 11, pp. 2418–2428, Nov. 2015.

[8] J. Zuo, S. Liu, H. Xia and Y. Qiao, "Multi-Phase Fingerprint Map Based on Interpolation for Indoor Localization Using iBeacons," in IEEE Sensors Journal, vol. 18, no. 8, pp. 3351-3359, 15 April15, 2018.

[9] M. Chen, K. Liu, J. Ma and C. Liu, "Spatio-Temporal Fingerprint Localization for Shipboard Wireless Sensor Networks," in IEEE Sensors Journal, vol. 18, no. 24, pp. 10125-10133, 15 Dec.15, 2018.

[10] L. Cong, J. Tian and H. Qin, "A Practical Floor Localization Algorithm Based on Multi Feature Motion Mode Recognition Utilizing FM Radio signals and Inertial Sensors," in IEEE Sensors J, to appear*ournal*.

[11] G. Wang, X. Wang, J. Nie and L. Lin, "Magnetic-Based Indoor Localization Using Smartphone via a Fusion Algorithm," in IEEE Sensors Journal, vol. 19, no. 15, pp. 6477-6485, 1 Aug.1, 2019.

[12] J. Luo, L. Fan and H. Li, "Indoor Positioning Systems Based on Visible Light Communication: State of the Art," in IEEE Communications Surveys & Tutorials, vol. 19, no. 4, pp. 2871-2893, Fourthquarter 2017.

[13] Cheok, A.D.; Li Yue, "A Novel Light-Sensor-Based Information Transmission System for Indoor Positioning and Navigation," in Instrumentation and Measurement, IEEE Transactions on , vol.60, no.1, pp.290-299, Jan. 2011

[14] M. O. Khyam, M. Noor-A-Rahim, X. Li, C. Ritz, Y. L. Guan and S. S. Ge, "Design of Chirp Waveforms for Multiple-Access Ultrasonic Indoor Positioning," in IEEE Sensors Journal, vol. 18, no. 15, pp. 6375-6390, 1 Aug.1, 2018.

[15] Y. Sun, W. Meng, C. Li and X. Wu, "Panoramic Camera-Based Human Localization Using Automatically Generated Training Data," in IEEE Access, vol. 8, pp. 48836-48845, 2020.

[16] W. Liu, Z. Li, S. Sun, R. Malekian, Z. Ma and W. Li, "Improving Positioning Accuracy of the Mobile Laser Scanning in GPS-Denied Environments: An Experimental Case Study," in IEEE Sensors Journal, vol. 19, no. 22, pp. 10753-10763, 15 Nov.15, 2019.

[17] K. F. Davies, I. G. Jones and J. L. Shapiro, "A Bayesian Approach to Dealing with Device Heterogeneity in an Indoor Positioning System," 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Nantes, 2018, pp. 1-8.

[18] S. H. Fang and C. H. Wang, "A Novel Fused Positioning Feature for Handling Heterogeneous Hardware Problem," in IEEE Transactions on Communications, vol. 63, no. 7, pp. 2713-2723, July 2015.

[19] Tzu-Ting Lin, Chun-Ju Lin, Chia-Min Su, Yi-Chun Lin, Huang-Chen Lee, Exploiting Temporal Variation of Received Radio Signal Strength for Indoor Human Tracking, The 15th International Conference on Information Processing in Sensor Networks (IPSN '16), Poster Session, Vienna, Austria, April 2016.

[20] Maps.google.com. 2020. Indoor – Google Maps. [online] Available at: <http://maps.google.com/help/maps/indoormaps/faqs.html> [Accessed 7 April 2020].

[21] Carey, N. (2005) Establishing Pedestrian Walking Speeds. Project Report, Portland State University, ITE Student Chapter.

[22] M. Bshara, U. Orguner, F. Gustafsson, and L. Van Biesen, "Fingerprinting localization in wireless networks based on received-signal-strength measurements: A case study on WiMAX networks," IEEE Trans. Veh. Technol., vol. 59, no. 1, pp. 283–294, Jan. 2010.

[23] "The Hitchhikers Guide to iBeacon Hardware: A Comprehensive Report by Aislelabs (2015)," *Aislelabs*. [Online]. Available: https://www.aislelabs.com/reports/beacon-guide/. [Accessed: 17-May-2020].