Poster Abstract: Using Low-Cost, Non-Sensor-Equipped BLE Beacons to Track People's Movements

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ABSTRACT

This study presents a room-level people tracking system capable of determining people's movements while carrying a non-sensor-equipped BLE (Bluetooth Low Energy) beacon. The BLE beacon broadcasts BLE advertisement while people are in motion. A beacon receiver (BR) was installed in a room near the doorframe to **determine people's movements (i.e., entering, departing, or passing by the room)**, based on the variations in received signal strength (RSS) over time. This system is aimed at providing tracking information for people in school buildings, hospitals, and nursing homes. Knowing in which room or area people are has many useful applications, and the system is low-cost and easy to install and maintain.

CCS CONCEPTS

• **Information systems applications → Location based services**

KEYWORDS

Indoor tracking, low cost, non-sensor, BLE

ACM Reference format:

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1 PRELIMINARY DESIGN AND RESULTS

Fig. 1 shows the system architecture and working scenario. The beacon receiver (BR) is an embedded system with a BLE interface installed near the doorframe in a room. The BR's function is to collect BLE advertisements from the BLE beacons people carry.

By receiving a series of BLE advertisements from a BLE beacon (corresponding to the people being tracked), the BR can distinguish three types of people's movements: passing, entering (in), and departing (out) the room. It is noted that the BLE beacon we used in this system is sensor-less; no other information, such as acceleration or direction, is provided and sent via the BLE advertisement; this reduces the BLE beacons' power-consumption and hardware costs.

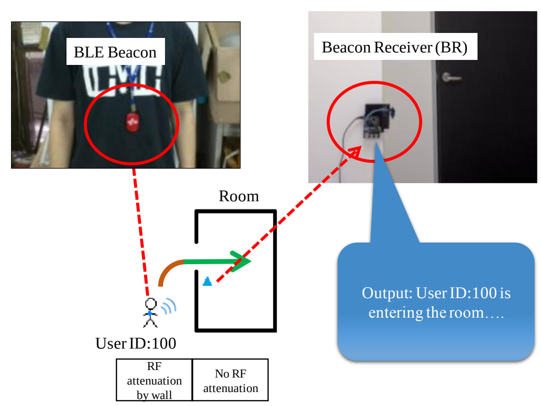

Fig. 1 System Architecture and Working Scenario

The BR collected advertisements from the BLE beacons and used them to determine corresponding people's movements. The major idea behind this system is that a room's walls cause RF attenuation and reduce the signal strength level of BLE advertisements. As Fig. 1 shows, the BLE beacon continued to broadcast advertisements while the user was moving to enter the room. The BR receives a series of advertisements, and the RSS changes over time, due to a portion of the RF signal of the advertisement being attenuated by the room's walls (indicated as the brown part of the arrow in Fig. 1, which, from the BLE beacon to the BR, is not in line-of-sight) and the remaining portions were not (indicated by the green part of the arrow in Fig. 1, which shows the BLE beacon and BR are in line-of-sight). This results in RSS patterns that are different when people move to enter, depart, or pass by the room. The BS uses the different RSS patterns to recognize people's different movements.

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When a person moves, the BR receives RSS changes over time. In the installation stage, the BR must pre-learn the ***RSS change curves*** and create the ***RSS models*** for each moving event. After that, when a person carries a broadcasting BLE beacon and walks according to these scenarios, the BR receives the RSS curve and matches it with the pre-learned RSS models to recognize the person's movements. We used Dynamic Time Wrapping (DTW) [1] to compare the similarity of RSS change curves to the pre-learned RSS models. Whenever the BR receives a RSS change curve, it compares it with the pre-learned RSS models of the three moving event, as shown in Fig. 2. If the ***warping distance*** is less than a predefined DTW threshold ***k***, we consider the RSS change curve to be similar to the corresponding moving event, and the BS outputs the detected results. The BS may transfer the results back to a central server via WiFi or LoRa wireless protocol to report the moving events.

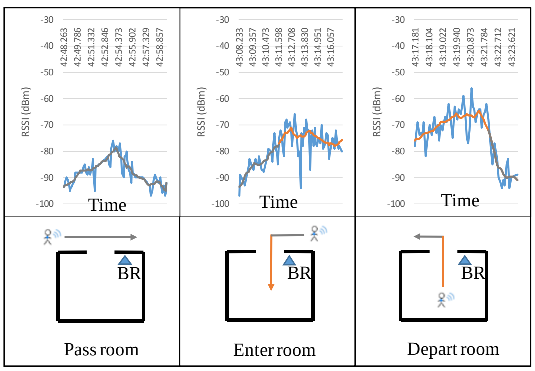


Fig. 2 RSS change curves in different moving events

We designed a proof-of-concept experiment to evaluate the system. Three BRs were installed in three rooms, nos. 309, 312 and 315, as shown in Fig. 3. Ten subjects (five males and five females) participated in the experiment. The subjects wore a badge-style BLE beacon (as shown in Fig. 1) and were asked to move along the path shown in Fig. 3. The subjects began the experiment at the starting point and moved to pass by rooms 315, 312, and 309, then moved back to pass by 312 and 315, and returned to the starting point. Then, the subjects continued moving to enter 315, depart 315, and enter 312, depart 312 and enter 309, depart 309, and move to the end point. Each subject moved along this path three times, and 30 data paths were collected. The results were used evaluate the performance of this system to show whether the BSs detected the correct events.

Fig. 4 shows how the DTW threshold *k* affects the correct detecting rate of the BS. In the experiment, **ACC** refers to the percentage accuracy that the BS can correctly detect regarding people's movements. **TPR** is the true positive rate, and **FPR** is the false positive rate of detecting the moving events. We can see that greater *k* will increase ACC and TPR, but also cause a higher FPR. According to the results, we set the DTW threshold *k* to 16, to strike a balance between ACC, TPR, and FPR.

Fig. 5 shows how the number of pre-learned ***RSS models*** for each type of moving event (entering, departing, or passing by the room) will affect the hit rate of the system. The greater the number of RSS models pre-learned in the installation stage, the higher the probability that an RSS change curve can find a higher similarity RSS model. This figure shows that Set 1 (only one pre-learned RSS model for each BS's moving event) has the lowest ACC and TPR. Sets 2 and 3 show almost the same rate in all factors, indicating that pre-learning two RSS models for each moving event is adequate. Therefore, in the latter experiment, the BS pre-learned two RSS for each type of moving event, to ensure system performance. Nevertheless, in all cases, the accuracy of detecting movement was high. This demonstrates that the proposed idea is practical.

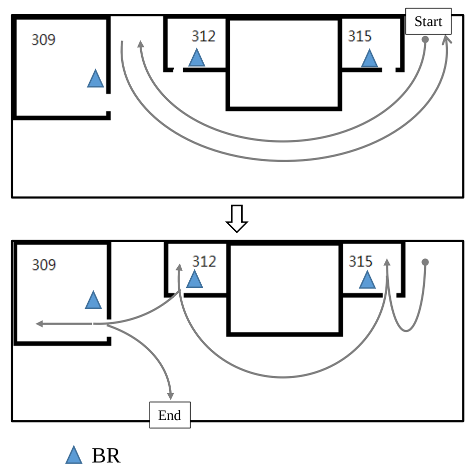
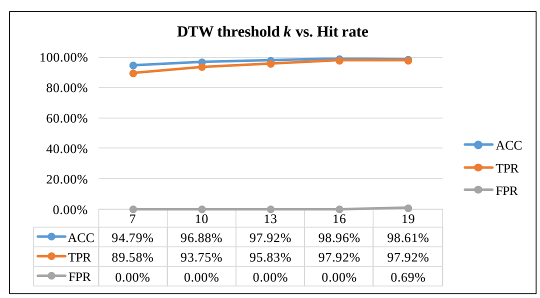
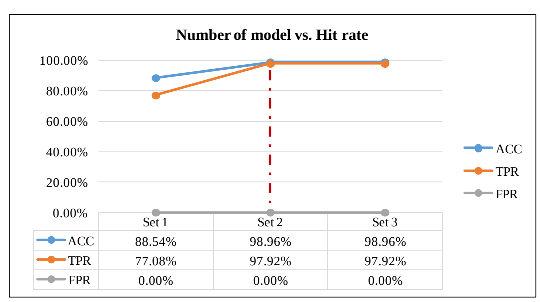


Fig. 3 A proof-of-concept experiment.



	7	10	13	16	19
ACC	94.79%	96.88%	97.92%	98.96%	98.61%
TPR	89.58%	93.75%	95.83%	97.92%	97.92%
FPR	0.00%	0.00%	0.00%	0.00%	0.69%

Fig. 4 DTW threshold *k* vs. Hit rate



	Set 1	Set 2	Set 3
ACC	88.54%	98.96%	98.96%
TPR	77.08%	97.92%	97.92%
FPR	0.00%	0.00%	0.00%

Fig. 5 Number of models vs. Hit rate

REFERENCES

[1] Donald J. Berndt and James Clifford. 1994. Using dynamic time warping to find patterns in time series. In *Proceedings of the 3rd International Conference on Knowledge Discovery and Data Mining* (AAAIWS'94). AAAI Press 359-370.