Occupant Tracking in Smart Facilities: An Experimental Study

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***Abstract*—The addition of occupant tracking -using location-based services (LBSs)- as standard functionality in next generation facilities can provide advanced personalized accommodations for the users and also assist in optimizing energy consumption, automation and safety operations. In this work, we present and experimentally evaluate a Bluetooth-based system for location-aware facilities. Our model follows a moving-transmitter fixed-scanner approach that exploits an edge-focused Internet of Things (IoT) architecture and results in a low-cost, scalable solution with centralized coordination. The focus is on presenting the benefits of such approach and quantify its performance and accuracy in tracking facility users. Specifically, our deployment's performance was experimentally measured and yielded up to 94% average accuracy in detecting user occupancy for decision intervals of 25 seconds.**

I. INTRODUCTION

Living essentially in the heart of the Internet of Things (IoT) revolution, this swarm of continuously interconnected and sensor-packed devices open a vast number of opportunities in equipping existing infrastructures. IoT has enabled applications that transform facilities to intelligent spaces able to critically affect and improve productivity and life quality of the occupants. Reducing energy costs, detecting and building knowledge based on human patterns as well as improving the human-building interaction are only some cases in point.

In this context, indoor-focused location-based services (LBSs) are becoming more and more important as a key feature for such next generation smart facilities. This type of services that provide the ability to efficiently track occupants in real-time are realized either by attempting to estimate the users 2D coordinates, which is referred to as micro-location [1], or by attempting to assign the user in the locality of certain points of interest (PoI), known as proximity sensing [2].

To facilitate these LBSs, a number of technologies and approaches has been proposed over the years. These implementations are in their majority RF-based and include the use of WiFi [3], Radio Frequency Identification Device (RFID) systems [4] and recently Bluetooth Low Energy (BLE) implementations [2], [5], [6]. However, (a) the unpredictability of signal propagation due to the variable physical indoor environment, (b) the fact that these technologies were not primarily intended for PBS, and (c) the often complicated data-collection and decision-taking system behind them, make the accurate and practical indoor localization problem still an ongoing research topic [1].

In this paper, we present an edge-to-cloud system able to equip future location-aware facilities where occupant tracking is desirable. Our solution is utilizing BLE technology and follows a moving-transmitter fixed-scanner approach inverting the usual logic used in similar indoor localization applications [2], [5], [7], [6]. We describe the deployment in detail and experimentally evaluate its accuracy in detecting user occupancy as well as user mobility inside the facility. The user-centric data that our system produces, combined with signal processing and machine learning methods, can be used for a variety of functions associated with smart buildings. Namely, such operations range from calculating visitor behavior patterns to ensuring the facility's energy efficiency or safety.

This work is organized as follows: In Section II, we discuss existing work while in Section III, we describe our proposed system's architecture and operation. We present the experimental setup and the associated results in Section IV. Finally, we conclude this paper and discuss future work in Section V.

II. BACKGROUND WORK

A. BLE Enabling Smart Spaces

Bluetooth Low Energy is a communication protocol developed for short-range wireless communications with energy efficiency being the main focus. The protocol utilizes two different types of messages that are distinguished by using different broadcast channels. *Data* messages require a connection between master and slave for transmission, but *advertisement* messages do not. The latter are broadcast messages used primarily for discovering devices. However, with simple modifications these advertisement messages can be used to carry a payload able to communicate essential information such as sensor data or other notifications. BLE beacons utilize this messaging feature to send short messages at flexible refresh rates. Such *advertisement* packets can be received by other BLE-enabled devices and can be utilized for localization purposes by exploiting signal strength measurements.

Since both BLE and WiFi operate on the same frequency bands they are often compared as IoT solutions for localization in smart buildings [7]. Clearly, the WiFi solution has the advantage of utilizing preexisting infrastructure and providing

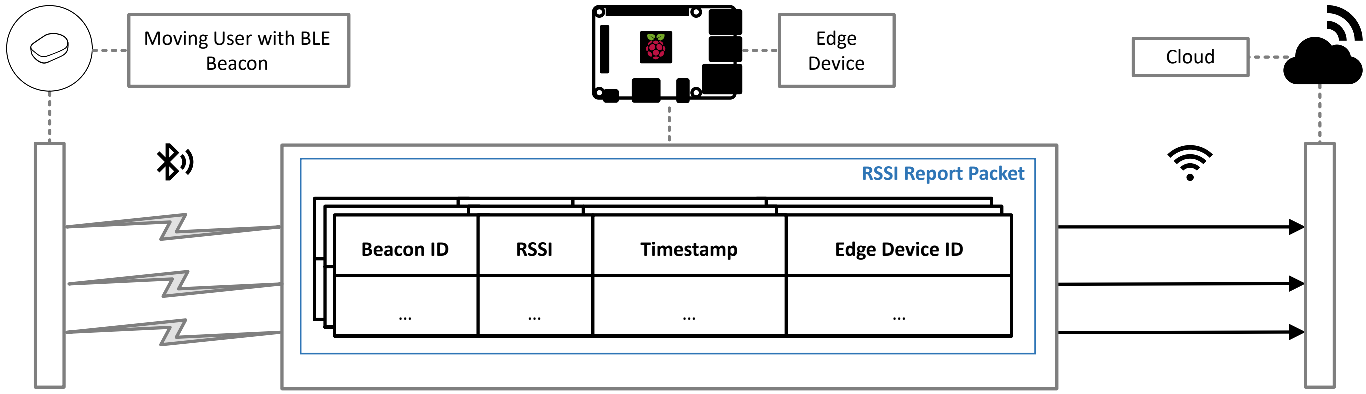

Fig. 1. Proposed system's architecture and operation

sufficient indoor space coverage. However, BLE equipment is extremely inexpensive. This fact along with the promise of low maintenance requirements, makes the extra infrastructure investment a negligible cost. Moreover, as WiFi was designed primarily for data transmission and not for localization purposes, it presents insensitivity in protocol parametric changes. For instance, the ability of BLE beacons to easily adjust their transmission rate is an important advantage over WiFi-based beacons. Finally, the low overhead of the BLE beacon packets allow deployment at scale and demand minimal power requirements, leading to small-factor, practical devices.

Taking into account features offered by BLE technology, the value of full scale deployment in IoT-equipped smart buildings becomes clear. Bluetooth beaconing can broadcast occupant-centric data inside a facility and provide insight on how visitors are using the smart spaces. These data can be used to optimize building operations, correlate occupant data to building systems, and tackle energy consumption issues.

B. Localization with BLE

Several existing works utilize BLE-beacons for indoor localization purposes. Zhao et. al. [7] use static beacon anchors to utilize trilateration techniques and propose propagation models for location estimation in various conditions including indoor/outdoor environments with line-of-sight (LoS) or non-line-of-sight (NLoS) situations. Another method is location fingerprinting, which is a technique that uses reference locations to construct an RSSI measurements map during a training phase before actual location tracking is carried out. During actual location tracking, a signal strength comparison is performed between incoming RSSI values and the previously assembled RSSI measurement map. Faragher et. al. [5] provides a study on a fingerprinting system based on static BLE beacons.

Apart from that, other works use techniques in order to improve beacon-based localization. Anagnostopoulos et. al. [8] use a beacon position weighted average method combined with a "nearest-beacon" approach while Chandel et. al. [9] propose an end-to-end system that utilizes floor maps, particle filter based IMU tracking, and static BLE-beacons. In [2], Zafari et. al. propose, among others, a Kalman-based algorithm that reduces the BLE RSSI values' fluctuation aiming to improve proximity detection. Regarding inertia sensors and BLE collaboration, Chen et. al. [10] use an IMU-based Pedestrian Dead Reckoning (PDR) approach where RSSI values from fixed BLE-beacons are used to calibrate the system frequently.

As seen above, the dominant approach in most relevant works is using BLE-beacons as static transmitters that mark certain areas. However, the inverse strategy is also encountered for case-specific applications. Komai et. al. [11] use a movable-beacon fixed-scanner approach for an indoor localization system that assists caretakers to track people in a day care facility. Narzt et. al. [12] use a similar moving beacon approach to implement a Be-In/Be-Out system for automatic ticket checking in public transportation.

In the same fashion, in [13] we describe the large-scale deployment of the moving-beacon system we will describe in this work. We realized a three-floor installation that is followed by an IRB-approved large scale trial with real participants and in an everyday-use environment. Over 30 fixed-scanners were deployed, continuously collecting real data from 46 participants during an experiment that lasted for over one month. This real-subject trial provides proof of the design's maturity to be practically realized as an IoT localization solution. Therefore the results of the present work are of significance as they provide confidence bounds of our system's performance and give insight for further improvements in future versions.

III. Architecture & Operation

In this work, we propose the use of BLE beacons not as static location indicators but rather as occupant indicators provided beforehand to visitors and continuously broadcasting advertisement packets on the move. In this scenario, the facility's sensing infrastructure consists of a set of edge devices that continuously scan their covering radius for a user's advertisement broadcasts. At the next level of this IoT-inspired architecture, the edge devices are forwarding information packets through the facilitys networking infrastructure to a remote server or a federated Cloud level that allows centralized, but scalable coordination. Figure 1 depicts our system in detail.

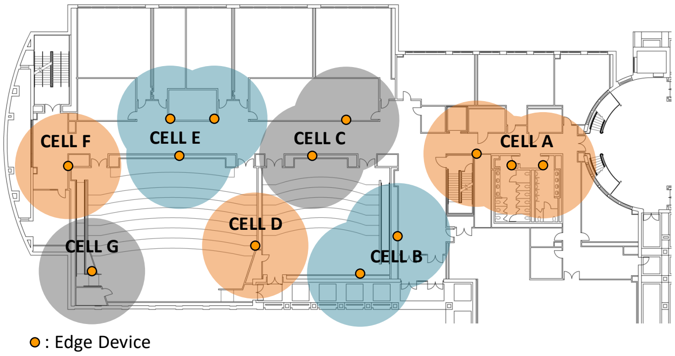

Fig. 2. Edge device and cell locations

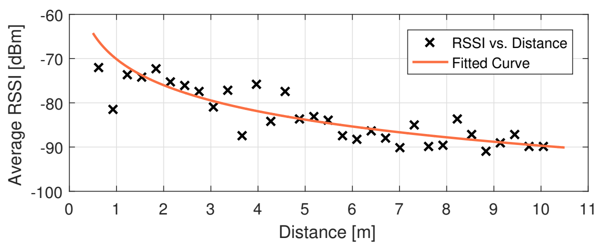

Fig. 3. Curve fitting for RSSI values at distances from 0 to 10 meters

As far as the realization of our system is concerned, we used Gimbal Series 10 iBeacons [14] that broadcast advertisement packets every second with 0dBM transmission power and in an omnidirectional setting. On the receiving end of the BLE beaconing, we utilized Raspberry Pi devices as edge nodes that continuously collect the broadcasted packets. Following that, they act as MQTT [15] clients forwarding RSSI Report packets in the form of Fig. 1 to a remote server. These scanning devices are essentially the backbone of our system since our deployment utilizes a Geofencing approach to define occupancy in the smart space [16]. Each edge node is considered a Point of Interest (PoI) and defines a virtual circular barrier of the same radius around it, where our system tracks incoming and outgoing users (Fig. 2).

At the remote server side, an MQTT broker is hosted to collect the edge structure's messages along with a monitoring application and storage for the user-centric information. This continuous string of a user's transmitted packets provide information regarding the reception date/time, RSSI, and identity of the scanner in his vicinity. Therefore, a proximity estimation method can be utilized to facilitate occupant tracking inside the smart facility.

Since after a transmission burst, multiple edge devices will receive the signals, a comparing method should be used to select the node where the user will be classified to. We will be using the "naive" classification approach of the stronger RSSI value where the system periodically assigns the user to the node that received the message with the greater RSSI. Given that, we should also consider the optimal refresh period of the central localization decision for every user. This second criterion is experimentally investigated in the next section

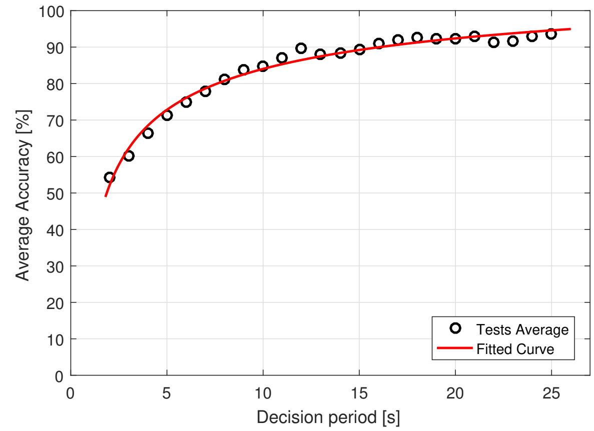

Fig. 4. Accuracy of near-edge cell occupancy - Tests average

along with the overall performance of our deployment.

IV. Experimental Setup & Results

In order to test our system, we carried out a large scale installation of Raspberry Pi-based edge devices (Fig. 2) followed by a series of performance experiments. Their positions were dictated by the presence of power outlets. For each node we chose a virtual ideal covering radius of seven meters. The radius was chosen to ensure area overlapping avoidance and by taking into account the relationship between the RSSI values and the user-scanner distances as shown in Fig. 3.

For this propagation model extraction we collected and averaged 30 RSSI samples at a number of distances starting from 0 meters up to 10 meters while the edge device was mounted on a wall at the height of 1.6 meters. The fitted curve is based on the log-distance path loss model:

$$RSSI = -10\,\gamma\,\log_{10}(\frac{d}{d_0}) + C \quad (1)$$

where γ represents the path loss exponent of the propagation channel, d is the user-scanner distance, d_0 is the reference distance and C represents the average value of RSSI at d_0.

Finally, closely installed edge devices were clustered into unified cells forming the final test topology shown in Fig. 2.

A. Cell Occupancy Experiments

To determine the applicability of our method in locations near the cell limit we performed a series of static experiments. A user equipped with an active BLE beacon was positioned at a seven meter distance from an edge device, as he was periodically assigned to the cell that receives the advertisement message with the strongest RSSI. The cell classification accuracy is defined as:

$$Accuracy\ (\%) = \frac{Correct\ Cell\ Assignments}{Total\ Cell\ Assignments} \times 100 \quad (2)$$

The number of assignments is variable and depends on the decision period which is a value also investigated in these tests with Fig. 4 showing the average accuracy while the decision rate changes. Since our beacon transition rate is 1 Hz we are

TABLE I
CELL OCCUPANCY EXPERIMENTS

	Accuracy [%]				
Decision Period [sec]	**Test 1**	**Test 2**	**Test 3**	**Test 4**	**Tests Average**
2	53.60	62.75	49.46	51.42	54.31
6	77.03	76.47	71.15	75.16	74.95
10	84.44	85.37	78.72	90.22	84.69
14	84.38	90.00	86.57	92.42	88.34
18	96.00	95.65	88.46	90.20	92.58
22	95.24	89.47	90.70	90.48	91.47
25	100.00	88.24	92.11	94.59	93.74

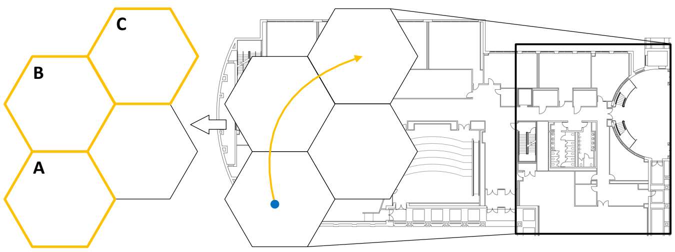

Fig. 5. User cell transition: $A \rightarrow B \rightarrow C \equiv$ "ABC"

considering decision period duration from 2 to 25 seconds. Table I shows in more detail the test results. As expected the accuracy is increasing along with the increase of the decision period. This is related with the BLE RSSI fluctuation observed in beacon-related measurements and is confronted either by increasing sampling periods (like this work) or with filtering efforts as reported in [2].

B. Cell Transition Experiments

By assigning the occupant to a specific and unique cell for each refresh time slot, our system is able to track movements inside the facility as depicted in Fig. 5. In order to test this tracking ability we performed a series of focused experiments where users moved on a walking pace, from a point A to a point B, crossing several cells in the process.

In order to evaluate the accuracy of the computed paths, and compare them with the actual paths followed, we are utilizing a custom performance metric. Cell transitions, as denoted in the description of Fig. 5, are expressed as path strings where each new character indicates a cell change. To extract the differences between the actual and estimated paths we compute the Levenshtein Distance [17] also known as Minimum Edit Distance [18] between the two strings. A zero Levenshtein Distance Error value signifies total match of the two paths.

Fig. 6 shows the average cell transition error and the standard deviation as computed from seven unique experiments. We use the central system's decision refresh rate as a tuning parameter to investigate the optimal value that accommodates the transition detection functionality. As expected the system's accuracy is increasing alongside the decision period as more RSSI samples are considered in each period. However, extended decision intervals (>18 seconds) eventually fail to detect the user movements and therefore fast cell transitions,

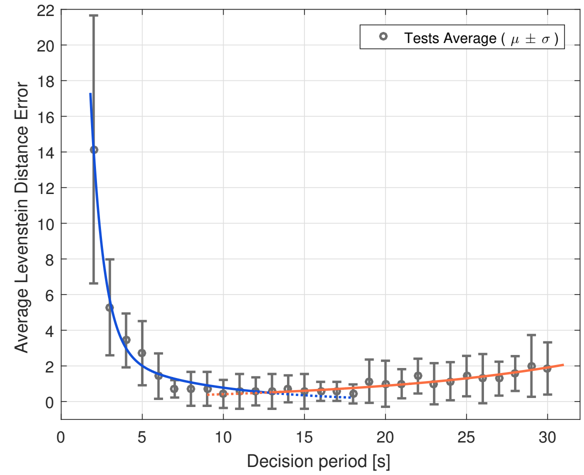

Fig. 6. Average cell transition detection error - Tests average

causing an increased observed error. These two trends are shown in Fig. 6 where using the experiment results we computed two exponential fitted curves to extract the functions of the expected error versus the decision refresh period. Evidently, depending on the specific facility needs (visitor mobility frequency), the decision period can be optimized to provide the necessary per use-case accuracy.

V. CONCLUSION & FUTURE WORK

In this paper, we described a top to bottom location-aware infrastructure able to provide location-based services through geofencing and proximity sensing. Our realization of this system was based on the BLE protocol following an edge-device based architecture where users are equipped with active beacons to denote their location in the smart space. The cloud-inspired central system divides the facility into non-overlapping cells and uses them to identify user occupancy and mobility.

The deployment's performance was experimentally evaluated and yielded up to 94% average accuracy in detecting user occupancy for decision intervals of 25 seconds. Regarding occupant mobility tracking, experiments yielded also accurate results that depend on the system's decision period as shown in Fig. 6. In general, the results prove our system to be a reliable solution for future smart facilities. Finally, this location-aware infrastructure model is highly scalable and will be able to accommodate occupants in high volumes.

As future steps, we consider working on improving the system's accuracy by utilizing edge-computing methods on the IoT nodes that equip our smart facility. An increased beacon transition rate in collaboration with RSSI smoothing methods [2] implemented on the edge (before forwarding measurements to the cloud) can further improve the accuracy and the same time reduce the localization latency that is very important for real-time applications.

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