Towards Optimization of Patients' Turnaround Time using Bluetooth Low Energy Based Solutions

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Abstract: Smart Healthcare can use the Internet of Things (IoT) to broaden the reach of digital healthcare by collecting patient data remotely using sensors. This can reduce Patient Turnaround Time (PTAT) and enable high-quality care to be provided. PTAT is the length of time from when a patient arrives at the hospital until they are allowed to return home. Malaysia's Ministry of Health claimed in 2016 that healthcare at government hospitals continues to encounter issues in providing high-quality care to patients, particularly in terms of the PTAT of patients who receive treatment versus those who are sent home without treatment. In this paper, we propose a Bluetooth Low Energy-based solution that optimizes PTAT using low calibrated transmission power, allowing hospitals to enable Real-time Patient Localization and Patient Movement Monitoring. The RSSI value is used to calculate the distance between a wearable device and the Access Points (AP) situated throughout the facility. When a patient passes an AP, data such as the wearable device name and RSSI value are taken and saved in a database, to determine the patient's location. A proof of concept was conducted using three AP points and 8 wearable devices to gauge distance measurement.

Keywords: BLE, Healthcare, RSSI, Optimization, Patients' Turnaround Time (PTAT).

Introduction

Overcrowding in hospitals, patients not receiving timely treatment, and people missing doctors' appointments are all common problems in the healthcare industry (Vize, 2017). Not only that, but patients must wait longer to be processed and seen by a doctor, which adds to their wait time. Patients may wander about the hospital property at this period, making it difficult for employees to locate them. Additionally, issues could arise if a doctor contacts a patient from a different department after finishing with another patient. As a result, a patient

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may wander aimlessly from one department to the next or be summoned by another doctor, and their whereabouts are ultimately unknown. This status quo does not just affect an individual but others as well. It makes the waiting duration for all patients (Patient Turnaround Time, PTAT) to be longer than usual and productivity to drop significantly.

Figure 1 shows an example of how the PTAT is calculated. Hospital optimization is therefore necessary to enhance better patient care by improving control of resource use and enhancing hospital productivity (Huang, Hwang & Lin, 2021).

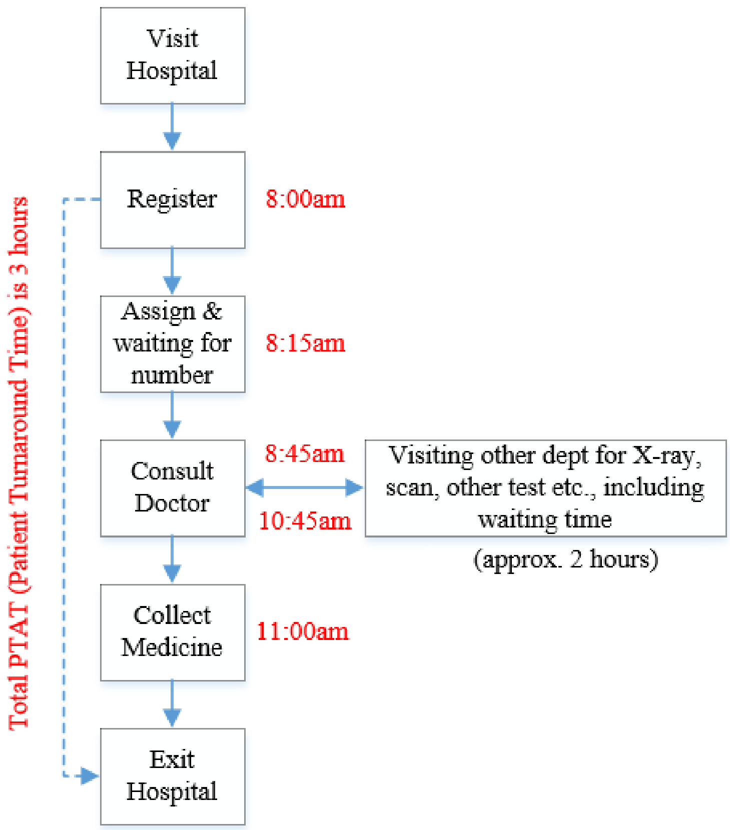

Figure 1. How PTAT is calculated

The risk of a patient missing an appointment exists even while they are in medical facilities because hospital employees cannot see or recognize the patient's position most of the time before the actual treatment. These problems culminate into dissatisfaction among patients, doctors and the public, as stated by Malaysia's Ministry of Health (Ministry of Health, 2016; National Institute for Health and Clinical Excellence, 2007). Thus, optimizing quality of care and better managing the resources at medical facilities are essential. Even so, not many studies or solutions have been able to combine localization and monitoring into a single complete solution for PTAT, as it is not an easy task to accomplish.

As the world progresses into an era of Smart Healthcare, it is crucial that a solution exists if developments are to commence in a fast manner (Zhu *et al.*, 2019). In general, an efficient and comprehensive Real Time Patient Location Tracking solution will mainly be based on two technologies: Bluetooth Low Energy (BLE) and Internet of Things (IoT) (Lin & Lin, 2018). BLE allows monitoring on its own (Mackey *et al.*, 2020), while IoT is used for data collection and analysis.

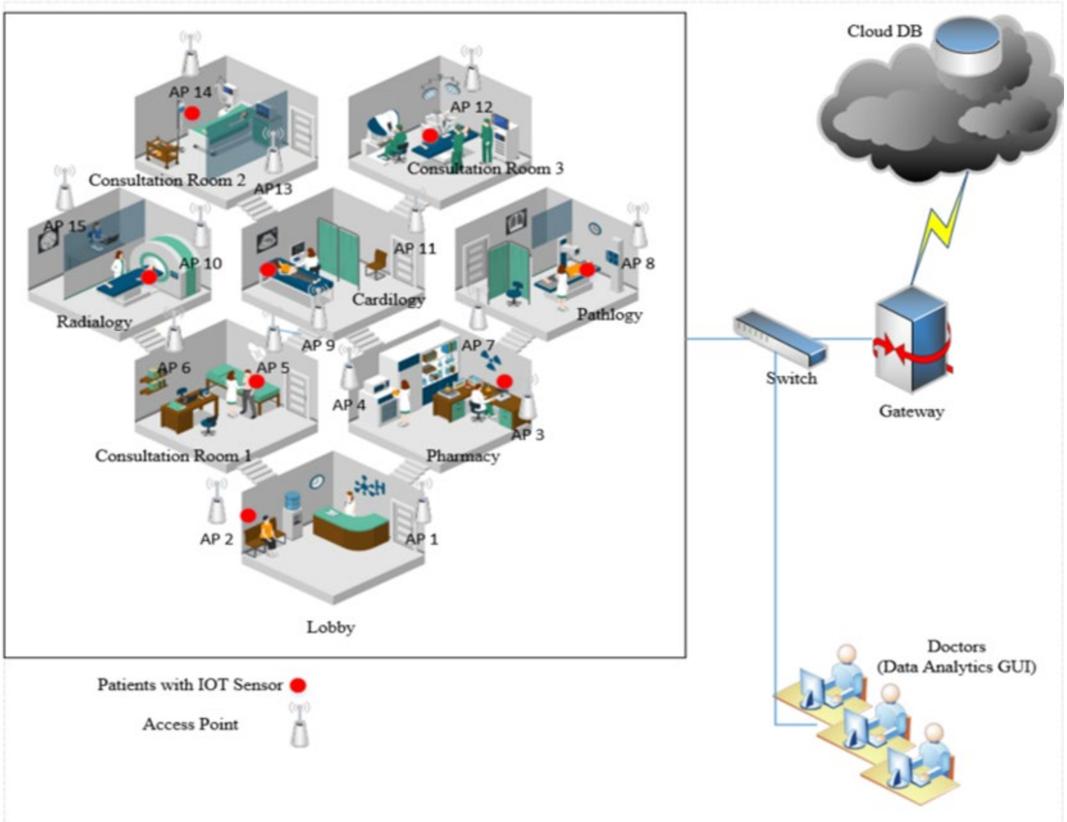

Figure 2. Real-Time Patient Location Tracking Solution architecture

In our solution, upon arrival at the hospital by a patient, a BLE-tagged bracelet will be issued in which each tag will include important patient information, such as ID, name, RSSI value and other details. When a patient travels around the hospital, readers called Access Points (APs) on the walls and ceilings of the hospital and its surrounding area obtain information about the location of the tags and send it to a cloud database for storage and analysis. Refer to Figure 2. for the architecture diagram.

To estimate the locations of patients, low calibrated transmission power (Tx) wearable devices are used and RSSI (Received Signal Strength Indicator) values are obtained, as shown in Figure 3. Patients receive RSSI signals via their hand-worn device, and a system server uses the APs and locations mapping table to map the estimated nearest beacons transmitted from the patient's side to the locations of the pertinent subareas. For the proof of concept, we tested with 3 APs and 8 wearable devices using the algorithm described in Figure 3.

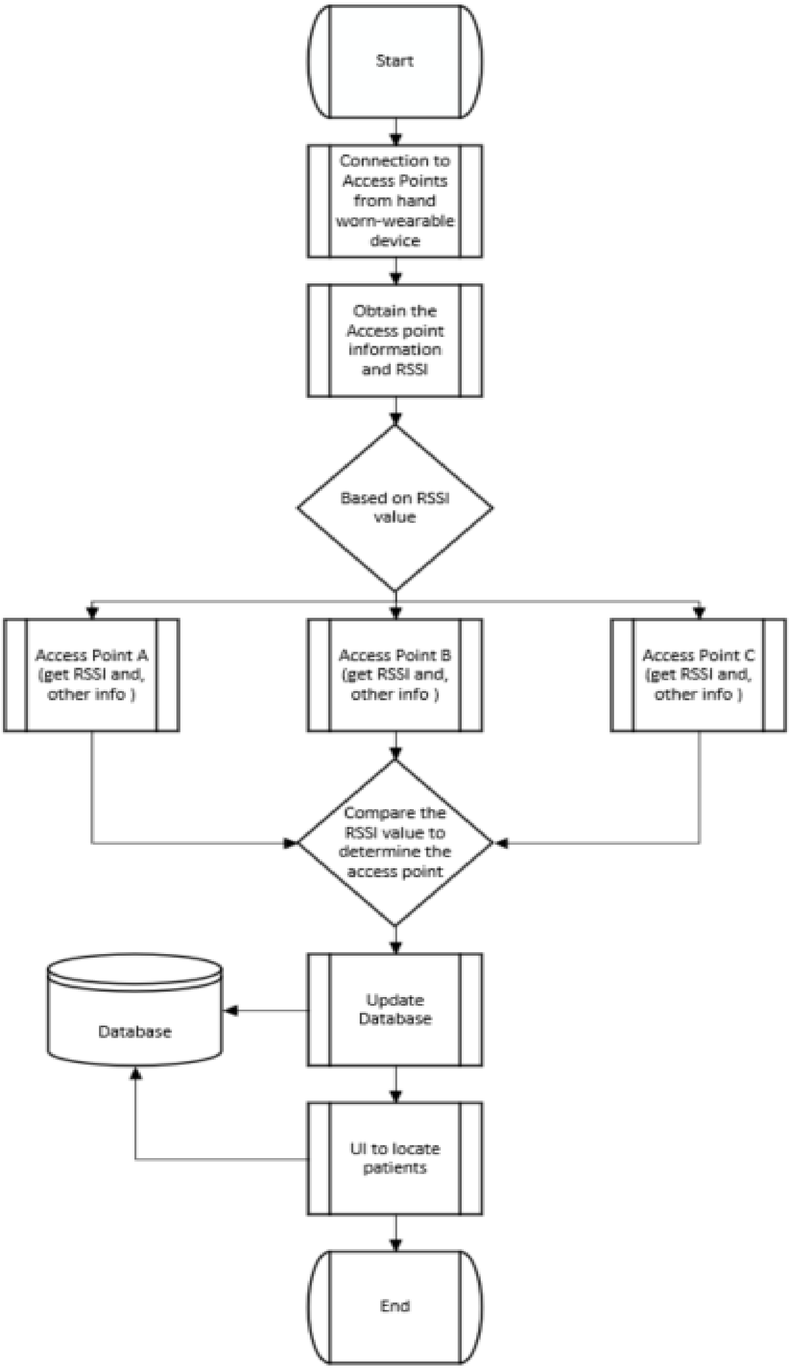

Figure 3. Flow chart of positioning and data capture algorithm

Related Work

The Received Signal Strength Indicator (RSSI) is the foundation of several localisation methods in Wireless Sensor Networks. Absolute location is not always possible, hence localization using RSSI is common compared with other technologies, such as Wi-Fi, infrared or ultrasonic-based solutions. We can determine the RSSI trends quite well based on the variation of radio signals. We will be able to tell if we are going closer to or farther away from an Access Point based on if the signal is getting stronger or weaker. Even better, if we are aware of the precise mapping between the RSSI and the position of the particular receiving device, we may be able to determine the distance with some degree of accuracy.

Numerous localization efforts are being carried out; governance, economy, administration, infrastructure, technology, and people are all part of the location and movement tracking techniques idea. This implies that they may have varying communication requirements. Wireless technologies, such as Wi-Fi, LiFi, BLE, ZigBee, RFID, LoRa, and LTE (Long Term Evolution) have emerged as answers to the communication requirements of localization techniques (García *et al.*, 2018) which link to the Smart Healthcare industry. Future smart healthcare systems, also known as the Internet of Medical Things (IoMT), will integrate a slew of wireless devices and apps that employ wireless communication technologies to share healthcare data.

Smart healthcare necessitates adequate bandwidth, dependable and secure communication linkages, energy-efficient operations, and support for Quality of Service (QoS). The incorporation of Internet of Things (IoT) technology into healthcare systems has the potential to greatly improve intelligence, flexibility, and interoperability. Currently, IoT communication protocols and technologies are appropriate for smart healthcare applications (Gardašević *et al.*, 2020). Furthermore, as the Internet of Things (IoT) evolves, the rate at which physical items are connected to the Internet is rising dramatically (Al-Fuqaha *et al.*, 2015). Low-power wireless technologies have received special attention as a major enabler for energy-efficient IoT-based healthcare systems particularly suitable for a Real Time Patient Location Tracking Solution.

Many wireless devices have been studied in order to minimize the expense and complexity of indoor position systems. A description of the common technologies (Glow labs, 2019) can be found in Table 1.

Table 1. Comparison of the Common Technologies for Optimization of Patient Turnaround Time Solution

Wireless Technology	Cost	Availability	Implementation Complexity	Interference	Accuracy
Wi-Fi	Moderate	High	Low	High	Moderate
Li-Fi	High	Low	High	High	Moderate
BLE	Low	High	Low	Moderate	High
Zigbee	High	Moderate	Low	Moderate	Low
RFID	Low	High	Low	Moderate	Low
LoRa	Moderate	Low	Moderate	Moderate	Low

RSSI is a measure that indicates how effectively the device can pick up a signal from a network or access point. It is a number that might help you figure out if you have adequate signal to establish a reliable wireless connection (Bensky, 2019). Note that an RSSI number is not the same as transmit power from a router or AP because it is derived from the client device's Wi-Fi card. Each received packet may have its received signal intensity (energy) assessed. The received signal strength indication is calculated by quantizing the observed signal energy. MAC, NWK, and APL layers have access to the RSSI and the time the packet was received (timestamp) for analysis (Farahani, 2008). RSSI is a relative index (Herres, 2021), whereas dBm is an absolute statistic that represents power levels in milliwatts. RSSI may be measured on a scale of 0 to 255, and each chipset manufacturer can select its own “RSSI Max” number, according to the IEEE 802.11 standard (a large volume of specifications for building Wi-Fi equipment). For example, Cisco employs a 0-100 scale, but Atheros uses a 0-60 scale. The manufacturer has complete control. However, the greater the RSSI score, the better the signal.

A better technology could be BLE, as lower in cost, higher in availability, and lower in implementation complexity, with moderate interference and high accuracy.

RSSI Values for Distance Estimation Definition

The first step in the experiment is to determine the average reference RSSI value, $RSSI_r$, at a distance of 1 m for Bluetooth applications (Maccari & Cagno, 2021). Apart from that, the maximum RSSI value at a distance of 5 m for the specified transmitted power must be observed. The results of the first stage of the experiment are shown in Table 2 based on the experimental BLE device, which used the nRF52832 chipset (Figure 4). The experiment was carried out with the nRF52832, a flexible Bluetooth 5.2 system-on-a-chip (SoC) with a maximum RSSI sensitivity of -96 RSSI value (Nordic Semiconductor, 2021).

Figure 4. nRF52832 chipset

Table 2. Results for RSSI Measurement for Three Different Distances using Two Devices under Line-Of-Sight Condition

Device Number, n	*Condition*	*Distance, m in meters*	*Average RSSI, $RSSI_{avg}$*
1	No obstacle – Line of sight	0	-34.01
2			-36.43
1		1	-50.01
2			-52.13
1		3	-67.12
2			68.15
1		5	-88.45
2			-89.14

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Table 2 shows that the average RSSI readings for both devices is -35 RSSI value at a distance of 0 m. A similar scenario was also discovered with the other two distances, but there is a tiny variance in value for the 1 m distance. However, a difference of merely -1 RSSI value is insufficiently large to suggest that the results acquired are unreliable. At a distance of 5 metres, both devices produced average maximum RSSI values of from -88 to -94 RSSI value, respectively, which will be utilized. A number greater than this indicates a user's distance is more than 5 m. The average of the RSSI values is obtained using the formula to determine the RSSI reference point:

$$For\ m = 1, \qquad RSSI_r = \frac{(RSSI_{avg1} + RSSI_{avg2})}{2}$$

RSSI drawback

In reality, there are several factors that might influence the RSSI (Figueiredo e Silva *et al.*, 2018), rendering it inaccurate for distance calculation. The two key elements that affect RSSI are discussed in this section, as well as how the technique overcomes some of these limitations.

When it comes to internal components, it is mostly the hardware and software that can have a big impact on the RSSI. The transmission power of a Bluetooth chipset can have an impact on RSSI. Not only that, but antenna architecture, orientations, and data transfer capacity can all have a significant impact on the signal strength (Zhao *et al.*, 2020).

When it comes to external elements, they are separated into two categories: physical obstacles and radio waves. Effects of radio waves include Wi-Fi, which may be set to operate on the same 2.4GHz channel as Bluetooth, allowing both signals to affect each other (Sibiński, 2021). Because the travelled distance is not great, using a calibrated low Tx method will make it less susceptible to interference from other radio waves. Additionally, angle of arrival (AOA) can significantly affect RSSI and cause variances, especially when the distance is vast. These physical barriers can cause the signal to weaken and vary, causing the calculation to be larger than the actual distance between two people (Labrique, 2020). This new strategy, on the other hand, causes the RSSI to be large in value, nearing the chipset's maximum sensitivity at the ideal distance of 5 m. Physical obstructions, such as people passing by or nearby walls, will merely raise the RSSI, making the chipset unable to identify it, resulting in less inaccuracy. Nonetheless, because the signal (Parker, 2017) travels a shorter distance and can only be received within a restricted range, the inaccuracy will be limited and smaller than in many other BLE-based solutions

Solution Approach – Proof of Concept

Point of Interest (PoI) information applications fall under the topic of proximity solutions (for example, departments in hospitals that provide the user with information about their location). This category also includes options for recovering lost or misplaced items, such as Bluetooth tags. Bluetooth tags send BLE broadcast frames on a regular basis in these implementations. The AP examines these frames for Bluetooth tag information, which it then sends to the location server through an access controller (AC). In PoI proximity applications, it is required to determine which PoIs are in close vicinity to the computed location.

Positioning systems comprise location-based services that use Bluetooth to determine a device's physical location, for real-time locating systems for people monitoring and indoor positioning systems for pathfinding solutions that assist people navigate through complex interior settings. Only by knowing the direction from which the received signal is coming, the estimated distance to that beacon, and the location of the beacon can the application establish the position of its host device.

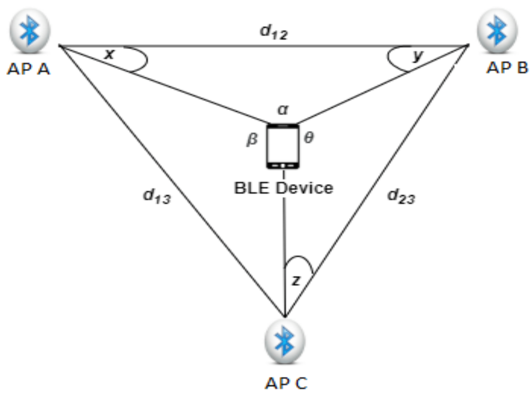

Figure 5. Triangulation-Based Location Estimation

The BLE standard is used to create Bluetooth beacon technology. A beacon sends out a unique ID. An application on a BLE device that receives that ID looks up the transmitting beacon in a database and then provides the user with information about its position. The strategy used to estimate the distance between the BLE device and the beacon are shown in Figure 5. Triangulation-based location estimation is a technique for calculating the position of a point that relies on a known distance between two or three reference points and the angles measured using the Bluetooth direction-finding feature between those reference points to that point. These angles can be the Angle of Arrival or the Angle of Departure. The triangulation technique uses angle measurements (Zhao *et al.*, 2020). Using this method, you may determine any point's location in two-dimensional (2-D) space, given three angles between it and three other reference points.

In 2-D space, however, estimating the position of every point requires a minimum of two angles. The distances between the Bluetooth beacons A–B, B–C, and A–C are denoted by d_{12}, d_{23} and d_{13}, respectively, in Figure 5. The known angle measurements between the BLE device and Bluetooth beacons, A, B, and C, are x, y, and z, respectively. The triangulation approach determines the BLE device's position from this known data.

Proposed architecture for Real-time Patient Localization and Patient Movement Monitoring

This section explains the proposed architecture to capture the data from the patient in order to determine the location the patient in hospital areas based on the RSSI value.

Experimentation setup for data collection

The experimental setup to simulate the deployment of a Real Time Patient Location Tracking Solution used an existing Wi-Fi network and a floor plan (in a private clinic). We set up environment parameters (AP name, model name, channel, bands, etc.), placed APs on the floor plan, adjusted the APs' location and parameters, viewed the planned results, and uploaded the data captured to a database. Figure 6 shows the APs on the floor plan in the clinic setup for experimentation, to get the RSSI values to identify the distance and determine the nearest access point to give patient location status.

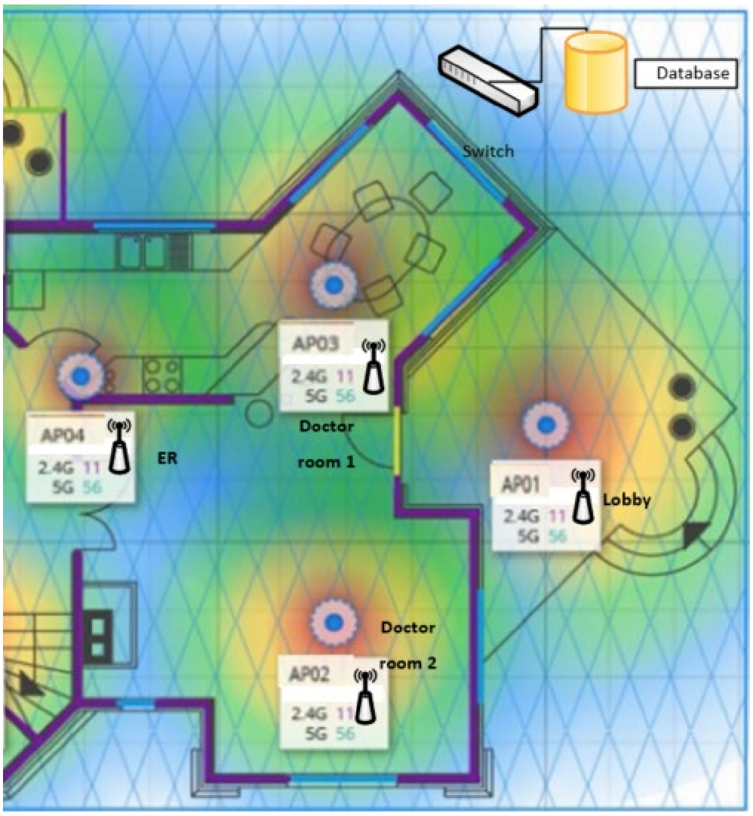

Figure 6. Experimental setup for data collection

Readings from five nRF52832 SoCs powered by a 5 V lithium-ion battery were used in this study. A proof of concept as used to determine whether the method performs as anticipated under ideal circumstances and to determine whether a distance estimate might be included. Two nRF52832s were used in the proof of concept to calculate RSSI readings at various distances for line of sight under perfect conditions. By employing APs to capture data packets from these client devices, the use of two BLE modules ensures that any deviations may be detected. The chipsets will send out advertising packets to the APs every 50 ms (this might vary depending on the scenario) and the AP will scan every 5 s. Following that, the data is entered into a database. The following pieces of data are included in the captured data: Medium Access Control Address, Patient Name, Device Name, RSSI value, Date and Time.

A maximum Tx of -4 RSSI value is more than capable of serving as the transmitter for testing the low-calibrated Tx technique for near location tracking. Tx is set at -8 RSSI value in this study, which is the optimal value because the RSSI reaches -96 RSSI value at a distance of 5 metres.

In the proof-of-concept section, a sample size of -100 to -200 RSSI value measurements was employed to ensure that the data was acceptable and trustworthy. It is worth noting that the experiment was carried out in a controlled setting with no additional network connectivity or barriers. Both the sender and receiver were lifted to 0.5 m at the same time to simulate true wearables on the wrist and provide a direct angle. Figure 6 depicts the Proof-of-Concept experimental setup, while Table 3. depicts a sample of data gathered from the scan.

Table 3. Sample of Captured Data which is stored in Database for Analysis

Access Point	AP Address	Device Name	Device Address	RSSI Value	Date	Time
AP01	00:1B:44:11:3A:B7	BLETag1	01:1C:44:11:3B:B8	-50	15/06/2022	10:00:34
AP02	01:1C:44:11:3B:B8	BLETag2	02:1C:44:11:3B:B9	-25	15/06/2022	10:23:29
AP03	00-14-22-01-23-45	BLETag3	04:1C:44:11:3B:B10	-10	15/06/2022	10:12:34
AP01	01-23-45-67-89-AB	BLETag4	05:1C:44:11:3B:B11	-15	16/06/2022	10:23:57
AP04	00-14-22-01-23-BC	BLETag5	01:1C:44:11:3B:B12	-7	16/06/2022	10:05:50

Data was taken and structured in a database with the same information as the proof of concept. Devices were raised to a height of 7 m to simulate actual wearing of wearables. The usage of four devices is intended to assess the approach's capacity to handle many users as well as the number of successful scans for various angles of arrival.

Analysis and results based on the data collection

In the case of Bluetooth, the distance travelled and the broadcasting power value affect the signal strength. Bluetooth uses broadcasting signals: the RSSI intensity of the signal ranges from -26 to -100. Using a different iBeacon standard value, Measured Power, it is possible to determine the Bluetooth proximity between two coupled or unpaired devices and the beacon. Measured Power (also known as the 1 Metre RSSI) is a read-only constant that has been factory calibrated and shows the anticipated RSSI at a distance of 1 metre from the beacon. RSSI has a tendency to change as a result of outside influences that affect radio waves, such as diffraction, interference or absorption. The RSSI becomes more erratic the farther away the device is from the beacon. Measured Power and RSSI enable calculating the distance between the device and the beacon:

Distance = 10^((Measured Power -RSSI)/(10*N))

where N is a constant that depends on environmental factors. It ranges from 2 to 4 (low to high strength).

For example, if Measured Power is -69 and obtained RSSI value is -80, with N=2 (low strength), then calculated Distance = 10^((-69 - (-80))/(10*2)) = 3 metres.

Table 4 shows the results of the RSSI value based on the distance experimentation with the number of 1, 4 and 8 devices.

Table 4. Results of RSSI value based on the distance and number of devices

Device Number, *n*	***Condition***	***Distance***, *m in metres*	***Average RSSI***, $RSSI_{avg}$
1	No obstacle – Line of sight	0	-34.01
4			-36.43
8			-37.55
1		1-2	-50.01
4			-52.13
8			53.14
1		2-3	-67.12
4			-68.15
8			-68.32
1		3-4	-88.45
4			-89.14
8			-89.53

Significance of the architecture

Many problems in healthcare facilities can be observed, such as hospital overcrowding. As described in the Introduction, patients may wander about, making their whereabouts unknown. Hence, using Real-time Patient Localization and Patient Movement Monitoring helps to locate the patient to minimize the turn-around time. A BLE-tagged wristband with each tag containing vital patient data, including an ID number, name, and other specifics, will be given to each patient upon their arrival at the hospital. When a patient travels around the hospital, Access Points on the walls and ceilings of the hospital and its surrounding area obtain

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information about the location of the tags and send it to the cloud database for processing and analysis (Figure 2).

Therefore, using this data and using the Real-Time Patient Location and Patient Movement system, the staff and the doctors can locate the patients and quickly contact them to be reported. By doing this, the patient will get treatment faster than expected and the throughput in every department will be increased, which can contribute to a reduction of patient turnaround time from 3 hours to 2 hours. At the same time, the doctors can treat more patients using the Real-Time Patient Location and Patient Movement system with the BLE IoT solutions.

Conclusion

An increase in patient turnaround time (PTAT) has a direct impact on health care industries as patients' quality of service is reduced. One of the crucial KPIs in the health care sector is the turnaround time for patients. Faster turnaround times are always the secret to raising patient satisfaction and quality of service. Additionally, it saves the hospitals money and resources. Low PTAT is not just a sign of a hospital's effectiveness, it also serves as a sign of high calibre hospital service. Real Time Patient Location Tracking can be used to detect patients more quickly in a hospital setting and provide quicker care. The current inability of the hospital staff to find a patient's whereabouts increases the PTAT.

In the current situation, without Real Time Patient Location Tracking, a patient spends almost 3 hours in the hospital from the registration process until he/she leaves the premises (Figure 1). During this time, hospital staff and doctors do not know the actual location of the patient and, as a result, it is difficult to be contactable and manage the consultation time with the doctor, as the patient can leave the hospital for meal breaks, talking to their fellow patients or friends, etc. This may also make the patient miss the consultation time with a doctor.

The Real Time Patient Location Tracking and Movement Solution allows hospital staff to follow the patient's whereabouts and swiftly get in touch with them for a consultation. Based on the data collection and analysis, the patient will receive treatment faster than expected. Real-time patient location tracking and increased departmental throughput will help cut the patient turnaround time from three to two hours. This will avoid the need to wait for the patient to show up for the consultation, because staff could contact them and ask for an immediate report for consultation. Table 5 shows the comparison of the benefits upon implementing the Real Time Patient Location Tracking and Movement Solution.

Table 5. Comparison of Benefits before and after Implementation of Real Time Patient Location Tracking and Movement Solution

Description	Before	After
Registration	✓	✓
Patient missed Doctor's consultation due whereabout in hospital	✓	×
Trackable after registration	×	✓
Locate the Patient where about within hospital	×	✓
Faster Doctor consultation	×	✓
Improve the Quality of Service (QoS)	×	✓
Optimize the throughput of the departments	×	✓
Saving Time	×	✓
Cost saving	×	✓
Patients are happy	×	✓

Future Work

In order to conduct efficient Real-Time Patient Location Tracking to minimize the Patient Turnaround Time (PTAT), we used low calibrated Tx in our proposed solution. RSSI will be used as a bonus feature for distance estimate in this method, and will be determined by the number of successful signal scans. Experimentation showed that our proposed solution is positive and accurate. It has been proven to have good accuracy for Real-Time Patient Location Tracking in order to optimize the Patient Turnaround Time (PTAT). As a result, it can be concluded that adopting a low-calibrated Tx technique for Real-Time Patient Location Tracking to improve Patient Turnaround Time (PTAT) is a useful method that governments and implementors may use.

Based on the findings of the study, low calibrated Tx for Real Time Patient Location Tracking to optimize the Patient Turnaround Time (PTAT) was highly successful and accurate. Nonetheless, there are still some limits and need for development. Mass testing, for example, has not yet been done, but it may be a future direction that researchers take before deciding to use in the real world. Not only that, but there are constraints in place, such as a limited number of devices and distance testing. If further experiments with more distances of 5 m can be undertaken, the results will be more robust. As a result, it is critical that more testing be done to determine the accuracy's consistency. When looking at the results of the experiment, it is evident that, as the number of devices increases, the number of successful scans decreases since the receiver has a limited time scan interval. However, this variable can be altered to improve precision or to accommodate more users. It should balance the number of users and the scanning interval to reach an appropriate level of RSSI accuracy. Otherwise, a large number of successful scans for a small number of users would give the impression of high accuracy when it is not.

Based on the experiment conducted real-time patient location tracking can make a significant contribution to public hospitals in Malaysia in terms of reducing patient waiting time. As a result, it appears necessary to determine hospital requirements, apply novel technologies such as BLE and the Internet of Things, and integrate them to gain maximum benefits to improve patient turn-around time in Malaysian public hospitals.

In the future work, BLE chipsets with even lower power consumption can be integrated with the Real-Time Patient Location Tracking system to save energy and improve tracking sensitivity.

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