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Using Bluetooth Low Energy devices to monitor visitor activity in remote amenity spaces

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Abstract

Tracking of pedestrian behaviour, particularly route selection and temporal behaviours, can be difficult to undertake. This is especially true of studies at a community or campus level where the anonymity of pedestrians can be difficult to protect. The introduction of the EU's General Data Protection Regulations 2016 (GDPR) has increased the complexity of this challenge. Advances in Bluetooth Low Energy (BLE) technology in recent years have increased the potential to monitor human behaviour by tracking and triangulating pedestrians. This paper describes an experiment undertaken along The Great South Wall at the Port of Dublin, which is considered a leading amenity location. Monitoring of visitor behaviour in places of this type can provide valuable information about the use of this and other public resources. The aims of this study were to test two prototypes to: i) determine the direction of participants carrying BLE devices, ii) determine the capabilities of two BLE scanning prototypes, (ESP32 & Raspberry Pi3), iii) test the ability of detecting a small number of BLE devices simultaneously while minimising interference or loss of passers-by data, iv) to investigate the use of a hash encoding scheme to anonymise BLE device identifiers.

The findings show that the direction of the visitors to the pier can be detected by correlating the received signal strength indicator (RSSI) from multiple Bluetooth scanning devices and this can work where scanning devices are as close as 10m apart. The locations of the BLE scanners has a slight effect on detecting the RSSI from different distances and the distance between scanners needs to be considered to facilitate accurate measurement of direction. As a pier like the South Wall has only one entrance and exit point, this approach can also be used to determine the length of time spent on the pier. The technical performance of the two BLE scanners was also reviewed and the ESP32 was shown to have significantly lower power consumption with only a slight decrease in performance. Finally, it was shown that the BLE scanners can detect multiple carried BLE devices successfully without interference or loss of data as long as those devices are within range of the BLE scanners.

Keywords: Pedestrian tracking, amenity space utilisation, Bluetooth Low Energy, RSSI

Introduction and related work

Urban and transportation planners and professionals in associated disciplines such as social scientists and geographers focus on understanding how people travel and conduct activities in order to improve urban mobility, accessibility and quality of life [1]. For instance, research in Geography, the study of human activities, in space-time has attracted considerable interest from researchers in a wide range of research areas including migration, retail, residential mobility, and travel behaviour [2]. A global focus on sustainability, including the development of the UN Sustainable Development goals [3], has led to urban transportation plans which increasingly focus on facilitating pedestrian movement more than vehicular movement [4]. The travel and activity behaviour of an individual is influenced by numerous spatial and temporal factors and constraints, travel and activity characteristics and personal attributes [5]. Moreover pedestrian flows are different from vehicle flows because they are not restricted to channelised lanes and can intermix in conflicting flows [6]. In that sense, the study of pedestrian behaviour is more complex than the study of motorised vehicles or cyclists.

Pedestrian tracking is the collection of trajectory data (direction, timestamp and location), or pedestrian volume data in form of sequential pairs of (time stamp, location) samples for each detected pedestrian, independent of direction. The approaches used for pedestrian counting and pedestrian tracking are not strictly delineated as both types of data can be used to count the number of people at arbitrary cross-sections [7]. Traditionally, researchers with clickers or sheets, who gather information manually, have carried out such studies. However, it was found that manual approaches for counting of pedestrians with clickers and clipboards are resource intensive and often proved to be less accurate and more difficult to control than video images [8]. Some technologies used for people counting are actually primarily used for people tracking. Shadowing is the oldest form of person tracking data and this kind of information is traditionally gathered manually by researchers who (with the consent of the chosen subject) observe and follow the tracked person and record the key locations on map either digitally or in hardcopy [7]. One great benefit of manual tracking is that the subjects can also be interviewed to get nuanced information about the reasons for their behaviour and to understand the pedestrian behaviour at a semantic level.

There is no denying the relative convenience of automatic approaches however. A number of technologies have been used for tracking pedestrians automatically, including video-based tracking which can be used to follow subjects within the field of vision of the camera [9], passive infrared-based methods and more recently, increasingly affordable horizontal laser scanners [10,11] can be used to measure the volume of pedestrian traffic crossing a line. Typically in a video-based tracking scheme, the first step is to detect a person in individual image frames and the second step is to associate the detected objects (for example a red jacket with orange logo) between the frames [7] and between numbers of cameras to get the trajectories [12].

Arguably the simplest automatic pedestrian monitoring systems are those that measure volume of pedestrian traffic. Horizontal Lidar or 3D laser scanners are typically mounted close to the ground; the height of the sensor determines whether it registers the hip or the foot of a tracked person [7]. In other anonymised intrusive localization methods, people are tracked by electronic devices carried with them such as smartphones and beacons. These devices emit unique signals which can be used to identify the user's location without necessarily knowing the identity of the person.

Other technological means can also be used to extract relevant information about pedestrians, such as trajectory or speed of motion from images and video footage. In [13] a model was represented to estimate how pedestrians move in relation to the motion and appearance features around them. Another example of using video cameras [14] monitored pedestrians for 62 days. The speed of each pedestrian was recorded by stopwatch and the flow rate and volume were calculated manually from the video data. However, cost and privacy issues in many cases, prohibit the use of highly accurate camera (with sensors) that cover the full pedestrian infrastructure [15].

Passive or short wave infrared imaging methods [7] by comparison rely on the idea that human/object temperature is often different from surrounding temperatures. The difference in temperatures detected by an infrared sensor allows it to detect moving objects. Nielsen et al. [16], tracked pedestrian in public plaza by using thermal cameras to take "heatmap" pictures of people as they move. This method showed reliable data on general patterns in plazas with a similar density of people. But challenges include when the Computer Vision Software is not able to track people consistently due to occlusion.

In past studies, a variety of different methods of recording human activity using modern smartphone technologies have been used, such as using Wi-Fi, GPS or a number of integrated sensors (IMU), along with specialist applications such as MapMyRun/Strava [17]. Many of these methods require a high level of user interaction, such as the installation of mobile apps to gather the required information. Bluetooth has been used for previous studies such as Oosterlink et al. [18], where a network of 56 Bluetooth scanners were deployed within a shopping mall.

Existing work does not place much focus on collection of data where there is no electrical power available and there is only limited literature on the tracking of individual pedestrians over large distances. Preservation of the anonymity of pedestrians is also not well-covered in the literature.

Bluetooth Low Energy (BLE) for pedestrian tracking

Bluetooth is the collective name that is used for a family of international standards for low-cost wireless technology that together allow electronic devices to communicate with each other over 2.4GHz radio links. Bluetooth Low Energy (BLE) is one of the latest enhancements which form part of the Bluetooth 4.0 specifications. BLE improves on the low power capabilities of previous versions of Bluetooth. Electronic devices with BLE can operate for months or even years using the power of a small coin cell battery. There are many diverse applications of BLE such as technologies connected to the Internet of Things (IOT), sports and fitness equipment such as smart watches, home automation, smart energy, automotive devices and security [19]. About 1 billion mobile devices with Bluetooth capabilities are produced every year [20]. Broadly speaking there are two types of BLE devices. Central Devices (typically a phone or a Raspberry Pi) or Peripheral Devices (usually a smart watch, a beacon or key finder). In the most basic interactions that follow the BLE Generic Access Protocol, peripheral devices broadcast information about themselves, including their MAC address. A MAC address is a unique 48-bit electronic identifier for each device in the form of “12:34:56:78:90:ab” [21]. When a peripheral device advertises in this way, the broadcasted information can be picked up by any BLE central device that is in the vicinity. Central devices can also attribute a signal strength for each received message with the Received Signal Strength Indicator (RSSI). RSSI is a measurement of the Radio Frequency (RF) power present in a received radio signal, and it is generally expressed in units of decibels (dB) and represented as a negative number. The closer the value to 0dB, the stronger the received signal has been. The variation of RSSI values changes with the changes at distances [22]. BLE-based beacons or sensor tags are simple BLE peripheral devices that broadcast specific information either to indicate their presence or to transmit certain sensor information periodically. They are typically small in size, lightweight, low cost and have low energy consumption. They can be used in indoor navigation or positioning systems [23].

Figure 1: The Great South Wall-experiment location (Source: Dublin City Council)

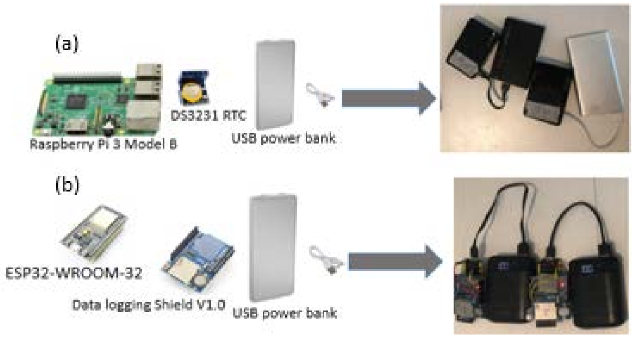


Figure 2: The Raspberry Pi3 based-tracking system (a) & The ESP32 based-tracking system(b)

Collection of personal data from electronic devices is governed by the EU’s General Data Protection Regulations 2016 (GDPR) which came into force across the EU on 25 May 2018 [24, 25]. GDPR aims to give control of personal data to the individual citizen. Public spaces are a complex scenario that need more attention to the use of data that is collected without consent from citizens. Where consent is not given there is a need to anonymise any personal data.

Implementation and initial testing of experimental embedded systems for person tracking

This paper presents the results of an anonymised person-tracking experiment carried out on the Great South Wall at the Port of Dublin. The remote location of the experiment site jutting nearly 2.5km into the Irish Sea away from any mains power supply for sensors makes this site well-suited for this project as a wireless 'sensor-network' can be created away from potential interference (figure 1). The collected data can be used to indicate the direction taken by the visitors as well as the time spent in locations. Two types of embedded system were selected for use in the experimental work,

A Raspberry Pi3 with real time module (RTC), which was programmed in Python to listen for all BLE advertisements and save the anonymized data in a local MySQL database as follows: [Date /Time Stamp, sha256, RSSI] and powered by a high capacity USB power bank (figure 2 (a)).

ESP32-WROOM-32 was also connected to Real time module (RTC) programmed in C to listen for BLE advertisements and saved the anonymized data as a csv file on the SD card, which mounted on another board (Data logging shield V1.0),as follows: [Date /Time Stamp, sha256, RSSI] and powered by a high capacity USB power bank (figure 2(b)).

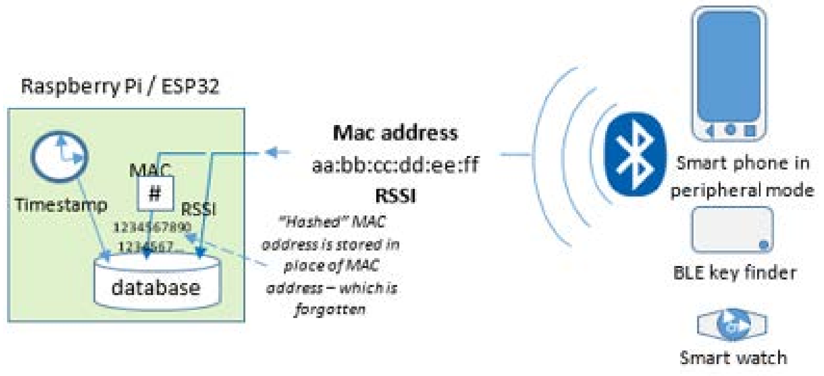


Figure 3: Schematic of the anonymization approach

Figure 4: Experiment poles 1 & 2

The protection of individual's privacy is paramount in this research design. To achieve this protection, MAC Addresses the unique identifier of the mobile device. Using the approach described in [26] the MAC address is converted (see figure 3) to a unique string by using sha256, a common hash function. The same function was used in both scanning devices to prevent re-identification of devices in other datasets while protecting the privacy of tracked persons.

In order to evaluate the likely lifetime of the Raspberry Pi vs other alternatives using the energy of a fully charged 5V power bank, the current consumption of different configurations were investigated where they were scanning for BLE devices and also in idle mode (i.e. switched on, but not engaged in useful activity). Three device combinations were tested; the Raspberry Pi 3 as shown in Figure 2(a), a Raspberry Pi Zero, an ESP32 with data logging shield as shown in Figure 2(b). To investigate the approximate lifetime of each configuration, the mean current for each device was recorded over a period for idle mode. The additional current when BLE was switched on was also recorded. From these measurements, an estimate of the lifetime under battery power of each BLE monitoring device could be determined.

Table 1 shows the results of this preliminary experiment. It can be seen that the ESP32 is comparatively power efficient, while the Raspberry Pi 3 consumes a lot of power and would run out of power in only 1.6 days. The calculations assume that the power bank actually delivered its full rated power of 10000mAhr. The main contributing factor appeared to be the idle mode power consumption of the Pi 3 which was much higher than the ESP32. This result was expected as the Pi3 uses a very powerful multi-core microprocessor whereas the ESP32 is designed for lower power microcontroller style applications. The Pi Zero power consumption is approximately halfway between the ESP32 and Pi3, this platform could be explored for future studies as it would give the flexibility of the Pi3 with a power consumption closer to the ESP32.

	ESP32	Raspberry Pi3	Raspberry Pi zero
CPU	40	220	100
BLE(On)	30	35	35
Total (mA)	70	225	135
Hours	143	39	74
Days	6	1.6	3.1

Table 1: Power consumption of 3 types of BLE scanner

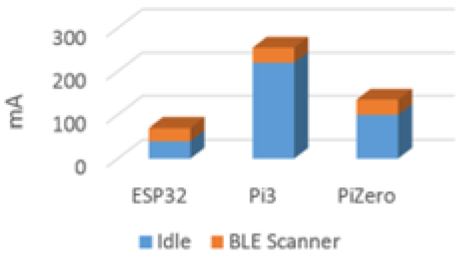


Figure 5: Comparison of power consumption in idle, and BLE scanning mode for BLE scanners

The advantage of the Raspberry Pi 3 as a platform for this work was usability. It has strong community support and it is relatively easy for researchers to use. For this reason, the ESP32 and Pi3 were chosen for the "live" experiments.

Methods and Results

Two experiments were carried out on the South Wall, as previously mentioned the characteristics of the location make it suitable for experiments of this type. The next sections will describe methodology and results for each experiment.

Experiment A: determining pedestrian direction (BLE scanners close together)

1. Two fixed stands (shown in figure 4) each one housing one of each type of tracking system, were located at the front and back side (figure 6) of the South Wall pump house building in such a way that the buildings were impeding the BLE signal in one direction but not the other.
2. 8 volunteers were asked to carry BLE devices (such as beacons and smart watches).
3. 5 Rounds of monitored walk-bys were conducted, each round with different BLE device and start time. In each round, participants were asked to pause at marked points and wait for a few seconds in each case.
4. Participants were asked to stop at the marked points for 15 seconds and waited for a sign to return back to the starting point following the same procedures in reverse.
5. "Ground truth" measurements were recorded manually at each round (the start time, time arrived at each marked point, time arrived to the scanner location and further point from the Bluetooth scanner location).

Following the experiment the SD storage cards were removed from each of the BLE Scanning devices and the captured data was processed on a desktop computer to identify underlying trends within the data. The processing involved filtering of the BLE advertisements based on known hash code of the Mac Address before the experiment day. Based on the recorded ground truth, the results of each BLE device was separated and analysed..

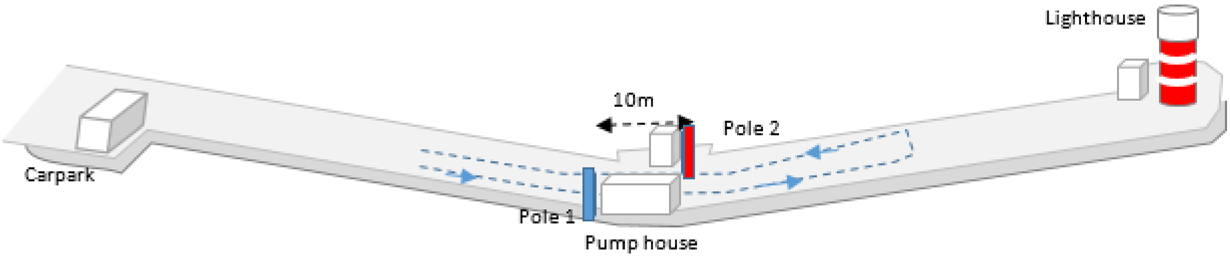
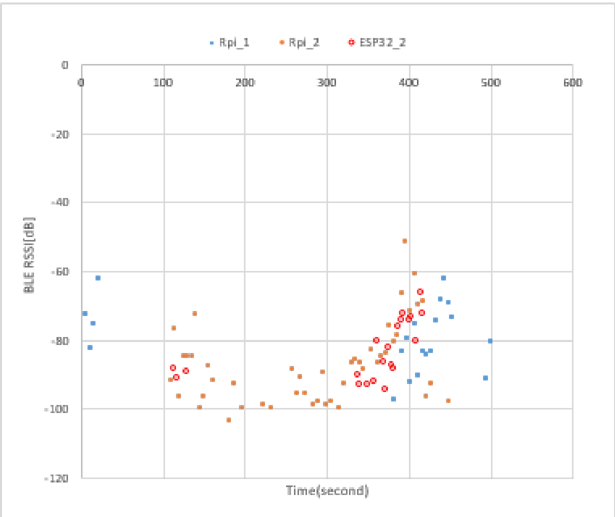


Figure 6: Pole 1 and Pole 2 location (Note: the figure is not drawn to scale)

Experiment A discussion of results

Figures 7 and 8 show selected results from experiment A. In total 9 BLE devices returned RSSI data. 4 of those devices produced RSSI measurements at the 2 poles when the volunteer pedestrian was travelling towards and away from the poles. Figure 7 shows a typical RSSI pattern for one of those 4 devices. For a pedestrian that moves towards pole 1, then away from pole 2 towards the lighthouse, then turns and walks towards pole 2 and then away from pole 1, the pattern would be blue-red-red-blue. Where blue represents an RSSI measurement taken by a device in pole 1 and red represents an RSSI recorded by a device in pole 2. For the other 5 devices as represented by figure 8, they only recorded RSSI values when the volunteer was walking towards a pole or just passing a pole and the pattern on the figure is blue - long break - red. It must also be noted that the RSSI values for this second category are typically quite low. Given that the devices are carried at the front of the body, it is possible that this effect is due to occlusion effects of the volunteer's body when the device emits a low power BLE signal.



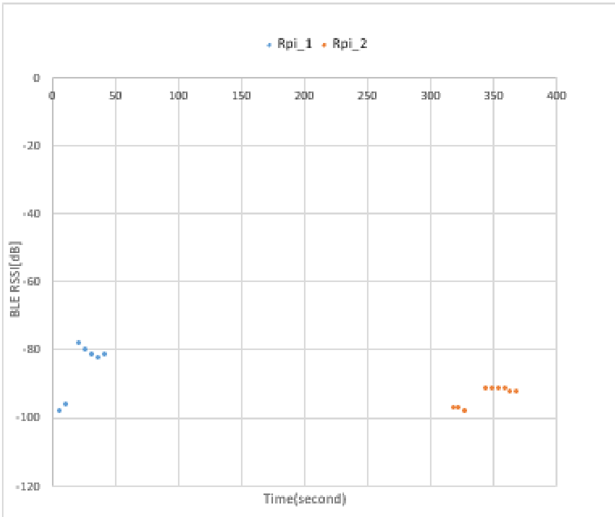


Figure 7: BLE RSSI values for Tile Pro, from Pi3 on pole 1 Pi3 & ESP32 on pole 2

Figure 8: BLE RSSI values for iTAG(1) from Pi3 on pole 1 & Pi3 on pole 2(no rssi on ESP32)

From figure 7, the direction of travel of pedestrians can be shown by knowing the RSSI and the detected times at which signals are saved in the two Bluetooth scanners (Raspberry pi3 and ESP32).The higher the value of RSSI, the stronger the signal for the closest Bluetooth scanner. The gradual fall and rise of the RSSI in the middle of the graph as the volunteer walks 150m towards the lighthouse and returns is also quite clear in figure 7. As expected, the building structure plays a role in blocking the signals between the two Bluetooth scanners which helps to identify the selected direction of pedestrian. However, in figure 8 and similar graphs, representative of over half of the BLE devices, it is not possible to discern direction from the graph data. It can also be seen in Figure 7 that the Raspberry Pi3 can detect RSSI values at a greater range compared to the ESP32. This result verifies the location of pedestrians at specific dates and times. The BLE devices show different RSSI values although the ratio is generally well correlated.

Experiment B: determining pedestrian direction & travel time (BLE scanners far apart)

Given the partial success of experiment A, it was decided to do a second experiment to investigate the use of scanning devices that were placed far apart in order to tell direction and activity. For this experiment, three tracking systems (1 Raspberry Pi3 and 2 ESP32) were located at two different locations at the South Wall site. A Raspberry Pi (blue pole 1 in figure 9) was placed at the top window at the front of the building adjoining the carpark at approximately two metre height. The two ESP32s (yellow and grey pole 2) were placed at ground level at the westerly end of the South Wall pier, adjoining the lighthouse building as shown in Figure 9. A volunteer was asked to carry three BLE devices (ID107 HR watch, iTAG and Tile Pro) and walk twice from the lighthouse to the car park and return back again to the lighthouse as shown in figure 9. "Ground truth" measurements were again recorded manually.

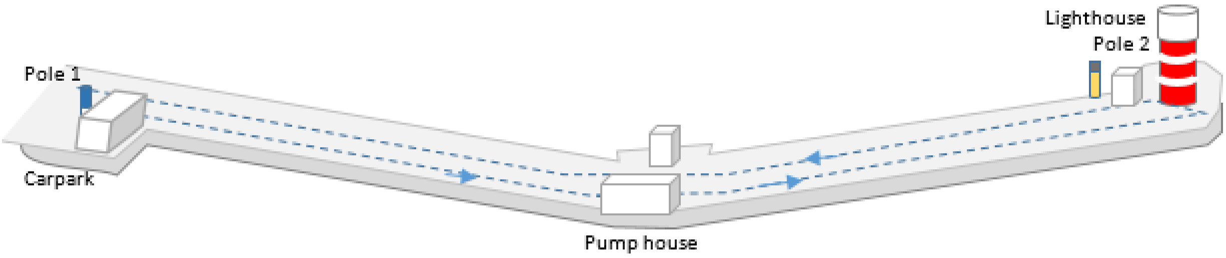


Figure 9: Pole 1 and Pole 2 location experiment B (Note: not drawn to scale; carpark & lighthouse about 1.6km apart)

The procedure from Experiment A for obtaining data from SD cards was applied again to get results shown in figure 10.

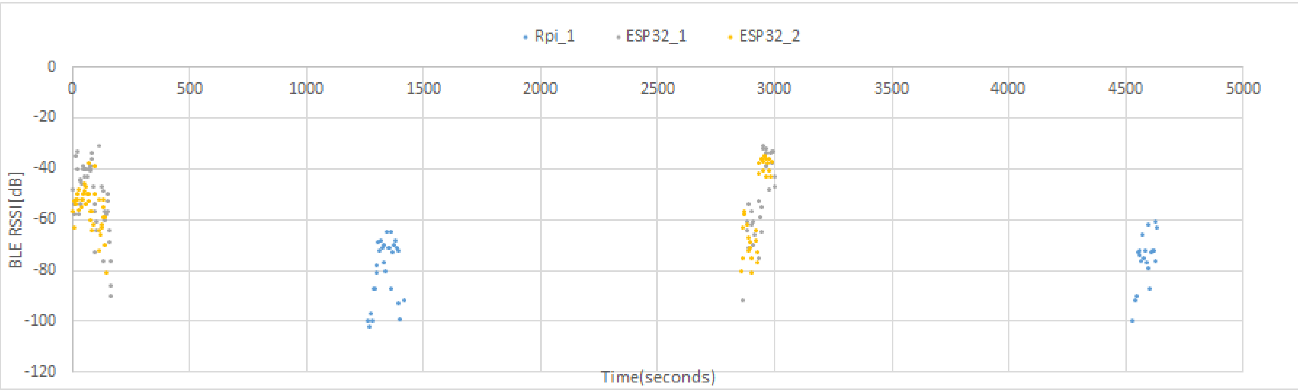


Figure 10: BLE RSSI values for Tile Pro

Experiment B discussion of results:

Figure 10 shows the RSSI data for two circuits of the route shown in figure 9. From the data in figure 10, it is possible to calculate the travel time of the pedestrian by observing the difference in the times of peak RSSI measurements recorded by the two sets of Bluetooth scanners (yellow /grey for lighthouse and blue for the carpark). For instance, the approximate travel time from carpark to lighthouse was 1300 seconds or 21 minutes. Using this approach it can be seen that the volunteer took around 3000 seconds or 50 minutes to complete the round trip from the lighthouse to carpark and back. Also by knowing the location of each Bluetooth scanner the approximate travel distance (1.6km) and average travel speed can be calculated (1.9 km/hr), this is true for many walkways like the South Wall pier where there is no other access to adjacent streets. The results of this experiment also show that the BLE scanners can detect multiple carried BLE devices successfully without any interference or loss of data. Three BLE devices, ID107 HR watch, iTAG and Tile Pro exhibited the same behaviour. Similar graphs to figure 10 were obtained for two other BLE devices (ID107 HR watch & iTAG).

Overall Conclusions:

It can be concluded that despite the good usability of the Pi the low power consumption makes the ESP32 is a good choice for low cost BLE scanner. Further consideration needs to be given to location of sensing devices in a given environment. For those devices with stronger BLE signals, the system can detect pedestrian direction. The effect of body occlusion on BLE signals for devices with weaker BLE signals is worthy of further investigation to inform placement and distance between scanning devices. Where scanning devices are placed relatively far apart (more than 100m) so that separation can be identified in the data set, then direction and journey can be extracted for a given subject. The hash encoding approach was found to be quite easy to implement and use and could also be used to link quantitative data to an anonymised questionnaire, where a study involves volunteer pedestrians. In the authors' opinion, the anonymisation approach used in this work can be used in other contexts and where subject privacy is important. Examples include tracking to understand pedestrian behaviour in medium scale geographies such as campus or neighbourhood scale.

In future work, the authors intend to reuse the apparatus in a path that is used by cyclists, pedestrians and runners to see how well this approach can be used to classify method of travel based on speed. The impact of height of scanning equipment, merits further investigation. Also, in order to scale this project for other applications, additional work is required to automatically (by mathematical algorithm) to detect the travel direction of pedestrians and to select and test each proposed location of a tracking system in metropolitan streets which are topologically more challenging.

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