Capturing the Behaviour of Volunteer Pedestrians in a Newly-Developed University Campus Using a Distributed Array of Bluetooth Low Energy Devices

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***Abstract*—Contemporary public infrastructure projects emphasise sustainable options that integrate pedestrian routes, leisure facilities and convenient access to public transport systems. It is important to understand the effectiveness of these contemporary designs. In the age of the General Data Protection Regulation (GDPR), there is a need to develop technology-based solutions that collect information about the behaviour of pedestrians in public spaces as they commute and engage in leisure pursuits while simultaneously preserving the privacy of these citizens. Bluetooth Low Energy (BLE), has privacy-preserving features that make it worth considering as part of a technology solution for studies of this type. This work presents the preliminary results of a multi-stakeholder study that collected data via BLE from 28 volunteer pedestrians who regularly used the public domain of the newly developed Grangegorman campus in Dublin's north inner city. Before the commencement of the data collection, each volunteer completed a short questionnaire about their intended movements on the campus, and for the next three weeks, they each carried a small keyring-sized BLE beacon with them as they passed through the campus. Bluetooth received signal strength indication from these beacons was collected at 17 points around the campus over the study period. The data for the volunteers were anonymised at the point of capture by hash encoding the MAC address of the beacons. The results of the work show that BLE can be used to monitor the approximate movements of volunteer pedestrians and so provide valuable privacy-preserving data on the utilisation of public infrastructure.**

***Index Terms*—Bluetooth low energy, pedestrian behaviour, sustainable transport**

I. Introduction

Mobility is our ability to move around freely and easily, and we need environments that allow us to move through them whether it is for the purposes of transport or leisure. With growing urban populations - 55% of the world's populace now reside in the cities [1] - urban areas are now dynamic environments that support a plethora of people and vehicles. Due to population migration patterns and the increasing expansion of cities, mobility is becoming a crucial aspect of urban environments. A growing population also results in increased commercial activities, which subsequently increases the transportation needs for goods, thereby adding to the use of vehicles. With road transportation being a leading cause of congestion and air pollution [2], a shift towards more sustainable modes of transportation, such as walking and cycling, is essential. These sustainable modes of transportation not only help mitigate the damaging effects of motorised vehicles on the environment, but also provide healthier lifestyles for the residents of the city. However, the built environment infrastructure is identified as one of the main reasons for reduced walking [3]. This indicates that there is a gap in the understanding of the utilisation and the planning of urban infrastructures. Various technological solutions can be applied to understanding the behaviour of pedestrians as they commute and/or engage in leisure pursuits. One of the common solutions is the use of imaging sensors to observe the users of a public space. However, the advent of stringent privacy regulations such as GDPR has influenced the usage of technologies that are privacy-invasive. This influence has encouraged the investigation of the use of non-traditional more privacy-preserving technologies for understanding pedestrian behaviour and subsequently, the utilisation of public infrastructure. One such privacy-preserving technology is BLE. The architecture of the BLE protocol supports several aspects of data collection, such as whitelisting, that are inherently favourable to privacy preservation. In this paper, we studied the BLE Received Signal Strength (RSS) values emitted from the devices of 28 volunteer pedestrians using the campus of a University, TU Dublin City Campus, Grangegorman. To collect these values, 17 locations across the campus were identified, both indoors and outdoors, where monitoring devices were deployed. To anonymise the identities of the volunteers, the Media Access Control (MAC) addresses of the BLE devices carried by each pedestrian was hash encoded. The core aim of this paper is to identify whether, by analysing aggregated synchronised BLE RSS values that are captured at multiple places, the approximate movement of volunteer pedestrians on the campus can be anonymously detected and subsequently, whether their journey and their usage of the campus infrastructure can be extrapolated. We also aim to find linkages between the qualitative features obtained through a survey with the volunteers and the quantitative data captured. In section II, we explore the existing literature concerning pedestrian behaviour monitoring and BLE. In section III, we delve into the methodology employed. In this section, we unravel the topology of the experimental ground architecture of the system, a method for the deployment of monitoring devices, the design of the experiment, and the structure of the accompanying participant survey. Section IV presents the results of our study. Section V entails the discussions and future heading of this research.

II. Background

A. Urban Mobility

Urban mobility includes collective transportation or public transit, individual transportation such as automobiles, cycling or walking, and freight transportation [4]. The increase in urban sprawl, which has ensued from the expansion of cities, has led to an augmentation in vehicle usage [3]. The research in [3] also suggests that the growth in the number of urban sprawls and subsequently, in the number of vehicles used for individual transportation prompts public agencies to develop the urban form ("spatial configuration of fixed elements within a metropolitan region" [5]) that can accommodate those vehicles. The increasing use of vehicles also leads to an abundance of aftereffects that are detrimental to the well-being of both the urban environment and its residents. There is thus an urgent need for a shift towards a more sustainable form of urban transportation to tackle the negative impacts of vehicle use. Authorities around the world have embraced this requirement. We find the emergence of programmes such as the *15-minute city* to increase the walkability of urban areas. Walking is considered to be the most sustainable form of transportation [3]. In addition, walking is also a therapeutic activity that offers numerous health benefits including increased mortality, adiposity and reduced risk of coronary heart disease [6]–[9]. To facilitate walking in urban environments, densely-populated urban settings should be designed to be encouraging and enabling, which requires data-driven planning.

B. Pedestrian Behaviour

Understanding pedestrian behaviour has resulted in several beneficial findings and actions including actions to ensure safety in crowded environments like train stations [10], observing and evaluating the utilisation of public space by visitors [11], assessing the built environment to deal with mobility limitations [12] and understanding linkages between pedestrian behaviour and traffic incidents [13]. Such studies, concerning pedestrian behaviour, have spanned quantitative [10], [11] and qualitative [13] realms and a combination of both [12]. The most common choice of technology for quantitative studies in the literature for pedestrian behaviour has been imaging/optical sensors [14]–[18]. The use of Global Positioning System (GPS) is also common for the collection of data to understand the behaviour of pedestrians [11], [19], [20]. However, growing concern towards the collection of personal data makes the use of such technologies a challenge. With the rise of privacy regulations, we see the emergence of the application of non-traditional technologies such as Wi-Fi and BLE for understanding pedestrian behaviour [21]–[29].

C. Bluetooth Low Energy

The BLE protocol offers several advantageous features to enable privacy-preserving monitoring. BLE devices discover other BLE-enabled devices by emitting small packets of essential information in their neighbourhood at periodic intervals. These packets, called advertisements, contain very limited information which makes personal identification of the carrier difficult. They contain a unique identifier and depending on the role of the device, data essential to establish a connection with another BLE device. The protocol specifies four roles that a BLE-enabled device can assume, Observer, Broadcaster, Central and Peripheral. As described in [21], the choice of roles of an Observer as a monitoring device and a Broadcaster as a monitored device offers the advantage of understanding the movement of pedestrians using only the advertisement signals emanating from the monitored device without even the need to establish a connection between the two devices. This means that data can be collected in an opportunistic manner without risking the exchange of personal data. Moreover, [22] highlights another feature, called Whitelisting, that allows the collection of signals emanating only from specified devices, allowing the technology to also be utilised in a participatory manner. When an advertisement is received by an Observer, another parameter associated with it, called the Received Signal Strength Indicator (RSSI), may also be evaluated. RSSI is the strength of the signal upon its arrival at the Observer. This parameter can be used to *roughly* interpret the distance between the Observer and the Broadcaster as the strength of the signal is proportional to the distance it travels [30]. This is a rough interpretation as other factors in the vicinity such as metallic objects [31], weather conditions [32], and even occlusion caused by the body of the carrier of the device [21] can impede the signal's propagation, thereby, influencing its RSSI. Despite the challenges associated with the use of BLE to understand pedestrian behaviour, we see opportunities to explore the application of this technology to understand pedestrians' movement in all of the related studies cited here. In this paper, we present our work to extrapolate the approximate movements of pedestrians and evaluate the application of aggregated BLE advertisement data for understanding the utilisation of public space by volunteer pedestrians. This study was conducted around the TU Dublin Grangegorman campus, which was still partially under development at the time of the quantitative experimental work. The Grangegorman campus is a major public infrastructure project in Dublin's north inner city about one kilometre away from the city centre. The area around the campus includes a number of vibrant and well-established neighbourhoods. The Grangegorman redevelopment project repurposedx a former mental hospital with high stone walls into an open and shared urban space that also increases the connectivity between these neighbourhoods. The redeveloped campus includes healthcare, primary and tertiary education provision as well as shared leisure and culture facilities for local sports clubs and organisations. The campus also features pedestrian commuter routes. The data collected in this study provides a snapshot of the campus at the moment of its inception, and also at the time when most of the undergraduate student population of the university was not attending the campus, due to Covid-19, although some staff and researchers were attending. During this time, members of the local community were also discovering this new amenity.

III. Methodology

A. Location

We selected 17 locations to deploy BLE Observers in the vicinity of the Grangegorman campus. We identified two categories of location, indoor and outdoor, for the deployment of these Observers. Following the identification of the main points of interest around the campus, a survey of locations of suitable lamp posts and windows that could be used for the study was identified, and contact was made with public and private sector owners to seek permission to install the BLE Observers in those places. The locations of the BLE Observers were selected to cover the approaches to the campus and exit/entrance gates, tram stations near the study area, pedestrian pathways, and routes to and through the campus. The Dublin Metropolitan tram system (LUAS) was chosen as an example of a public transport mode. Figure 1 shows an overview of these selected locations.

B. Participants

After an informed consent process of the 28 participants, the participating volunteer pedestrians were asked to complete a survey providing general demographic details and information about their commuting preferences. Each completed survey response was associated with a hash-encoded string derived from the MAC address of a unique BLE Tile wearable device (Broadcaster) shown in figure 5 which was assigned to the participant. In this way, the anonymised qualitative "commuting intentions" survey responses were linked to the quantitative results from the Observers.

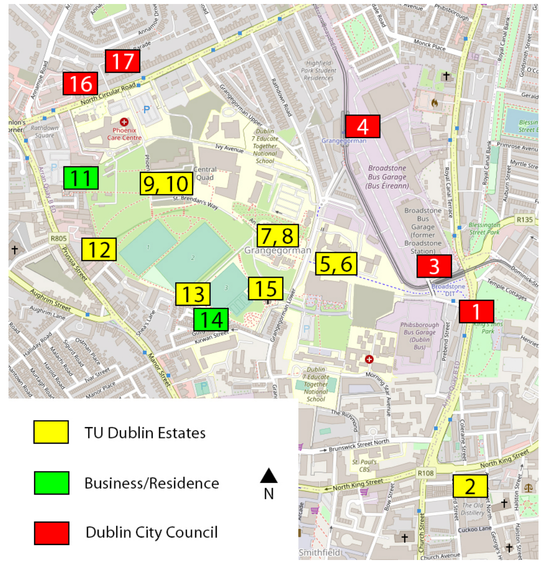

Fig. 1. Location of the map.

C. System Architecture

We employed two types of BLE Observers, the Raspberry Pi 3 (RPi), which is generally connected to a mains power source, for indoor locations, and the ESP32, which is powered by a power bank, for outdoor locations. The use of indoor BLE Observers is a desirable choice to reduce the extra burden of replacing the power bank every two to three days. The optimum indoor location is typically a relatively unused room that involves minimum disruption to workers, with a main power supply that is near a window that overlooks the chosen point on a pathway and with options to install the device on the inside of windows at an optimum height.

However, not every important location in the selected study area had a suitable overlooking room with a power supply. For instance, locations that were away from suitable buildings, such as bus stops, tram stops or remote pedestrian pathways required the use of an outdoor Observer. This introduced the additional requirement of a standalone power supply and hence, a lower power solution to enable data collection in these other locations was required. This outdoor Observer was based on an ESP32 microcontroller, with a real-time clock and SD card breakout attached. The ESP-based Observer units were housed in weatherproof enclosures figures 2 and 3 which could be magnetically attached 3-4 m high on a metallic pole using a purpose-built hook and form mechanism figure 4. The ESP32s were each powered by an off-the-shelf 10000mAH power bank. In normal operation, preliminary experiments showed that a power bank was able to continuously power an ESP32-based Observer for over 48 hours. For this reason, depleted power banks were swapped with fully charged power banks every two days by the researchers. At the same time, the data recorded on their SD cards was also downloaded.

Since the indoor Observer is based on RPi, it features a complete operating system, the data was stored on a MySQL

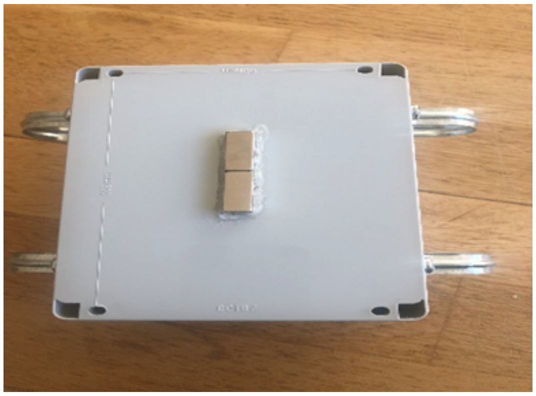

Fig. 2. Enclosure with magnets at the back to deploy on metal poles.

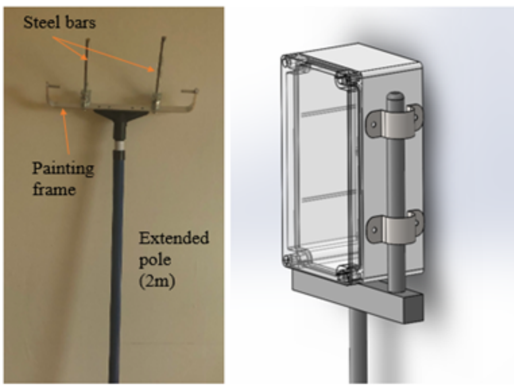

Fig. 3. Enclosure hooks and forks to facilitate deployment.

Fig. 4. Attaching the enclosure to a pole.

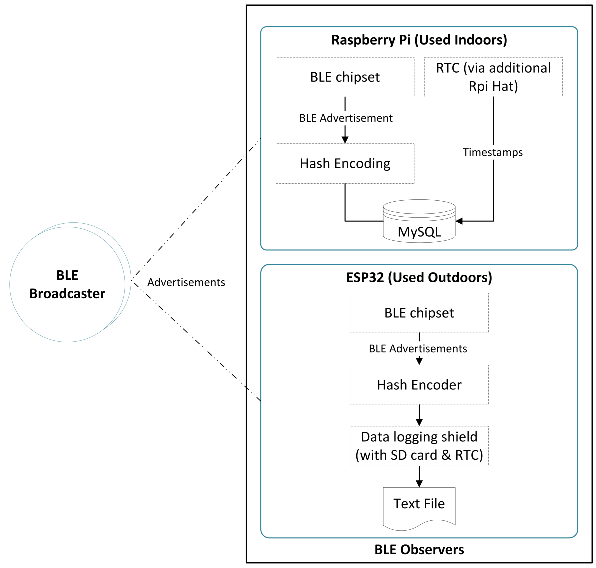

Fig. 5. Architecture of the system.

database, whereas, on the ESP32-based outdoor Observer, data was written to an SD card in a CSV text file format. Another feature of the RPi is that it can generally be configured to be accessed via line-of-sight, through single-glazed windows using a phone hotspot which means that its database can be checked from outside the window without needing to enter the room. Each of the Observers recorded BLE RSS values, timestamps and a coded representation of BLE advertisements emitted by the observed Broadcaster device. Following the approach described in [33], the BLE observers recorded for the coded representation, only the hash encoded strings derived from the MAC addresses of the Tile BLE Broadcasters carried by the volunteers with an added “salt” string. This meant that the MAC addresses of individual devices were never recorded by the system, but all devices recorded the same anonymised string for the same BLE Broadcaster. In this way, the progress of a device carried by a volunteer pedestrian could be recognised as they passed through the campus without compromising the anonymity of the pedestrian carrying it.

IV. Results

Of the 28 volunteers who activated their Broadcaster devices, 21 of them were local residents, 3 were TU Dublin (TUD) postgraduate researchers, 1 was a TUD undergraduate student and 3 were TUD staff members. There were 15 males and 13 females among the volunteers. 1 volunteer was in the 18-24 age group, 8 were in the 25-34 age group, 14 were in the 35-44 age group, 4 were from 45-54 age group and 1 was in the age group 55-64. Over the study period, 126,130 BLE advertisements were collected by the 17 Observers from the Broadcasters carried by the participating volunteers. The RSSI data was accompanied by a record of the their intentions.

One key intended output of the research is to show that by grouping the RSSI record for a particular shared hash encoded

TABLE I
NUMBER OF BLE EVENTS FOR ALL VOLUNTEERS AT EACH BLE LOCATIONS.

Volunteer ID	Locations																
	Constitution Hill	**Breseford**	**Broadstone LUAS**	**GG LUAS**	**Clocktower Meeting**	**Clocktower Office**	**Rathdown Office**	**Rathdown Store**	**Northhouse Art**	**Northhouse Annex**	**Blend Cafe**	**Fingal Place**	**Pedestrian Pathway**	**Kirwan St**	**GG by church**	**Parkhouse**	**HSE gate**
2	0	44	0	158	30	259	37	0	145	69	211	0	13	0	264	154	798
3	0	4	0	0	2	8	9	0	103	22	179	0	19	0	55	105	346
4	0	0	0	0	0	2	1	0	0	0	0	0	0	0	78	0	0
5	181	3	175	3	19	90	71	0	12	426	0	18	885	6	512	3	0
6	1	0	0	102	138	2009	781	54	846	2705	61	1497	2646	0	4909	121	77
7	1	9	0	84	211	1980	1360	102	746	3486	450	502	2590	42	9352	84	494
8	18	0	14	0	0	1	0	0	952	866	270	133	1513	0	500	1004	689
9	0	0	0	0	0	0	0	0	0	0	0	0	147	0	0	0	0
10	0	7	0	54	31	142	132	0	13	630	0	16	684	0	1243	0	0
12	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0
13	81	0	112	24	41	344	30	37	0	19	0	0	2	0	8	0	9
14	0	0	0	114	53	829	34	75	135	345	451	4	41	0	77	186	244
15	1	0	0	13	0	23	16	0	4	80	0	11	132	53	127	2	0
16	0	0	0	52	60	339	74	38	58	558	0	41	888	1	767	17	15
17	56	0	2	47	18	293	13	7	53	292	77	35	251	0	167	157	175
18	0	0	0	12	11	40	19	0	14	523	54	57	335	87	323	0	0
19	0	1	0	24	4	57	39	0	4	185	0	12	1762	110	339	0	0
20	0	2	1	72	30	179	53	24	23	609	0	45	640	0	753	53	34
21	3	13	0	63	58	340	124	31	255	380	62	32	1004	9821	1401	133	102
22	0	0	0	826	215	2004	299	212	909	2523	0	147	1486	0	786	36	123
23	31	0	21	123	118	752	626	0	546	1721	68	282	14921	622	1981	50	29
24	0	0	0	49	60	313	212	0	159	647	336	102	662	150	508	33	41
25	3	5	8	442	39	354	94	20	219	490	253	82	1103	258	1251	47	98
26	1	11	0	45	22	332	100	30	57	212	41	44	230	125	461	82	102
27	0	0	0	11	12	64	33	0	19	221	67	84	336	61	302	0	0
28	13	0	0	7	7	105	28	0	123	266	206	98	403	63	262	96	88
29	0	0	0	5	3	31	13	0	15	193	0	0	112	33	126	4	9
30	9	4	16	24	8	51	13	0	0	0	12	0	2	313	87	0	0
Total events	399	103	349	2354	1190	10941	4215	630	5410	17468	2798	3242	32807	11745	26639	2367	3473
Median events count	0	0	0	34.5	20.5	160.5	35.5	0	55	318.5	47.5	33.5	369.5	3.5	331	34.5	31.5

alias across the data set, it is possible to generate an aggregated record of the activity of the pedestrians. The aggregated data reveals that between them, the 28 active volunteers undertook 272 pedestrian journeys that led to peak RSS values of over -80dBs being recorded by at least three different Observers at different points in the pedestrains' trips.

TABLE II
DISTANCES IN METRES BETWEEN LOCATIONS 1 TO 6 FROM FIGURE 6.

Location 1 to Location 2	275 m
Location 2 to Location 3	175 m
Location 3 to Location 4	150 m
Location 4 to Location 5	150 m
Location 5 to Location 6	400 m
Location 6 to Location 2	50 m

Table I simply presents a count of the BLE events or advertisements that were observed for a period of 24 days of the experiment at each location by each volunteer pedestrian. The

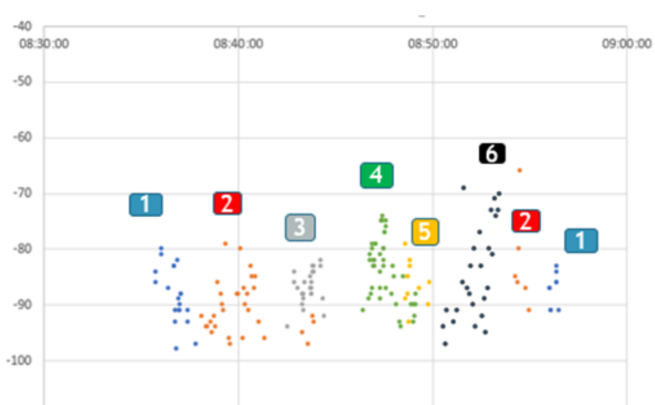

Fig. 6. Scattered RSS of Observed advertisement by different Observers from a single volunteer pedestrian representing a journey: Example 1.

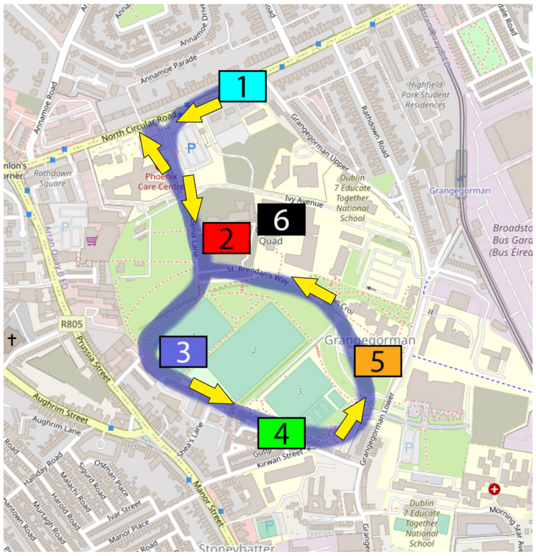

Fig. 7. Journey estimation of a selected pedestrian: Example 1.

presented data appears rudimentary, however, it informs the utilisation of the regions of the observed part of the campus. For instance, *Pedestrian Pathway* has the highest number of detected advertisements, meaning that it is widely used by our volunteer pedestrians. It is essential to note that just under half of these advertisements at Pedestrian Pathway result from the BLE Broadcaster carried by one particular volunteer. Even if we are to consider this as an outlier, a median of the count of advertisements, that can counter the effect of outliers [34], suggests that the Pedestrian Walkway is still the most frequently visited place on the campus amongst the participating volunteers. Similarly, the data in the table indicates that places like *Constitution Hill*, *Breseford*, *Broadstone Luas*, *Rathdown Store*, and *Kirwan Street* were less visited by the volunteers. Moreover, the captured data can also provide information at a finer level of granularity. For instance, figure 6 shows the aggregated RSSI record of an individual pedestrian for what appears to be a 30-minute morning walk. The graph shows that the detected advertisements for this volunteer lead to a sequence of RSS values. Bearing in mind that an RSSI value between -70 dBs and -80 dBs can be associated with a passing pedestrian at a distance of 10 to 20 m from an Observer [33], it is possible to infer the approximate trajectory of the pedestrian from the locations of the Observers. The campus map in figure 7 shows the location of each of the Observers numbered 1 to 6 in figure 6 and also shows the inferred path that the pedestrian took based on the aggregated RSSI record. From a comparison of the RSSI record and the campus map, it seems likely that the volunteer entered the campus through one of the main campus gates, and then did a circuit of one part of the campus for a period of 30 minutes before exiting through the same gate. Another impactful estimation that can be made about a pedestrian's behaviour from this data is their pace of travel. Considering figure 6, we can identify the approximate time of proximity of the pedestrian to the Observers. This approximate time when compared against the distance between these locations, which can be obtained using open mapping software, can provide a crucial insight into the probable pace of the pedestrian. For instance, table II provides the distances between the locations traversed by the pedestrian, and based on the trajectory which passes through points 1 2 3 4 5 6 2 1, the volunteer travels 1475 m in approximately 30 minutes yielding a mean walking pace of 0.8 m per second, which is a brisk walking pace. Figures 8 and 9 present another example where a journey of an individual pedestrian is estimated.

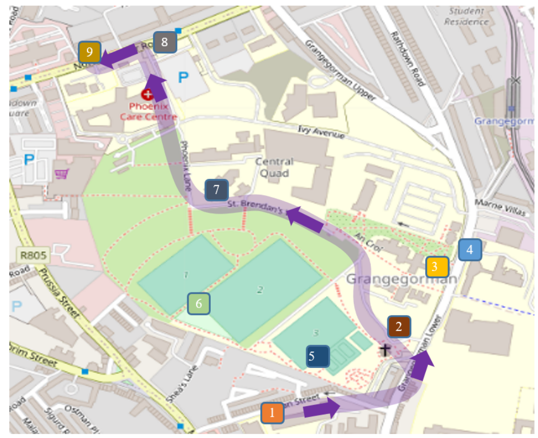

Fig. 8. Scattered RSS of Observed advertisement by different Observers from a single volunteer pedestrian representing a journey: Example 2.

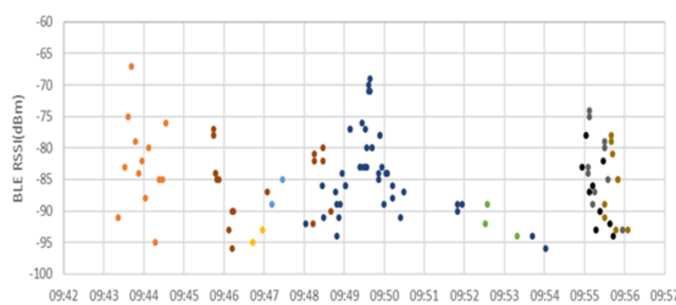

Fig. 9. Journey estimation of a selected pedestrian: Example 2.

V. Discussions and Future Work

This study is a conclusive evaluation of the use of BLE to understand the behaviour of pedestrians and subsequently, estimate the utilisation of spaces. A mere counting of observed advertisements over an extended period of time has been seen to be sufficient in identifying aggregated insights of space utilisation. This is favourable from the privacy preservation point of view since the presented method neither requires personal identification nor personal data. If we look at the RSSI record for an individual volunteer, we are also able to infer details of his/her journey and estimate the walking pace of the pedestrian. Such information is useful to identify frequently used routes and the type of pedestrian using the route, whether casual or purposeful. A casual or leisurely walker may walk at a slower pace and may even make stops along the journey. These crucial details, are, as presented, easy to identify through this approach.

The presented experimental data also poses a challenge. For instance, we observe a greater advertisement count from volunteer number 23 at Pedestrian Pathway, volunteer 21 at Kirwan St, and volunteer 7 at GG by the church. This presents a likelihood that these volunteers may either reside in close proximity to this space or work in the vicinity. Identification of such information impacts on the privacy preservation itself. Therefore, future studies should aim at exploring methods to mitigate such concerns. Another future plan is to address the issue with the observation of low-strength advertisements from the Broadcasters which are far away but still within line-of-sight distances of the Observers. While they do not pose a risk, they may influence the assertions about the route taken. For example, in figures 8 and 9, we find that advertisements are detected by Observer 3, 4 and 6 when the pedestrian's journey, more than likely, did not pass close to these locations. While the pedestrian may have stayed nearby, we cannot infer this with any degree of certainty. It also reduces our confidence in the purposefulness of the journey of this pedestrian despite knowing that they passed by Observers 7, 8, and 9. Future work that uses, for example, threshold-based filtering to prevent unreliable and low-strength signals should be beneficial for the presented system.

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