Estimating real-time highstreet footfall from Wi-Fi probe requests

Balamurugan Soundararaj[a], James Cheshire[a] and Paul Longley[a]

[a]Department of Geography, University College London, United Kingdom.

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ABSTRACT
The accurate measurement human activity with high spatial and temporal granularity is crucial for us to understand the structure and function of built enviroment. With increasing mobile ownerships, the Wi-Fi probe requests generated by these devices can be an excellent source of data for such measursement. The major challanges in using Wi-Fi technology for such purpose are precisely delineating the field of measurement and arriving at accurate estimates without compromising the privacy of the users of the mobile devices. In this paper we demonstrate that, with the application of class intervals and a novel graph based technique, we can overcome the challanges and reliably measure real-time pedestrian footfall at retail highstreets.

KEYWORDS
Highstreet footfall; Wi-Fi Probe requests; Sensors; MAC Randomisation

1. Introduction

In the past decade Wi-Fi has emerged as the most commonly used technology in providing high speed internet access to mobile devices such as smartphones, tablets and laptops in public and private spaces. This has resulted in multiple Wi-Fi networks being available at almost every location in dense urban environments. Traversing through this overlapping mesh of Wi-Fi networks, modern mobile devices with Wi-Fi antennae regularly broadcast a special type of signal known as 'Probe Requests', in order to discover Wi-Fi networks available to them. This helps these devices to connect and switch between the WiFi networks seamlessly.

Probe requests are low level signals standardised by IEEE 802.1b/g specification (IEEE 2013) as the first step in establishing a Wi-Fi based connection between two devices and is implemented in any Wi-Fi capable device irrespective of the manufacturer or the model. This ubiquity and standardisation make them an excellent source of open, passive, continuous, and wireless data generated by Wi-Fi capable devices present at any given time and location. Considering the unprecendented levels of mobile device ownership in recent years, we can in turn use this data to understand the population distribution in highly dynamic urban environments with high spatial and temporal granularity (Freudiger 2015, Kontokosta and Johnson 2017).

While a Wi-Fi based method to collect data offers us various advantages such as, easy scalability and efficiency in terms of cost and time, It also introduces few systematic biases, uncertainities in the collected data along with the serious risk of infringing

CONTACT Balamurugan Soundararaj. Email: s.bala@ucl.ac.uk

on the privacy of the mobile users. In this paper, using a set of probe requests and manual counts collected at various high street locations across London, we demonstrate that pedestrian footfall at these locations can be estimated with considerable precision and accuracy while protecting the privacy of the pedestrians.

2. Previous Work

Though WiFi is a 'location-less' technology, there are reliable methods to triangulate the location of Wi-Fi enabled mobile devices by the known locations of APs and the signal strength reported by them from the mobile devices (He *et al.* 2003, Moore *et al.* 2004, LaMarca *et al.* 2005). This can overcome the usual shortcoming of GPS, which struggles for precision and accuracy in indoor and densely built environments (Zarimpas *et al.* 2006, Kawaguchi 2009, Xi *et al.* 2010). Utilising this, we can easily and quickly estimate trajectories of the mobile devices just using the WiFi communication the device has with multiple known APs (Sørensen and Berglund 2006) which can be used similar to the GPS trajectories to understand individual travel patterns (Kim, 2006;(Rekimoto *et al.* 2007, Sapiezynski *et al.* 2015), crowd behaviour (Abedi *et al.* 2013, Mowafi *et al.* 2013), vehicular (Lu *et al.* 2010) and pedestrian movement (**?**Fukuzaki *et al.* 2014, Wang *et al.* 2016). Such data can also be used in transportation planning and management to estimate travel time (Musa and Eriksson 2011) and real time traffic monitoring (Abbott-Jard *et al.* 2013).

Using techniques demonstrated by Franklin *et al.* (2006) and Pang *et al.* (2007) and globally unique information present in the probe requests one can also successfully track people across these access points (Cunche *et al.* 2014), their trajectories (Musa and Eriksson 2012), and the interactions between them (Cheng *et al.* 2012, Barbera *et al.* 2013, Cunche 2014) such as predicting which of them are most likely to meet again (Cunche *et al.* 2012). Using the semantic information present in these probe requests it even is possible to understand the nature of population at a large scale (Di Luzio *et al.* 2016).

Though extensive research has been done on this subject with feasible and favorable results, in recent years, one of the major challenges faced in such attempts has been the increasing attempt by mobile phone manufacturers to protect the users' privacy by anonymising the globally identifiable portion of the probe requests, (Greenstein *et al.* 2008). There are various methods which have been devised to overcome this anonymisation process such as decomposition of OUIs where detailed device model information is estimated by analysing an already known dataset of OUIs (Martin *et al.* 2016); Scrambler attack using a small part of the physical layer specification for WiFi (Vo-Huu *et al.* 2016, Bloessl *et al.* 2015); and finally, the timing attack where the packet sequence information present in the probe request frame is used (Matte *et al.* 2016, Cheng and Wang 2016). A combination of these methodologies has been proven to produce de-anonymised globally unique device information (Vanhoef *et al.* 2016, Martin *et al.* 2017). These approaches usually result in serious risk of infringement of the privacy of the users of the mobile devices by revealing their identifiable personal information.

There is a clear gap in the research for exploring methodologies which enable us to estimate the number of unique mobile devices from a set of anonymised probe requests, without the need to reveal their original MAC addresses. Such technique has various applications in numerous fields such as uncovering the urban wireless landscape (Rose and Welsh 2010), revealing human activity at large scales (Qin *et al.* 2013), estimating pedestrian numbers in crowds (Schauer *et al.* 2014, Fukuzaki *et al.* 2015) and even counting people in hyper local scales such as queues (Wang *et al.* 2013) With enough infrastructure to collect such information we can aim to generate a real-time census of the city (Kontokosta and Johnson 2017). It has also been demonstrated by (Pinelli *et al.* 2015) through series of experiments on a telecom operator dataset that using such network-driven approach is more advantageous compared to the widely used event-driven approaches.

With this background we set out to device and implement a methodology to reliably estimate human activity such as pedestrian footfall from Wi-Fi probe requests without infringing the privacy of the users involve.

3. Methodology

The primary aim of this research is to enable us to collect a series of probe requests and process them into an usable pedestrian footfall count. We do this by using a Wi-Fi receiver to collect probe requests broadcasted by mobile devices, filtering out the background noise and aggregating them based on the device that generated them. We begin by looking at the characteristics of probe requests in detail, device a methodology to collect these probe requests in public areas, examine the systemic biases and uncertainties in the data collection method and device data processing methods to overcome these challanges. Finally we compare the processed footfall counts to the ground truth recorded by primary surveys.

Probe requests are a special type of management packets broadcast by Wi-Fi enabled devices as part of the various functions such as scanning for available access points (AP), quick geo-location by triangulation based known APs, etc. These are broadcast by all Wi-Fi enabled devices regardless of the manufacturer, type or model of the devices though there is some variation on the frequency and the information transmitted through them. In some cases, such as Android devices, these are broadcast even when the Wi-Fi functionality has been turned off by the user. Thus these signals can be used to reliably identify the presence of Wi-Fi enabled mobile devices.

Being a first step of connection initiated by the mobile device, these packets have information regarding the characteristics of the mobile device itself. Some of the key information we can infer from these requests are,

(1) **Media Access Control (MAC) address** which is an unique identifier for the wireless hardware of the mobile device,
(2) **Sequence number** of the request for the mobile device to keep track of the responses,
(3) **Timestamp** at which the request was received by the AP,
(4) Total **length** of the request in number of bits, and
(5) The **strength of the signal** which transmitted the request.

The MAC address is the primary unique identifier for the mobile device. It has two parts, first part is called an Organisation Unique Identifier (OUI) which gives information about the manufacturer of the device and the second is unique to the device. The MAC address can be randomised (hence non unique) and is marked as such. Though sequence number and length of the packet are not strictly unique, we hypothesize that we can use them to estimate unique devices.

Data collection was done with the help of custom sensors built from modifing the Smart street sensor (CDRC 2016) hardware and updating them with custom software.

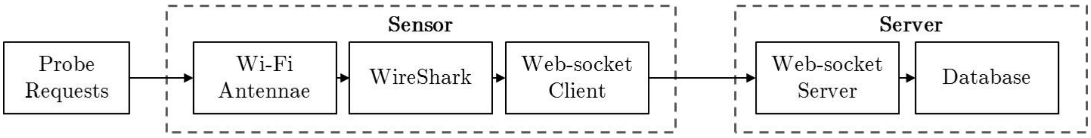


Figure 1. Schematic diagram showing the process of collecting probe requests using the sensor

The sensor is essentially a Raspberry Pi connected with Wi-Fi and 3G antennae. It keeps the Wi-Fi module in 'Monitor' mode and uses the open source software - wireshark cite to passively collect all packets sent to 'broadcast', marked with type - 'management' and subtype - 'probe requests'. The MAC address in these probe requests is anonymised using a cryptographic hashing algorithm and transmitted through 3G connection to a central database via web-sockets protocol, where it is stored in a PostgreSQL database for further analysis. A overall schematic of the data collection process is shown in Figure 1. The ground truth on number of pedestrian footfall was recorded using a purpose built Android application cite.

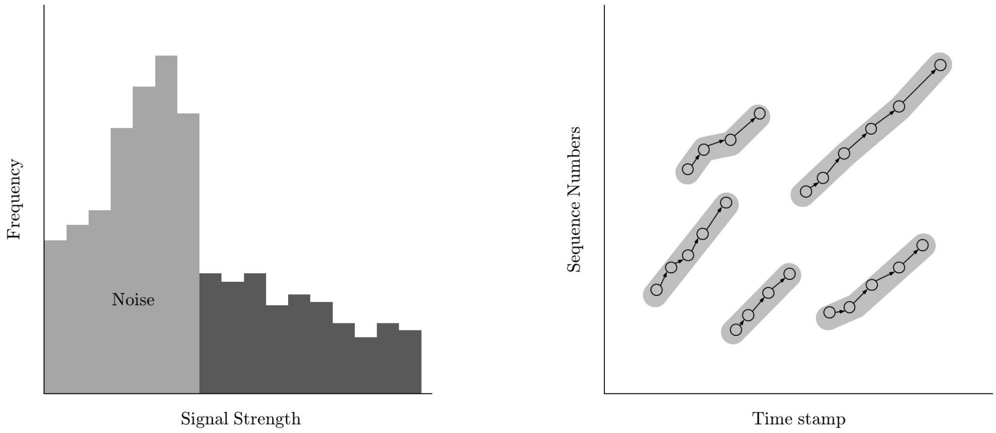
The next step after collecting data was to estimate the footfall or pedestrian activity from them. We identified the following major challanges which arise from our collection methodology.

(1) **Background noise** - since the extent to which Wi-Fi signals travel differs subject to various factors such as interference and humidity, it is close to impossible to restrict our data collection to a finite area of interest. This can lead to a signicant background noise at certain locations. E.g. a phone shop or a bus stop located next to the study area can increase the number of probe requests received by the sensor.
(2) **MAC randomisation** - The mobile devices in recent years have been using randomised 'local' MAC addresses for probe requests to protect the users from being tracked. This makes it impossible to tell if the probe requests are being sent by the same mobile device which is being stationed next to the sensor. This along with the previous problem can further increase the magnitude of error by several fold.
(3) **Mobile ownership** - Since the rate of mobile ownership can vary widely across geography and demography, we cannot assume that every mobile device translates to one pedestrian footfall. In addition to this, there is a long term overall increase in mobile ownership which may lead to the number of probe requests collected overtime.

We propose the following methods to tackle each of these challages.

3.1. *Filtering with Signal Strength*

One of the clues that we can use to estimate the distance between the mobie device and the sensor is the strength of the signal received by the sensor. The obvious approach here is to try and establish a relationship between the signal strength and distance first and use this to filter out the unwanted probe requests. This approach has numerous pitfalls and uncertainities since the decay of signal strength with distance is not always constant. It varies with atmospheric conditions, presence of obstructions between the source and target, the nature of these obstructions and the strength (power level) of the source transponder. This severely limits our ability to establishing a simple conversion between reported signal strength and distance. There is a need for a method which



(a) Distribution of signal strengths showing the filtering of background noise

(b) Clustering probe requests as nodes in a graph using increasing sequence numbers

Figure 2. Schematic diagrams explaining the methods for filtering by signal strength and clustering using sequence numbers

takes in to account these variables across varous locations.

We hypothesise that in configurations where a specific source of background noise is at a constant distance, there must be a distinct break in the number of probe requests reporting signal strength corresponding to that distance. For example, if there is a phone shop next to our sensor where hundreds of phones regularly send probe requests there should be a sharp rise of number of probe requests with reported singal strength corresponding to the distance between the sensor and the phone shop at any given set of conditions as shown in Figure 5. We could identify these breaks in the data using traditional one diamensional classification algorithms such as Jenks natural breaks, k-means, quantile and hierarchical clustering, etc. Since we are only looking for the break in the data and not for absolute values, the methodology should apply for all the variations due micro site conditions thus reducing the overall noise in the collected data.

3.2. *Clustering with sequence numbers*

Since our primary unique identifier - MAC adddress, is being anonymised by new devces, we need to find other information present in the probe request for a unique identifier. Obvious approach here is to establish a factor of randomisation and adjust the counts for these probe requests based on this factor. We found this aproach not feasible, since the proportion of devices which randomise the MAC addresses increases over time. There is also a wide variation in the frequency at which the devices randomise the MAC addresses and the method used for the process. This leads us to look for a more generalisable approach which is independent of the device model.

From our initial analysis we found that OUI, length of the packet and sequence number of the packet being the most promising information to acheive this. First we divide our dataset into sets of probe requests with randomised and non-randomised MAC addresses and keep the MAC address as the unique identifier for the latter set. For randomised ones we futher divide them in to sub categories based on their OUIand length of the packet. Since the length tends to stay unique to specific models of devices we are left with the task of identifying the unique mobile devices from within these distinct models.

The proposed algorithm creates a graph where the probe requests represented the nodes, and links are created between them based on the following rules:

- A link could go only forward in time.
- A link could go from low to high sequence numbers.
- A link could exist between nodes with a maximum time difference of α - time threshold.
- A link could exist between nodes with a maximum sequence number difference of β - sequence threshold.
- A node could have only one incoming link and one outgoing link, which is the shortest of all such possible links.

The nodes were then classified based on the unique connected component they belong to as shown in Figure 5. This classification was assigned as the unique identifier for the anonymised probe requests in the place of MAC address. Though the recycling of sequence number after 4000 leads to multiple classifications reported on single device, the maginitude of error is greatly reduced.

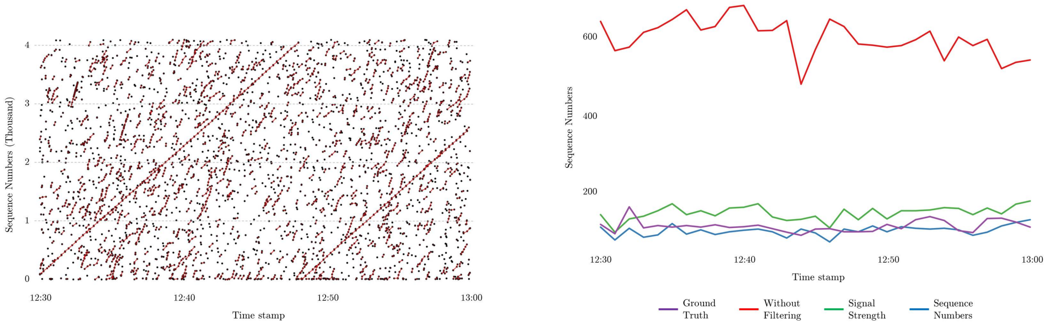
3.3. *Calibrating with ground truth*

Since mobile phone ownership is an external uncertainty to our study and could arise from variety of spatio, temporal and demographic factors, we propose to solve this using external source of information. We hypothesize that an adjustment factor could be arrived at for each location of data collection, comparing the sensor based counts and ground truth and it can be used to adjust the data reliably to reflect the ground truth in absolute numbers for the future. This calibration can be carried over periodically and the frequecy of which will improve the quality of the estimation.

4. Pilot Study

To start we designed a small pilot study with the aim to validate the classification and clustering methodology against the scale and complexity of data collected on a open public area such as a retail highstreet. We also want to find the algorithm which is best suited for classification of signal strengths. The data was collected at Oxford Street in London on 20 December 2017 from 12:30 to 13:00 hrs, where Wi-Fi probe requests sets were collected using the Wi-Fi sensor described earlier and pedestrian footfall was manually recorded using the Android app. Being located at one of the busiest retail locations in the United Kingdom, the WiFi sensor captured approximately 60,000 probe requests during the period, and 3,722 people were recorded manually.

When we just aggregated the probe requests by their MAC address for every minute, the mean error between the sensor counts and the manual counts was observed to be on average 425%. This suggested that there was a large amount of noise in the data which might have included signals from devices outside the area where the manual count was conducted and anonymised probe requests with different MAC addresses from a few devices stationed next to the sensor. We then classified the probe requests as ”high signal strength” and ”low signal strength” using ‘k-means’ classification algorithm which resulted in the lowest mean error percentage closely followed by ‘quantile’. The cut-off point or threshold for the collected data was -71 dBm. We eliminated the



(a) Clustering probe requests based on increasing sequence numbers present in them.

(b) Comparision of counts after filtering with manual counts

Figure 3. The results of the clustering process and the comparison with ground truth

noise from devices outside the area of interest by removing all the probe requests which reported a "low signal strength" below the threshold. We found this process of filtering highly effective and reduced the mean minute by minute error to 30%.

We then move on to assign an unique field identifying the mobile device generating the probe requests. For the 45% of the probe requests which were not randomised, we kept the MAC addresses as the unique identifier. For the rest of the probe requests we applied the clustering algorithm to assign the unique identifier. With the help of the known stationary device (the mobile device used by the surveyor to record pedestrians manually) and through trail and error, We found the suitable time threshold, α to be 15 seconds and threshold for sequence numbers, β to be 60. Figure 4 shows the clustering of probe requests. The dots are individual probe requests and the red lines connect probe requests within the same cluster which are generated by the same mobile device. We finally combine both normal and anonymised probe requests, aggregate them based on their unique identifier which further reduced the mean error to -18%.

The minute by minute comparision of counts from the filtering processes along with the ground truth is shown in Figure **??** From the pilot study, we find that both classification and clustering methods work on complex real world data and results in a final pedestrian counts within a error of 20%. We also find 'k-means' and 'quantile' are best algorithms for classifying signal strengths.

5. Main Study

The main study was designed to validate the results of the pilot study over different locations at different times. We choose five different locations across central London, to install the sensors and collect data for a long period of time. We also carry out manual counting on these locations along with this across different time of the day. We then apply the filtering based on signal strength and sequence numbers and compare with manual counts and evaluate the effectiveness of the process with the mean error per minute on these locations. Finally we calculate the ajustment factor for the first interval of manual counts and check if that works on the consecutive intervals.

The locations where the data were collected are shown in the table. The location are chosen for their variety of configuration and sources of noise. Location 1 is the 'cleanest' of while location 2 is the one with the most complexity. The configuration, installation and data collection schedule is shown in the figure.

Table 1. Locations where sensors were installed

ID	Location	Type	Installation notes
1	Camden High Street	Phone Shop	Bus stop in front
2	Central St.Giles Piazza	Restaurant	Seating area on both sides
3	Holborn Underground Station	Information Kiosk	Overlooks station entrance
4	Brunswick Center	Fast Food Restaurant	Has seating area on one side
5	The Strand	Tea Shop	Has phone shop next door

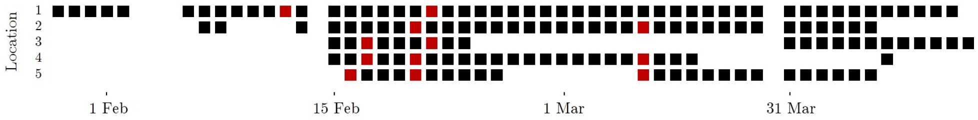


Figure 4. Days when the sensors were active at the corresponding location. The red square shows that manual data collection was also done.

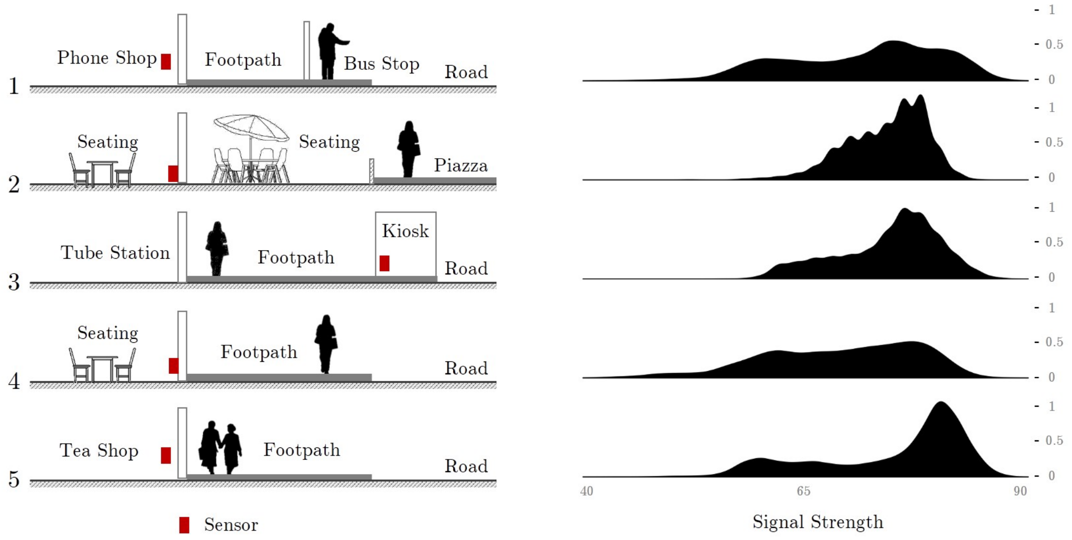
Though data was collected for many continous days, for the purposes of comparing with ground truth we just consider the only the data from sensors corresponding to those sessions. We have 12 sets of data over 6 different days. We have atleast two set manual counts for each location for verification of calibration.

5.1. *signal strength filtering*

First we see the distribution of the signal strength varies with location and configuration. The density plot for signal strength is shown alogn with configuration in figure. We can see that the signal strength distribution shows distinct patterns of high and low when the installation is that there is a clear distant source of noise but this distinction get more and more obscure as we move towards difficult installations. For example, location 2 is almost a normally distributed noise as it is too far to pick up any pedestrians but location 5 with a clear view of footpath and a phone shop next door shows clear distinction between the two. Intuitively the classfication algorithm should give us better results in the latter. It is important to note that we are dealing with relative singal strengths, this can vary with location and time of the analysis but we should be still be able to differentiate signal from noise. We run the kmeans classification algorithm and filter out the probe requests which are randomised and have signal strengths less than the second break (or the threshold). We then count the number of Unique MAC addresses present in every minute and remove MAC addreses which reappear within 30 minutes of previous appearance. We then compare this with the minute by minute aggreagation for the manual counts and find the average error per minute for the sensor count. The results are shown in the table.We see that the location XXXX has the most error while location XXX has the least error confirming our intuition. We also see that the error follows the complexity of the installation. It is also very promising that this method alone reduces our margin of error by a lot. For some practical purposes which does not require absolute numbers, this should be sufficient. talk about examples of indexes and dashboards and short term trends.

The comparision between global and local. comparision between different types of vendors. Specifics on top 5 manufacturers.

This is also done for different locations hourly for all the data we had. we compare it to the manual counts and see that the average mean error has been reduced/increased. The finger print works well for all the locations. It also works over a period of time and



(a) Installation configuration of sensors at various locations

(b) Density distribution of signal strength (lower values show higher signal strength)

Figure 5. Distribution of signal strengths across locations

gives us a comparable and close footfall count to the manual count. The thresholds found in the pilot study works as well.

Finally we normalise the sensor counts to match the manual count using a fraction/ adjustment factor calculated from the know manual counts. we have three sets of counts. We check if the adjustment factor holds the same in all three counts across locations. It does with a variations from xxx to xxx. The results are shown in the table.

we see that the signal strength filtering works and reduces error by xxxxx. there is variation by locations. we see that sequence number algorithm works as well. The threshold stays constant well and works well across locations. The calibration also works and ajustment factor stays consistent short term. This needs more work long term.

6. Conclusion

We have established methodology for collection and estimation of footfall from Wifi data. It is important to note that the filtering process was done based soley on the information present in the probe requests and their temporal distribution. This ensured that although the mobile devices were uniquely identified, there was no further personal data generated by linking the probe requests to the users of the mobile devices. This method essentially gave us a way to estimate the footfall in real-time without identifying or tracking the mobile devices themselves. A real time footfall in these locations are shown in the figure.

This Wi-Fi based footfall counting methodology offers a large number of applications and benefits for real time spatial analysis. Since Wi-Fi based sensors are inexpensive and the data model is scalable, it is possible to use this methodology for a large network of sensors to gather granular data on pedestrian footfall. Projects such as SmartStreetSensors (CDRC 2016), may utilise this methodology to overcome the challenges introduced by the implementation of MAC address randomisation. Such precise and granular data also enables us to confidently model the pedestrian flow in urban road networks, and will be an indispensable tool in the smart city framework. It can also be used to understand and classify geographical areas based on the spatio-temporal distribution of the volume of activity in them.

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