Development and Testing of a Real-Time WiFi-Bluetooth System for Pedestrian Network Monitoring and Data Extrapolation

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ABSTRACT

Real-time data collection and monitoring of pedestrian networks is an important topic in research and practice. A real-time pedestrian monitoring system should be able give information about volumes (counts or flows) and speeds for all links of interest. There are many applications for pedestrian network monitoring such as counting and extrapolation, activity modeling, management of public areas like airports, train and metro stations, malls. Moreover, there are some more specific applications like security checks, waiting time and travel time in public hubs like airports. There are some available technologies to get count data at specific locations; however these types of technologies cannot provide detailed data of pedestrian walking patterns and speeds. To achieve this, the system should be able to collect anonymous data of pedestrians in a network. In recent years, Bluetooth technology has widely been used in studies to capture the unique Media Access Control (MAC) addresses of Bluetooth devices in order to track them throughout a network to assess their activity patterns. Because of the security and power consumption concerns and less applications due to new wireless protocols like WiFi, the penetration of this technology is getting smaller in smartphones. Hence, an integrated WiFi-Bluetooth system was designed in order to take advantage of the benefits of WiFi technology like higher penetration rates between users of smartphones. Some criterion like travel time and detection rate are used in this paper to evaluate the performance of the developed system. The primary results show high detection rates of WiFi system as well as, a high correlation between the number of detections between sensors and ground truth data. These features can be helpful for extrapolation and estimation of pedestrian flow furthermore more accurate travel time and waiting time estimations.

1. INTRODUCTION

In the transportation field, there has been a growing interest in the development of traffic monitoring systems, often referred to as intelligent transportation systems (ITS) technologies. There is also a burgeoning interest in collecting pedestrian traffic flows in specific facilities or locations (downtown areas, terminals, public buildings, etc.). These metrics can be used to obtain volumes, facility usage, walking speeds, and so on. Among the popular technologies for monitoring and collecting counts (referred also as volumes or flows) in a pedestrian network one can mention sensors such as infrared and ultrasonic counters. Most of the common pedestrian monitoring systems place an emphasis on counting devices – providing data only for a point in the network. However, count data does not provide detailed information about the pedestrian activity through the network (such as travel times and volumes in an entire network, frequency of visits, etc.). In addition, traditional sensors might present some challenges under high volume conditions because of occlusion issues. Moreover, when detection areas are very large or not well defined such as in open spaces, traditional detection sensors can perform very poorly. These sensors lack the ability to anonymously track these individual pedestrians as they move outside of each individual sensor's range and through the network. This issue led us to look at anonymous identity-retaining tools. In this direction, smartphones have become the device of choice for many people. In Canada, more than half of mobile phone users use smartphones – and penetration is expected to reach 60% in 2016. Most smartphones have both Bluetooth and WIFI. These wireless communication protocols (IEEE 802.11 for WIFI, formally IEEE 802.15.1 for Bluetooth) offer convenient ways for users to connect peripherals or to the Internet and also allow for devices to be detected by appropriate hardware.

To overcome the high cost and limitation of traditional data collection methods, simpler approaches have emerged using wireless technologies, such as Bluetooth (Bullock et al., 2010; Malinovskiy et al., 2012) and WIFI access points (Danalet et al., 2013; Musa and Eriksson, 2012). Mainly these applications have been documented for vehicular traffic on road networks. However, very few studies using these technologies have looked at pedestrian flows.

In fact, Bluetooth surveillance has been researched heavily in recent years for monitoring motor-vehicle traffic in highways. In broad terms, a Bluetooth-enabled device that is discoverable will be detectable by another Bluetooth radio, which in this case would be the detector. Every Bluetooth device has a unique hardware MAC address (a 12 character hexadecimal number), which is uniquely identifiable. Bluetooth has a range of anywhere from 3.3 meters to 33 meters (depending on the device), and communicates power levels as users move radially closer and further from the sensor. A basic device to collect travel time data is simply composed of a reader unit, logic to store MAC addresses, and an antenna.

Using multiple detectors throughout a network, the path and rough speed of each device can be determined and used to generate OD matrices, travel times and speeds. Several applications in which Bluetooth devices have been used to compute travel time measures and other traffic performance measures have been reported recently. Among the first works, some researchers have focused on using the technology to monitor cyclists and pedestrians (Hainen et al., 2013; Jansen et al., 2014; Utsch and Liebig, 2012) employed the use of Bluetooth sensors to measure

pedestrian travel times at airport security checkpoints at George Bush Intercontinental Airport.(Utsch and Liebig, 2012) used the technology to try to track the location of pedestrians in a laboratory. Additionally, (Jansen et al., 2014) attempted to estimate the Bluetooth ratio of cyclists in Oldenburg, Germany, using inductive loop data. In a more recent work, Porter et al. (2013) have evaluated the impact of the use of different antennas, and concluded that an antenna with a large gain and a lower sampling rate may provide more accurate travel time samples if the main focus is the collection of travel time data.

The advantages of Bluetooth methods over conventional technologies have been highlighted in several documents including relatively lower costs (hardware and software is inexpensive), ability to collect large quantities of data over time, and ease of installation. Given their flexibility, Bluetooth data collection devices are suitable for temporary or permanent installation in roadway facilities of interest. These sensors can be used to monitor pedestrian traffic in pedestrian environments (Malinovskiy et al., 2012).

Despite the important advantages listed above, a number of limitations have also been documented. The issue with Bluetooth detectors is that many users disable the service altogether on their devices, or otherwise keep their devices undiscoverable. This is partially due to the fact that for many people the Bluetooth service is not frequently used. Also, leaving Bluetooth enabled can have a negative effect on battery life. This, along with detection error, leads to low detection rates. Most of the detection rate studies of Bluetooth technology can be found in vehicular network. Detection rates for Bluetooth are usually reported between 5 and 12 percent (Malinovskiy et al., 2012).

In some recent studies, MAC address of connected devices to WiFi access points are used to track people through network. However, WIFI access point tracking requires that devices be connected to a specific wireless network and that the network encompasses the entire detection area. Cellular tower triangulation is very coarse so it is only appropriate for origin-destination surveying (Caceres et al., 2007).

To overcome the issues with Bluetooth and increase its accuracy rate, some researchers have begun considering Wireless Internet (WIFI) detection as an alternative (Danalet et al., 2013; Musa and Eriksson, 2012). WIFI is another common wireless service, but it has a much higher use-rate than Bluetooth because while enabled it allows users to connect to known networks when in range to save on cellular data usage (if applicable). WIFI has been used in existing networks to track devices that are connected to a specific network (Danalet et al., 2013, 2014). This is particularly useful for networks with a large wireless coverage area and many nodes, such as a university campus. Devices must be connected to the given wireless network. The area studied thus cannot be expanded without extending the network coverage, which can be difficult as it means expanding the area supporting access to the Internet to its users. This could be an issue if the area under study is, for example a highway, a neighbourhood, or anything other than a campus. Because of the mentioned shortcomings of using access point data to monitor traffic network using WiFi protocol in recent years a growing interest in developing independent WiFi sniffer systems can be seen. In these systems, capturing MAC addresses in not limited to the devices that are connected to a specific network.

In the literature, few studies have compared the performance of Bluetooth and WIFI scanners in providing usable and representative travel data. In regards to pedestrian traffic, Schauer et al. (2014) compared various pedestrian flow techniques using WiFi/Bluetooth scanners at Munich Airport.. The number of unique MAC addresses captured by the WIFI and Bluetooth scanners per day in the public area was 6,211 and 250 respectively, while in the security area, it was 3,784 and 107 respectively. It was found that WIFI overestimated and Bluetooth underestimated flow compared to the number of boarding pass scans (ground truth). This study however used a small sample for validation. On a different note, (Vu et al., 2010) devised a pedestrian monitoring system which makes use of both WIFI and Bluetooth technologies. The Bluetooth data is used to assign a unique ID to each user based on MAC address while the WIFI data is used to obtain user location. This data is then used to evaluate how long a person stays at one location and which location is the most popular. Another issue that has not investigated is the stability of the detection rates in outdoor pedestrian networks (university campus, parks, pedestrian and bike trails, etc.). Detection rates and travel times with WiFi have not yet been validated with respect to a known ground truth obtained with other means (such as video data). Also, the feasibility of WiFi-BT extrapolation has not been investigated.

To overcome these gaps in the literature, this work has several objectives: (i) Development and test the performance of a WiFi-BT system to detect anonymous MAC addresses of devices at short distances at fixed locations. Proposed herein is a technique for capturing signals from WiFi and Bluetooth enabled mobile devices for the purpose of measuring travel times, and potentially estimating volumes with appropriate extrapolation methods. (ii) Investigate the advantages of a WiFi data collection system as an alternative to or complement to Bluetooth technology for monitoring devices throughout a network. (iii) Investigate the feasibility of extrapolation WiFi-BT signals with the combination of video sensors to obtain pedestrian flow estimations. For this, a simple extrapolation approach is introduced to obtain total volumes from video sensors.

2. SYSTEM OVERVIEW

The developed system is inspired by the best elements of WiFi and Bluetooth: Taking advantage of the portability of Bluetooth and the detection levels of WiFi. After reviewing the 802.11 whitepaper (Committee, 1997), it became clear that it was possible to detect packets that are broadcast periodically by WiFi-enabled devices in a similar manner to the way Bluetooth devices are detected. The system we set out to create is able to (i) track MAC addresses from WiFi traces from phones regardless of their network connection status or user settings (assuming WiFi radio is on), and (ii) extract travel times and flow rates per direction of travel. In this section, the developed system is described. First, the hardware design and elements are discussed and then software development and data analysis methodology are explained.

2.1 Hardware Components

The first step in developing the system was designing the different components of the WiFi/BT sensor. These tasks required a number of steps, including the selection and testing of the best components, design of a microprocessor, integration of a BT and WiFi modules and data logger. Additional details are provided as follows:

1. *Processor:* The designed system uses a 600MHz processor with 64M RAM with OpenWRT, an open source Linux based OS. The built image of the OS kernel includes different programming languages and libraries to interface the processor with a USB 3G Modem, Bluetooth module and a wireless packet handling.

2. *Bluetooth Module:* To capture the Bluetooth MAC addresses, a serial Bluetooth module is used in our system. The Bluetooth module is a "class I" Bluetooth device (high sensitivity) with an external antenna.

3. *WiFi Module*: This module is used to scan the 2.4GHz spectrum and capture probe signal of WiFi devices.

4. *Data Logger:* In order to record locally and transfer timestamped data to a web server, a unit including Real Time Clock module, SD card and 3G Modem is used.

   The final system is illustrated in the following pictures:
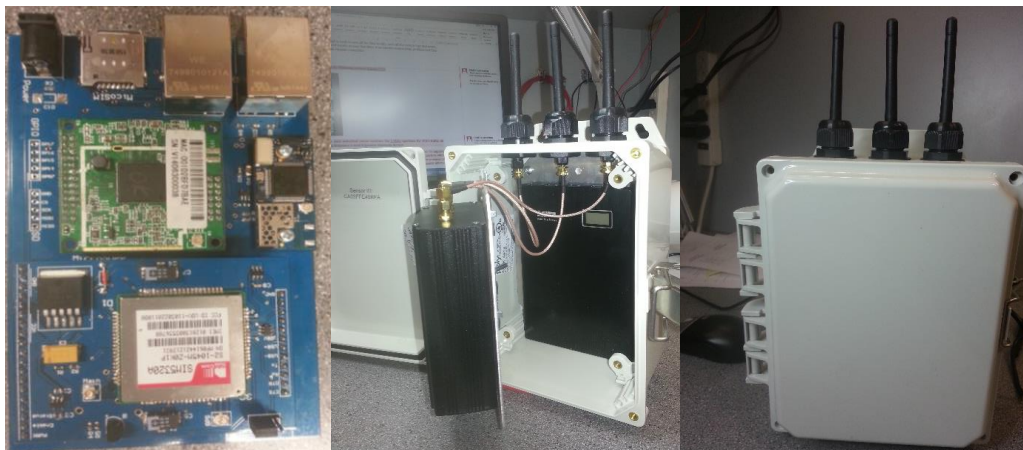

Figure 1 System hardware development

It is worth mentioning that each individual sensor monitors the 2.4 Ghz spectrum for WiFi traffic on multiple channels. The same frequency is used to monitor Bluetooth devices. A class I Bluetooth module is used in our system to increase the sensitivity of the Bluetooth scan unit and capture more Bluetooth MAC addresses from nearby devices. Moreover, packets are stored to an internal database or transmitted via WiFi or GSM to a central database. In order to improve results, multiple sensors can be placed at a single site to increase the probability of catching packets while scanning channels. For short-term studies, the sensors can be powered by battery while for long-term studies, they can be plugged into the municipal electrical system or powered by solar panels. Secure, waterproof housing is used to protect the equipment against adverse weather and tampering.

The proposed WiFi detector exploits a part of the IEEE 802.11 protocol that has stations actively and frequently broadcasting the identities of their desired access points. Typically, this data is ignored by access points and other routers unless is it directed toward them specifically. Our device passively listens to all packets from all stations and records their specific MAC addresses. Such detectors can be used as a standalone way to retrieve information, or can be coupled with other counting devices, such as infrared and microwave sensors, video analysis systems, and depth-based counters. These other counters do a good job of catching and classifying all traffic as they pass by, but are not well suited for identifying individual paths. The ability to single out the identity and speed profile of most of the traffic moving through a network has two implications: (i) the paths of smartphone-carrying users can be extracted, and (ii) the paths of non-smartphone-carrying users can be better estimated based on the known paths and data from other sensors.

The same criteria are used to capture the Bluetooth signals and get the MAC addresses of Bluetooth devices, but with some differences. In regards to Bluetooth technology, capturing a MAC address requires an active handshaking between a sensor and a device, i.e. a sensor transmits probe signals to other enabled and discoverable Bluetooth devices and listens to their response.

Among the advantages of the developed system with respect to the existing one, is that the full coverage of the entire facility with a set (cluster) of devices is relatively low cost. Devices are not intrusive and make use of infrastructure that already exists (such as posts and barriers). Additionally, the designed system is also completely compatible with a developed pedestrian counting system based on ultrasonic technology. The pedestrian counting system is connected to the WiFi-Bluetooth system through a wire or Bluetooth communication protocol to transfer data to the main processor which then relays the data to a server.

2.2 Data Collection and Analytics

For data analysis, first some basic parameters and notation are defined. For this, assuming that our sensory network has N sensors, then the following parameters can be defined:

K_i = total number of MAC addresses seen by sensor i at time interval t_int.
t_w = search time window.
Then, if a MAC has been detected in time t then we look for the same MAC in other sensors database in a time window $t \pm t_w$.

D_{ij} = **Distance between sensor i and sensor j, with $i, j = 1 \dots N$ and $i \neq j$**

V_{ij} = **Total volume of pedestrian moving from sensor i to sensor j, with $i, j = 1 \dots N$ and $i \neq j$**

C_{ij} = **Total number of captured MACs moving from sensor i to sensor j**

DR_{ij} = **Detection rate of captured MACs moving from sensor i to sensor j**

T_{ijn} = **Travel time of MAC n moving from sensor i to sensor j $i, j = 1 \dots N$ and $i \neq j$**

Then, the travel time between sensor i and j in time interval t_int is computed using the following algorithm:

MAC_i = **set of all MACs detected by sensor i in time interval t_int**
$n_{ij} = 1$ & $n_{ji} = 1$
for mac in MAC_i:
$\quad t_i$ = **set of detection times of mac in sensor i**
$\quad MAC_j$ = **set of all MAC detected by sensor j in time interval** $[\min(t_i) - t_w : \max(t_i) + t_w]$
$\quad$ **if** (mac **is in** MAC_j):
$\quad\quad t_j$ = **set of detection times of mac in sensor j**
$\quad\quad$ **if** ($\max(t_i) < \min(t_j)$)
$\quad\quad\quad C_{ij} = C_{ij} + 1$
$\quad\quad\quad T_{ijn_{ij}} = \max(t_i) - \min(t_j)$
$\quad\quad\quad n_{ij} = n_{ij} + 1$
$\quad\quad$ **if** ($\max(t_j) < \min(t_i)$)
$\quad\quad\quad C_{ji} = C_{ji} + 1$
$\quad\quad\quad T_{jin_{ji}} = \max(t_i) - \min(t_j)$

$$\mathbf{n_{ji} = n_{ji} + 1}$$

Then DR_{ij} and T_{ij} are computed as:

$$DR_{ij} = \frac{C_{ij}}{V_{ij}} \quad and \quad DR_{ji} = \frac{C_{ji}}{V_{ji}}$$

$$T_{ij} = \frac{\sum_{m=1\ldots n_{ij}} T_{ijm}}{n_{ij}} \quad and \quad T_{ji} = \frac{\sum_{m=1\ldots n_{ji}} T_{jim}}{n_{ji}}$$

It should be noted that in the above algorithm we also included some upper and lower limiting values of travel time to filter out samples of MAC addresses with very small or big travel times. We considered 20 and 400 seconds as lower and upper limits of travel time, respectively. These thresholds were defined based on the distance of the sensors. The lower limit is defined based on the shortest distance between sensors (50 meters) and with respect to the average walking speed of 5 km/h which amounts to about 35 seconds between sensors. Then we adjust the threshold from 35 seconds to 20 seconds to address the cases with overlap between sensors that change the effective distance between sensors. The upper limit is defined as twice of the maximum time that a pedestrian needs to travel between sensors that is about 190 seconds. Then we adjust it to 400 seconds to address cases that people stop in their path to take pictures which is common in the case study location. Also, the time window threshold should be large enough to make sure the user has enough time to get to another sensor. It can be defined based on the distance between the sensors, the normal walking speed of pedestrian and the minimum driving speed of a vehicle in rush hour traffic conditions.

3. SYSTEM EVALUATION AND DATA EXTRAPOLATION

The developed system was tested on the McGill University campus which is a pedestrian-only network. The goal of this test was to evaluate the system detection rate. The system performance was also compared to existing systems. Moreover, we investigated the relationship between the number of detections and the total number of pedestrians walking along a specific path.

### 3.1 Testing Definition and performance measures:

The test location (McGill University campus) is located in downtown Montreal, Canada. The testing area is composed of pedestrian streets, with low bike traffic and almost no vehicular traffic. The aim was to investigate the performance of our real-time system in a pedestrian environment to determine travel times, paths (O-D matrices) in a given facility and detection rates in order to explore the potential of this technology as a counting device. In this test site, our integrated BT-WiFi system was used and performance of both technologies are evaluated. The system evaluation was done based on 6 days of data collection (with more than 50 hours recorded video for manual counting and validation) in June and July, 2015.

As shown in **Figure 2**, three BT-WiFi sensors were installed in three strategic locations (Roddick Gate, in an intersection and Milton Gate). In addition, a camera and a counter (infrared sensor) were installed between two sensors for validation and extrapolation purposes. McGill campus is a pedestrian-only network with minimal cyclist traffic, so it is a good place to test single mode sensors. Detection rate analysis was performed at different intervals. Network flows between campus entrances and exits were determined. Bluetooth and WiFi technologies were also tested and compared in parallel.

For the test, three devices were built each of them with a water-proof enclosure. The details of the testing sites and results are provided in the following subsections.

It is important to mention that the criteria to evaluate the performance of the system were (i) the number of detections per location, (ii) the number of matched MACs between two sensors with respect to the total volume (detection rate = Total unique MAC addresses read in two locations / Total traffic volume (in a single or both directions) in 15min, 30min or 1hr intervals), and (iii) travel time (speed) measurements. Detection rate criteria can be used for extrapolation and origin-destination studies while pedestrian travel speeds in can be used in study of passenger transfer time in public hubs like airports, metro and train stations, shipping malls, etc. Ground truth volumes were obtained using a video camera installed during the test from which video data was obtained and processed manually.
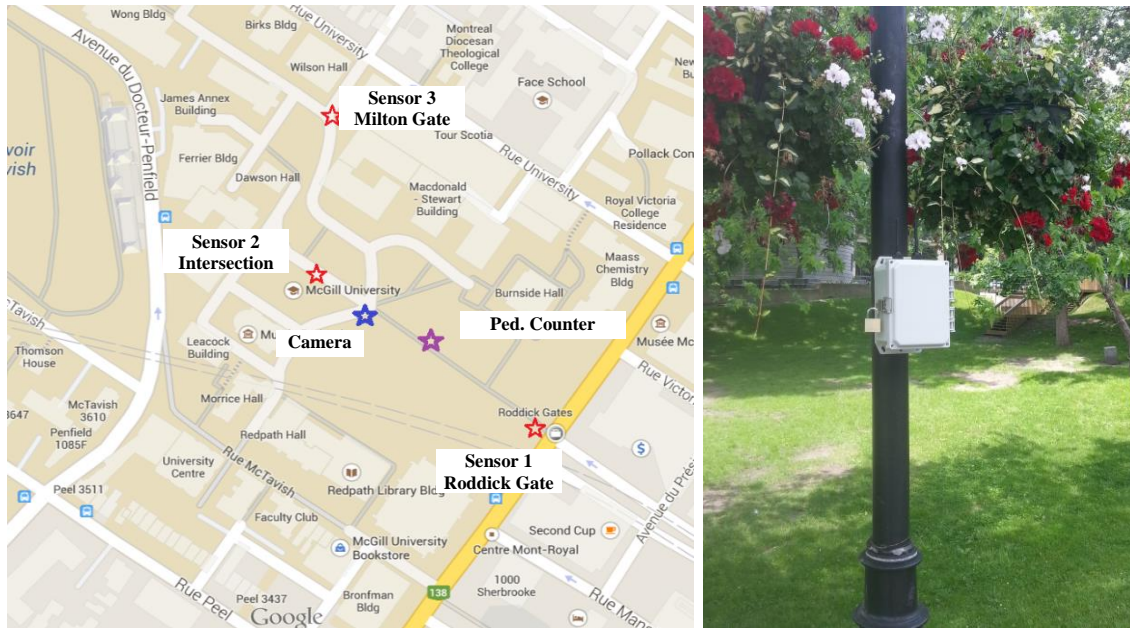
Figure 2 Sensor locations on McGill University downtown campus and sensor installation

3.2 Detection Rate Analysis

In our first analysis, we compared the number of paired MAC addresses between sensors with the manually counted number of pedestrians in each direction. Then, detection rates in each direction were computed. **Table 1** shows a one day sample detection rate of both the Bluetooth and WiFi technologies. Note that the total number of pedestrians travelling from the main gate (sensor 1) to sensor 2 (as illustrated in **Figure 2**), was determined using video. In addition, in order to count a pedestrian, the person had to be detected by at least 2 sensors. That is, a pedestrian passing sensor 1 needed to have been detected either at sensor 2 or 3, in order to be counted. After analyzing the videos, one can see clearly, WiFi had a much higher detection rate than Bluetooth. This is not surprising given the low usage of Bluetooth technologies in pedestrian networks – as reported in previous research (Malinovskiy et al., 2012).

Table 1 Sample of one day directional number of detection and detection rate for each technology

Time period		Total volume		WiFi				Bluetooth detection rate			
				Detected WiFi signals		Detection WiFi Rate		Detected BT signals		Detection BT Rate	
start	End	Dir. 1	Dir. 2	Dir. 1	Dir. 2	DR* (Dir. 1)	DR (Dir. 2)	Dir. 1	Dir. 2	DR (Dir. 2)	DR (Dir. 2)
11:00	11:15	82	69	21	17	25.6	24.6	1	3	1.2	4.3
11:15	11:30	149	164	33	32	22.1	19.5	0	2	0.0	1.2
11:30	11:45	127	113	49	19	38.6	16.8	1	0	0.8	0.0
11:45	12:00	64	78	8	18	12.5	23.1	2	1	3.1	1.3
12:00	12:15	82	89	21	18	25.6	20.2	0	0	0.0	0.0
12:15	12:30	75	99	21	18	28.0	18.2	0	1	0.0	1.0
12:30	12:45	108	132	20	18	18.5	13.6	1	1	0.9	0.8
12:45	13:00	154	173	28	38	18.2	22.0	2	0	1.3	0.0
13:00	13:15	138	130	55	30	39.9	23.1	1	0	0.7	0.0
13:15	13:30	70	87	22	15	31.4	17.2	0	2	0.0	2.3

DR = Detection rate

Figure 3.a presents all the sample intervals that are used in this work. Again, the detection rate of WiFi was many times higher than BT, with average detection rates of 27% and 2%, respectively. **Figure 3.b** compares our developed system with a Meshlium sensor, a Bluetooth-WiFi sensor designed by Libelium (*www.libelium.com*). In order to fairly compare the two systems, we used the same antenna and installed both sensors at the same location. **Figure 3.b** shows the hourly number of unique MAC addresses detected by our system and the Meshlium sensor.

1 Based on the plot, we detected more than twice as many unique Mac addresses using our system in comparison with
2 Meshlium. These results clearly show the better performance of our system.
3
4
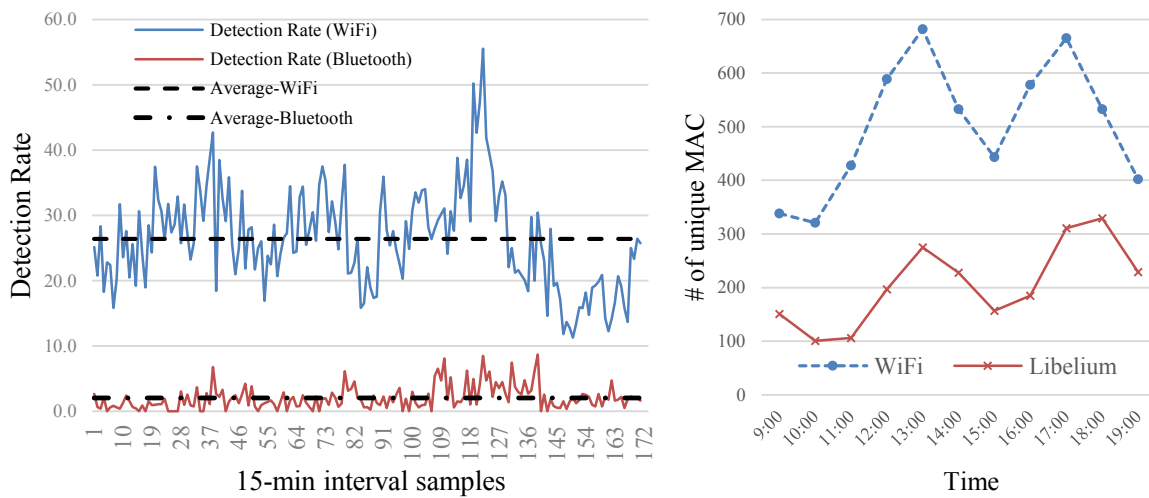
5 **Figure 3 a) detection rate samples using Bluetooth and WiFi technologies in each 15-min intervals (left), b)**
6 **Comparison between our developed system with Libelium (right),**
7

8 Moreover, **Table 2** shows some statistics on detection rate using both technologies. Due to different patterns in the
9 number of trips captured by a sensor for different flow rates, we divided the pedestrian flow into different categories
10 and calculated statistical parameters for each category separately. Based on the results, we can see a drop in the average
11 detection rate as the volumes increased. This drop can be due to the short available time for the system to process
12 WiFi probe signals in high-volume conditions. A potential solution to be tested in the future is the use of a redundant
13 system (e.g., two WiFi modules could be implemented in the same sensor). In **Figure 2**, we can also see some patterns
14 in the standard deviations of the detection rates for different intervals. We expect more noisy behaviour for the
15 detection rates in time interval with high pedestrian flows, i.e. peak hour at noon. As an example, in two intervals with
16 the same high pedestrian flows, depending on how flow rates are distributed in that 15-min interval, we can see
17 completely different detection rates. If several individuals come to a detection zone as a group, the probe signals might
18 be so noisy (high interferences ratio) that the signal processing becomes too complex. On the other hand, if the high
19 pedestrian flow is distributed uniformly, interferences between the signals would be minimal and then the sensor can
20 differentiate between them. This concept can be seen in practical results in **Table 2** where the standard deviation of
21 the detection rate samples increases when the pedestrian flow increases.
22
23   **Table 2 Some statistics on detection rates (15-min intervals)**

Ped. Flow	# of samples	WiFi				Bluetooth			
		Average	**Std.**	**Min**	**Max**	**Average**	**Std.**	**Min**	**Max**
<80	9	28.22	5.26	18.42	35.82	3.42	3.02	0.00	8.70
80-120	22	30.09	5.92	20.99	42.70	2.35	1.97	0.00	6.74
120-160	59	27.23	7.01	14.17	55.56	2.17	1.99	0.00	8.50
160-200	31	25.89	8.79	12.28	47.34	2.10	1.41	0.00	5.20
200-240	19	26.04	8.62	15.76	50.22	1.28	1.09	0.00	4.93
>240	29	22.13	8.86	11.27	38.85	1.43	1.16	0.26	6.23
Dataset	**169**	**26.40**	**7.75**	**11.27**	**55.56**	**2.02**	**1.80**	**0.00**	**8.70**

24
25   Based on the results, the high detection rates of WiFi is very promising with respect to Bluetooth technology.
26 For instance, an average detection rate of 26.4% was observed. On the other hand, the Bluetooth technology detection
27 in this test was very low (less than 2.02%). This is a little lower to those reported in the literature (3 to 5%)
28 (Malinovskiy et al., 2012). Our preliminary results demonstrates the advantages of integrating WiFi with a traditional
29 Bluetooth system, in particular in walking environments with very low detection rates for Bluetooth. The main reason
30 for the low sample rate of the Bluetooth technologies can be explained with a concern about the safety and power

1 consumption of the BT technology. To address these concerns, in recent versions of Android and IOS, Bluetooth
2 device is being put in undiscoverable mode after a short time (about one minute). Thus, even if the Bluetooth is active,
3 it cannot be discovered by other devices.

3.3 Monitoring origins & destinations

5 As the MAC is a unique address set by manufacturer of the device, capturing the address and keeping in data base,
6 we can track user activity through different locations and times. This approach is very critical in management and
7 planning of public pedestrian networks like airports, malls, public transit stations. As a simple example, in an airport,
8 it is very important to know how people spend their free time between transits and waiting for their flight for more
9 efficient infrastructure improvement and development. Here in our case study, having knowledge about the activity
10 of the pedestrians in an entire network (such as origins and destinations, as well as time spent on different places) can
11 help improve available infrastructures like cafeterias, restaurants, libraries and even available green areas on campus.
12 **Table 3** shows a sample of detected activity of a pedestrian coming to campus to leaving it. In this test, there were
13 devices that stayed within campus throughout the day; however there were also devices that we can just see entering
14 the campus and leaving it. If sensors were to be installed on all the floors of every building, it would then be possible
15 to track all human activities. This high quality data would be beneficial for planning, management and emergency
16 evacuation purposes.

17
Table 3 A sample of user activity tracking

48:94:24:--:--:--		50:55:27:--:--:--		F4:37:B7:--:--:--	
Sensor ID	**Time**	**Sensor ID**	**Time**	**Sensor I**	**Time**
3	10:54:16	1	11:45:02	3	10:01:26
2	10:55:19	2	11:51:15	3	10:01:34
2	10:55:45	3	11:51:19	2	10:03:09
2	10:56:14	3	13:31:04	1	10:04:48
1	10:57:47	2	13:33:36	1	11:56:43
1	15:04:30	1	13:35:14	2	11:56:58
2	15:05:13			2	11:57:39
2	15:05:32			3	12:02:33
3	15:07:04				

3.4 Extrapolation

19 Based on these results, it can be seen that in about 80% of the samples, detection rates were over 20%. Having higher
20 detection rate with WiFi in comparison with Bluetooth shows a strong potential in using the system for extrapolation
21 and flow prediction purposes. **Figure 4.a** shows the manually counted pedestrian flow vs the number of captured trips
22 in each 15-min interval. Based on the plot on figure the data can be described in two different categories: The first
23 category shows more of a dense linear pattern and the second category describes a sparser pattern with a bigger
24 variance that cannot be identifies with a simple linear function. The high pedestrian volumes are associated with the
25 second category. In this paper, based on the plot, we considered samples with detected flow rates less than 60 trips
26 per 15 min intervals as the threshold to categorize the dataset. However, more complex and automated classification
27 methodologies can be applied for future studies. Then, we calibrated a model for each category and predicted the total
28 flow based on the calibrated model. In order to calibrate the model, we divided dataset into two groups. The first group
29 was the training dataset which was used for model calibration and the second group was the test dataset which had not
30 been subject to model training and was used to test the performance of the model.
31 Different models were calibrated for each category of data and based on some statistical parameters such as
32 R-squared, the best model was chosen. For the first category, a power function was calibrated while for the second
33 category, a Fourier function was calibrated. The respective R-squared values were 0.91 and 0.18 for each model. The
34 low R-squared value of the second model may most likely be attributed to the fact that in the six days data, we did not
35 have enough samples in that category. The calibrated models for each category were as follows:

$y = 21.2x^{0.53}$ First category, power function

$y = 232.9 - 6.798\sin(0.1879x) + 64.88\cos(0.1879x)$ Second category, Fourier function

36 **Figure 4.b** shows the plots for the number of detected trips using the WiFi sensor, the total number of trips
37 counted manually as ground truth and the model prediction results. Based on the results, the proposed model could
38 adequately track the pattern on the 15-min interval pedestrian flow. The average prediction error was around 15%
39 while the median prediction error was around 9% which is promising. However, the model still needs to improve in
40 order to operate accurately in peak hour period with high pedestrian flow.
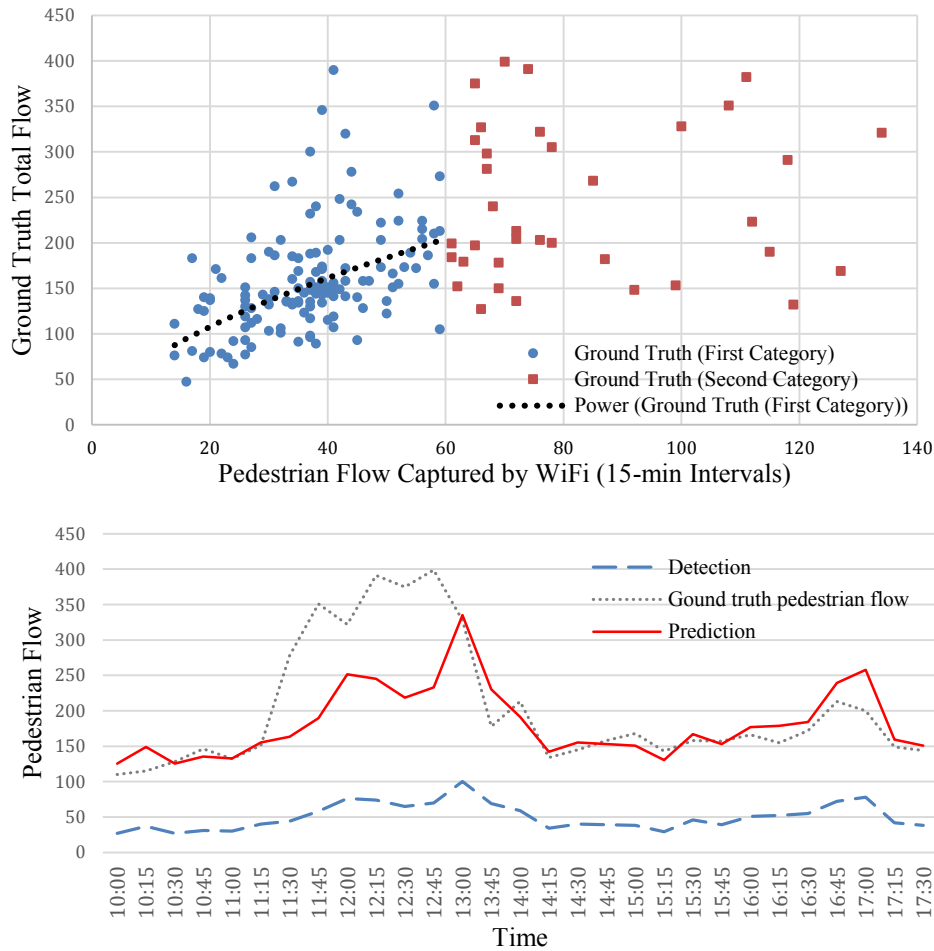
Figure 4 a) Pedestrian flow, ground truth vs. detected by WiFi in top, b) Ground truth, captured by WiFi and predicted number of pedestrian at bottom

3.5 Travel Time Analysis

In addition to the detection rate, travel times were computed based on timestamped detected MAC addresses and were compared with the expected travel time of a pedestrian walking at a normal pedestrian average walking speed (5 km/h). **Table 4** shows the hourly average speed and variance between each pair of sensors. It is worth mentioning that issues may arise when computing travel times (speeds) regarding people loitering near the coverage area of a sensor or staying on campus for extended periods of time (working inside a building, etc.). These pedestrians can report incredibly long travel times to the system. In order to account for this issue, these observations must be filtered out in the speed analysis. In this paper we set the upper limit as 10 min (twice the travel time based on a normal walking speed of 5 km/h) and the lower limit as half the time needed to travel between the two closets sensors.

Table 4 Hourly average speed between sensors

start	End	From Roddick to Intersection (Km/h)	From Roddick to Milton (Km/h)	Average (Km/h)
11:00	12:00	5.2	4.8	5.0
12:00	13:00	5.8	4.7	5.4
13:00	14:00	5.3	4.8	5.2
14:00	15:00	5.3	5.0	5.1
15:00	16:00	5.5	4.7	5.1
16:00	17:00	5.4	4.9	5.1
17:00	18:00	5.0	4.7	4.9
18:00	19:00	5.3	4.7	5.1
19:00	20:00	6.4	4.9	5.6
Variance		**0.16**	**0.01**	**0.04**

When the travel time was calculated it is important to know if the MAC address was detected at the entrance or exit of the detection area of sensor or somewhere else. This time will change the effective distance between sensors. To find the travel speed, assume that the detection radius of the sensor i is r_i and also we define the distance and travel time between two sensors as d_{ij} and t_{ij}, then the average speed between two sensors would be $S_{ij} = \frac{d_{ij} \pm r_i \pm r_j}{t_{ij}}$. We name nominator term in that equation as effective distance. In practice, it is not possible to find the exact coverage area of each sensor and exact location of the detected MAC address in this area. Therefore, it is not possible to find the exact effective distance between two sensors. When the detection area of each sensor is much smaller than the distance between two sensors, then a change in effective distance will be negligible. In this test, the distance between sensor one and two was small (about 150 meters). We expected a bigger variance for average travel time measured between sensor one and two in comparison with average travel time measured between sensor one and three (which were 350 meters apart). This concept can be seen from data in **Table 4**. The variance of the average speed between sensor one and sensor two was 10 times more than the variance of the average speed between sensor 1 and sensor 3. Based on these results, it is suggested that a network of sensors spaced far apart be used to increase the accuracy of travel time measurements.

4. PRELIMINARY CONCLUSIONS AND WORK IN PROGRESS

This research developed and evaluated the performance of a BT-WiFi system to detect anonymous MAC addresses of devices at short distances at fixed locations. The sensors were able to capture signals from WiFi-enabled mobile devices and enabled and discoverable Bluetooth devices for the purpose of measuring travel times and speeds.

The performance and flexibility of the proposed WiFi-BT system over existing systems was shown through a case study. Promising results were obtained with higher WiFi detection rates to those typically reported in past studies using only Bluetooth technologies. Testing the system in a pedestrian network for six days resulted in an average detection rate of 26% for the WiFi system (with detection rates up to 50%). In comparison, this average detection rate for the Bluetooth technology was as low as 2.02%. In fact, Bluetooth technologies alone are unfeasible in pedestrian network given the low detection rates. Therefore, WiFi protocol can then be seen as a much better alternative to Bluetooth sensors in pedestrian networks.

The system performance was also tested against the Meshlium WiFi-Bluetooth sniffer sensor developed by Libelium. Our developed system detected more than twice the number of unique MAC addresses demonstrating its adequate performance with respect to what is available in the marketplace.

Furthermore, the combination of our WiFi-Bluetooth system with video data for pedestrian flow extrapolation was also explored. We proposed a simple approach to calibrate and estimate pedestrian flows by assigning an extrapolation function to the number of detections in each interval. Using our primary results, two models for classified dataset were fitted with R-squared values of 0.91 and 0.18 respectively were fitted. Also, we could get average and median prediction error of 15% and 9% respectively that looks promising. However, there is still room to improve the extrapolation modeling and methodologies. Additionally, promising results were obtained regarding capturing the average travel time and speed of pedestrians in comparison to a normal walking speed (5km/h). An error of around 3.8% for the hourly average travel time estimation was achieved. These results show the promising performance of our system for monitoring pedestrian networks for estimating travel times, modeling activity, conducting origin-destination studies, and pedestrian flow extrapolating, among other applications.

Our system is designed to work in real time in the sense that all the captured MAC addresses can be transferred to a web server at a predefined time frame that can be set by the user. We can power our system with a battery to collect data for few days at mobile or fixed locations. We are able to control all the parameters that can affect the performance of the system and improve them. More importantly, we are able to integrate other sensors with our system in order to efficiently monitor facilities in real time.

Several aspects of our research are still being explored:

- Software optimization is already underway to ensure that we are not missing any data and are only collecting relevant data. This will include packet truncation, optimized channel scanning, and device lookup tables for classifying both manufacturer and type of device (laptop, smartphone, vehicle, etc.).

1   -   The system will be integrated with other designed automated pedestrian counting systems such as ultrasonic
2   technology. The counting sensory system will be connected to the main processor through a wire or Bluetooth
3   and data will be transferred to a server though the Internet.

4   -   The system will integrate WiFi and Bluetooth information to increase the detection rate while considering
5   the over-counting issue (capturing a person with both active Bluetooth and WiFi). For Apple devices, the
6   over counting issue solved relatively easily, given the fact that WiFi and Bluetooth MACs differ just in the
7   last character. But for other manufacturer, more investigation will be required. Alternatively, traffic
8   parameters (e.g., travel times) could be computed with each technology and fused together to produce reliable
9   estimates. The classification of pedestrians, cyclists and vehicles is another topic that can be investigated.
10   The initial idea would be to use the database of all the detected MAC addresses over time and check the
11   average speed of the same MAC address at different times. The MAC address could be classified based on
12   historical data.

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