University Transportation Research Center - Region 2

Final Report

Portable and Integrated Multi-Sensor System for Data Driven Performance Evaluation of Urban Transportation Networks

Performing Organization: New York University

September 2018

Sponsor:
University Transportation Research Center - Region 2

University Transportation Research Center - Region 2

The Region 2 University Transportation Research Center (UTRC) is one of ten original University Transportation Centers established in 1987 by the U.S. Congress. These Centers were established with the recognition that transportation plays a key role in the nation's economy and the quality of life of its citizens. University faculty members provide a critical link in resolving our national and regional transportation problems while training the professionals who address our transportation systems and their customers on a daily basis.

The UTRC was established in order to support research, education and the transfer of technology in the field of transportation. The theme of the Center is "Planning and Managing Regional Transportation Systems in a Changing World." Presently, under the direction of Dr. Camille Kamga, the UTRC represents USDOT Region II, including New York, New Jersey, Puerto Rico and the U.S. Virgin Islands. Functioning as a consortium of twelve major Universities throughout the region, UTRC is located at the CUNY Institute for Transportation Systems at The City College of New York, the lead institution of the consortium. The Center, through its consortium, an Agency-Industry Council and its Director and Staff, supports research, education, and technology transfer under its theme. UTRC's three main goals are:

Research

The research program objectives are (1) to develop a theme based transportation research program that is responsive to the needs of regional transportation organizations and stakeholders, and (2) to conduct that program in cooperation with the partners. The program includes both studies that are identified with research partners of projects targeted to the theme, and targeted, short-term projects. The program develops competitive proposals, which are evaluated to insure the mostresponsive UTRC team conducts the work. The research program is responsive to the UTRC theme: "Planning and Managing Regional Transportation Systems in a Changing World." The complex transportation system of transit and infrastructure, and the rapidly changing environment impacts the nation's largest city and metropolitan area. The New York/New Jersey Metropolitan has over 19 million people, 600,000 businesses and 9 million workers. The Region's intermodal and multimodal systems must serve all customers and stakeholders within the region and globally.Under the current grant, the new research projects and the ongoing research projects concentrate the program efforts on the categories of Transportation Systems Performance and Information Infrastructure to provide needed services to the New Jersey Department of Transportation, New York City Department of Transportation, New York Metropolitan Transportation Council , New York State Department of Transportation, and the New York State Energy and Research Development Authorityand others, all while enhancing the center's theme.

Education and Workforce Development

The modern professional must combine the technical skills of engineering and planning with knowledge of economics, environmental science, management, finance, and law as well as negotiation skills, psychology and sociology. And, she/he must be computer literate, wired to the web, and knowledgeable about advances in information technology. UTRC's education and training efforts provide a multidisciplinary program of course work and experiential learning to train students and provide advanced training or retraining of practitioners to plan and manage regional transportation systems. UTRC must meet the need to educate the undergraduate and graduate student with a foundation of transportation fundamentals that allows for solving complex problems in a world much more dynamic than even a decade ago. Simultaneously, the demand for continuing education is growing – either because of professional license requirements or because the workplace demands it – and provides the opportunity to combine State of Practice education with tailored ways of delivering content.

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UTRC's Technology Transfer Program goes beyond what might be considered "traditional" technology transfer activities. Its main objectives are (1) to increase the awareness and level of information concerning transportation issues facing Region 2; (2) to improve the knowledge base and approach to problem solving of the region's transportation workforce, from those operating the systems to those at the most senior level of managing the system; and by doing so, to improve the overall professional capability of the transportation workforce; (3) to stimulate discussion and debate concerning the integration of new technologies into our culture, our work and our transportation systems; (4) to provide the more traditional but extremely important job of disseminating research and project reports, studies, analysis and use of tools to the education, research and practicing community both nationally and internationally; and (5) to provide unbiased information and testimony to decision-makers concerning regional transportation issues consistent with the UTRC theme.

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16. Abstract

The primary objectives of this research study are (1) to deploy some promising low-cost portable and integrated multi sensor systems for data-driven performance evaluation of urban transportation networks and (2) to develop a system capable of real-time remote monitoring of external changes, such as air quality, noise, humidity, temperature, and crowd and vehicular densities in an urban setting. This report describes the design, fabrication, and characterization of such a portable and integrated multi-sensor system for the performance evaluation of urban transportation networks and their environmental impacts. The system uses multiple low-cost, yet effective, sensors to capture particulate matter level, humidity, and temperature of ambient air as well as pedestrian and vehicular traffic. The major outcome of this research project is the development of a smart sensing system capable of acquiring and then sending detailed critical environmental and traffic information wirelessly from the fixed installation location to a remote server with the ultimate goal of making on- and off-line decisions to improve urban operations.

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2. EXECUTIVE SUMMARY

The primary objectives of this research study are (1) to deploy some promising low-cost portable and integrated multi sensor systems for data-driven performance evaluation of urban transportation networks and (2) to develop a system capable of real-time remote monitoring of external changes, such as air quality, noise, humidity, temperature, and crowd and vehicular densities in an urban setting.

This report describes the design, fabrication, and characterization of such a portable and integrated multi-sensor system for the performance evaluation of urban transportation networks and their environmental impacts. The system uses multiple low-cost, yet effective, sensors to capture particulate matter level, humidity, and temperature of ambient air as well as pedestrian and vehicular traffic.

All sensors were tested in a laboratory environment; the resulting performance, the discovery and development of the sensors, and the sensor testing are all described in this report. Section 5 of this report also describes the demonstration of similar sensors in a real-world application to identify secondary crashes. This is done to illustrate the applicability of such low-cost ubiquitous sensor systems to some of the most important transportation safety and operations problems.

The air quality, temperature and humidity readings of the multi sensor platform were found to be consistent with the samples collected using commercial sensors in the testing environment. Although the noise sensor is not calibrated up to the level that it can accurately represent sound pressure levels, it still provides a nominal noise level to make comparisons between different installation sites. The major outcome of this research project is the development of a smart sensing system capable of acquiring and then sending detailed critical environmental and traffic information wirelessly from the fixed installation location to a remote server with the ultimate goal of making on- and off-line decisions to improve urban operations.

3. INTRODUCTION

New York City (NYC) and many urban areas need to keep track of the impacts of vehicles on their transportation system as well as the residents of the city. These impacts can be in terms of congestion, emissions, and noise. In urban areas, disruptions of traffic such as double parking, commercial vehicle deliveries, pedestrian jaywalking, and taxi pick-ups and drop-offs are potential impediments to road capacity and vehicular speed and cause traffic delays and safety risks. Due to advances in sensors and computing, information related to traffic flow, parking, emissions, noise, trajectories of individual vehicles or pedestrians can be obtained from traditional point sensors (infrared, loop detector, acoustic, emissions) as well as video and thermal cameras, RFID detectors and tracking apps installed on smart phones. These new sensing technologies, which are also highly mobile and relatively inexpensive, can be integrated with innovative data analytics capabilities. Thus, they have the potential to change the way we collect and analyze traffic data in urban areas. These encouraging developments are even more promising due to the development of wireless and mobile communication technologies which allow for collecting very large amounts of data from the entirety of the urban landscape without the need for the expensive communication infrastructure required for deploying traditional sensors. Unfortunately, these integrated inexpensive multi-sensor solutions are not widely and commercially available yet.

During the last decade, the research team has been working on developing, deploying and testing these low-cost sensing and data analytics platforms that can collect and process data for multiple applications (Kurkcu & Kaan Ozbay, 2017; Kurkcu & Ozbay, 2017; Ozbay et al., 2017; Shlayan, Kurkcu, & Ozbay, 2016). In this project, we propose to develop and deploy a customized integrated multi-sensor platform to record vehicle and pedestrian movements, and to measure noise and emissions due to these movements. These inexpensive and ubiquitous sensor boxes are envisioned to be deployed at various key locations throughout NYC. They are small and thus very easy to mount on any city-owned structure after the necessary permissions are obtained. Each integrated sensor box costs less than a few hundred dollars and will have Wi-Fi / BT capabilities for remote data acquisition and communication. They can provide the DOT with the unique ability to collect video, noise, and emissions data simultaneously at a large number of important locations.

In summary, this project is shown to be an ideal pilot test for the demonstration of the applicability of advanced sensing systems towards solving urban transportation-related issues. This project also demonstrates the economic feasibility of the deployment of a large number of multi-sensor systems in the city with the ultimate goal of using multi-sensor data for data-driven decision-making.

4. LITERATURE REVIEW & BACKGROUND

Human movement behavior research has received increasing attention particularly in the field of transportation planning. The traditional methods for pedestrian mobility monitoring include surveys, fixed pedestrian counters, and vision-based technologies. However, these techniques are neither easy to implement nor cost-effective. In addition, video-based technologies rely on a clear view of the crowd over a limited spatial range, which requires integration of data from a number of cameras over the whole spatial range for which mobility data is collected. In recent years, several studies have been reported in the literature on automating pedestrian detection or counting to explore economic and reliable methods (Bu, Greene-Roesel, Diogenes, & Ragland, 2007; Ozbay, Bartin, Yang, Walla, & Williams, 2010; Hong Yang, Ozbay, & Bartin, 2010, 2011). These researchers reviewed the available automated pedestrian counting technologies such as infrared and thermal sensors (Ozbay, Yang, & Bartin, 2010). With the increase in smart devices, research has started focusing on tracking mobile phones to estimate pedestrian movements. If the detection system is equipped with Wi-Fi and Bluetooth receivers, it is possible to capture Origin-Destination (OD), travel time, wait time and flow information for some subset of the pedestrians with visible Wi-Fi and Bluetooth devices. People with electronic devices, such as most cell phones, tablets, and computers carry unique information, a Media Access Control (MAC) address, in their devices that can be used to collect pedestrian data for estimating measures such as travel time (Malinovskiy, Saunier, & Wang, 2012). This type of traffic detection systems can be supplemented by traditional sensing technologies to improve crowd monitoring systems (Abedi, Bhaskar, & Chung, 2013).

MAC addresses are the most common unique identifiers in IEEE 802 network technologies. There are 6 bytes/48 bits, making it possible to generate 2^{48} potential unique MAC addresses. The first three bytes contain an organizationally unique identifier (OUI), and the following three are assigned by the organization in any manner as long as it is unique. Every Bluetooth or Wi-Fi device is defined by a MAC address. Therefore, individual devices can be tracked, and this feature has been utilized in various applications and data collection processes in the literature.

To be able to manage transportation systems efficiently, information about non-motorized traffic is required. However, decision makers and transportation officials in the U.S. have not yet extensively examined non-motorized traffic (Lindsey, Nordback, & Figliozzi, 2014). In addition, most agencies lack comprehensive pedestrian counts mainly because of technological limitations. Some of these challenges can be explained as:

- Unlike motorized vehicles, pedestrians do not travel in fixed lanes or paths and make unpredictable movements.
- Pedestrians sometimes travel very closely to each other creating platoons, and some sensors have difficulty counting individuals within the group (Ozbay, Bartin, et al., 2010).

- The number of locations for which pedestrian data are needed is exponentially higher than is the number needed for monitoring vehicular traffic.

Although FHWA's Traffic Monitoring Guide (TMG) does not address technologies such as Wi-Fi and Bluetooth sensing for O-D or travel time, it summarizes the potential options for pedestrian counting technologies and respective costs (USDOT & FHWA, September 2013). Table 1below illustrates available technologies and costs adapted from that guide; the table is updated with the addition of relevant information about wireless sensors.

Table 1: Available Pedestrian Counting Technologies - Source: USDOT and FHWA (September 2013)

Length of Time Technology is Usable	Technology	Pedestrian Detection	Cost
Permanent	Wi-Fi & Bluetooth Sensors	TP	$
↕	Pressure Sensor	TP	$$
	Radar Sensor	TP	$-$$
	Seismic sensor	TP	$$
	Video Imaging: Automated	TP	$-$$
	Infrared Sensor (Active or Passive)	CP	$-$$
	Video Imaging: Manual	TP	$-$$$
Temporary/Short Term	Manual Observers	CP	$$-$$$
TP:	Indicates what is technologically possible		
CP:	Indicates a common practice		
$, $$, $$$	Indicates relative cost per data point		

Most of the common pedestrian monitoring technologies mentioned in the table above focus on counting pedestrians according to the location specific point data in the network. However, it is not possible to anonymously track pedestrians or groups as they move outside of each particular sensor's range. Tracking pedestrians may be achieved by using video imaging and matching the same pedestrians but not preferred due to the high cost and computational complexity. Therefore, there is a need for building low-cost, customized ubiquitous sensors. The sensors and the codes used to collect wireless traces were developed in-house in this study. These sensors use wireless technologies and algorithms to track individual movements, measure wait times, and estimate flows. One disadvantage of using such sensors is that not everyone carries a detectable smart device, and some carry more than one. Estimating flows and counts rely on some assumptions about the crowd and conditional factors, depending on the site of the study. Although almost all of these applications used similar datasets, only a few developed their own sensors and comprehensive techniques for removing erroneous detections (Chilipirea, Petre, Dobre, & van Steen). In addition, measures other than pedestrian movement and O-D data were not investigated.

Woznowski et al. (2015) have presented a study of Ambient Assisted Living (AAL) sensors to help seniors and people with medical needs. The U.K. has more than 10 million people over age 65. On average, the National Health System (NHS) spends two times more money for a retired household than what is spent for a non-retired household. Therefore, it is critical to build AAL systems based on sensor technologies. The understanding of Activities of Daily Living (ADL) plays a crucial role in provisioning of appropriate and efficient care. To report these boundaries, they have proposed a multi-modal system architecture for AAL remote healthcare monitoring in the home, gathering information from multiple, diverse (sensor) data sources. Their vision is to develop a multipurpose, multi-modal platform of home sensors called SPHERE (Sensor Platform for HealthCare in Residential Environment). The proposed platform is based on three different sensor technologies. SPHERE aims not only to extend state of the art in a number of technology domains but to engage with stakeholders across disciplines and across sectors to illuminate the applications of current technologies to known health needs and of new technologies to emerging health needs. Their work in SPHERE addresses critical issues such as cost, power consumption, scalability, interoperability, and privacy to enable large-scale deployment of the system for healthcare studies and real-life AAL applications.

Sreejith et al. (2014) studied the altitude sensor to use as a building block in a closed-loop pointing stabilization platform for balloon-borne payloads. Their goal is to make observations of extended nearby objects (e.g. comets) and of diffuse sources (e.g. zodiacal light or airglow) with wide field of view (FOV) instruments. The total payload weight is limited to less than 6 kg in lightweight balloons, placing constraints on the sensor size, weight, and power. They have used commercial inertial measurement units (IMU), which combines an accelerometer, a magnetometer and a gyroscope on a single chip. The cost of their equipment is ten times less than commercial products (Sreejith, 2014). They have measured the feasibility of altitude sensors by applying different calibration techniques. These techniques include gyroscope, magnetometer, and pointing. They developed an altitude sensor by utilizing a Raspberry Pi. The sensor can operate in two modes; with and without a magnetometer. After the calibration process, the altitude sensor was examined in different temperatures for thermal dependence. An insulated box provided better performance in keeping the sensor at the ideal temperature. Last but not least, the altitude sensor was flown in different altitudes and tested for accuracy. The overall accuracy of the sensor was 0.5^{O} due to errors in magnetometer.

Geipel, Jackenkroll, Weis, and Claupein (2015) studied sensor technologies to increase productivity in agriculture. Commercial sensor systems are operated with vendor-specific control units, user interfaces, and communication protocols. To overcome the absence of standardized procedures for sensor monitoring and access, Geipel et al. (2015) suggest applying standards from the Open Geospatial Consortium’s (OGC) proposals to systematize agricultural sensor data processing. The most significant attribute of the sensor layer is that the communication between layers can be provided with 2.4-GHz WLAN and 3G network. Weather sensors, solar radiation sensors, and fluorescence sensors are built into the sensor systems in order to maintain and monitor the field-plants’ health. Their work can be applied to machinery and sensor systems for Precise Farming (PF) applications.

Leccese, Cagnetti, and Trinca (2014) proposed a Smart City model to improve traditional city notion. Their plan is to create a better solution for lamp posts and public lighting where the sensors lack 3G and ADSL communication systems in rural and distant areas. By using a Raspberry-Pi control card, they can drop down computing costs to a very low price. They decided to use ZigBee technology, as it has resulted in the best alternative to create sensor networks with low energy consumption. During their research, they met break-even point on their economic analysis.

Kotsev, Pantisano, Schade, and Jirka (2015) studied an approach to enable the interoperability of environmental sensors through the integration of on-board storage and web service capabilities (Kotsev, 2015). Their process was to install out-of-the-box sensor nodes, create independence from particular platforms and simplify provision of sensor data access to the lower barrier for users to rely on standard environmental data. They used a cost-efficient plug-and-play sensor device capable of broadcasting data in an interoperable manner .This can allow farming communities to better observe agro-ecological conditions. Users' Wi-Fi will retain its main role for low-cost, best effort data delivery, particularly for indoor scenarios. On the other hand, the upcoming generation of mobile cellular networks will cater to the high-traffic, low-latency, low-energy requirements by mainly focusing on outdoor urban scenarios. They will develop their initiative further in future research.

Santiago Gaitan, Luca Calderoni, Paolo Palmieri, Marie-Claire ten Veldhuis, Dario Maio, Member, IEEE, and M. Birna van Riemsdijk (2014) worked on monitoring the weather to anticipate emergency events like heavy storm and floods. They developed a fast and coordinated solution to relieve the impact of these events by working on existing sensor infrastructure in Rotterdam. They used Raspberry Pi board to implement this system because of its low cost and power efficiency. In the final analysis, they inducted ICT infrastructure integrating data to gather citizens' feedback such as complaints and social media feeds to gain a high level view of the overall situation in emergency events. Vujovic and Maksimovic (2014) studied home-automation by using sensor web elements as part of Internet of Things (IoT). Their goal is to create comfort, time, and cost efficiency for home owners by following the steps in HVAC (Heating, Ventilation, and Air-Conditioning) control systems. They integrated this traditional system to produce many other rich features, including safety, lighting, access-control, and entertainment. They implemented Raspberry Pi with GPIO connectors as a Sensor Web node to assist with home automation. Vujovic and Maksimovic (2014) investigated the popular boards (MicaZ, TelosB, Iris, Cricket, Lotus) to compare with Raspberry Pi. The results indicated comparative advantages in favor of Raspberry Pi. Processing power, memory and connectivity are the key benefits, while lack of real-time clock (RTC) and SD card requirements are the crucial disadvantages Raspberry Pi represents. Maksimović, Vujović, Davidović, Milošević, and Perišić (2014) studied detailed analyses of Raspberry Pi to prove that it is the best platform for interfacing with many different devices with large amounts of input. To summarize their study, results show that less energy consumption corresponds to cost expenditure and increased convenience, which supports the implementation of Raspberry Pi in web sensor nodes.

Leng, Zeng, Xiong, Lv, and Wan (2013) studied origin-destination (OD) information in the subway system. Their goal is to solve occupancy problems by gaining real-time comprehensive information about passenger flows. Traditional models offered a station-oriented approach, which provides a better prediction than the Metro-net oriented method. However, they do not satisfy forecasting several kinds of passenger flow in real time. In order to close this loophole, they used a probability tree-based passenger model based on historic OD information. They aim to provide a practical, proper and advanced prediction model for passenger flow.

The literature review section attempts to highlight key research efforts related to low-cost portable sensor developments. The extensive literature about these devices shows that they are heavily used in smart city applications. The following section describes the details of the multi-sensor platform, its system architecture, and components.

5. SENSOR DEVELOPMENT

5.1. System Architecture

A cloud-based server structure is implemented to enable tracking and accessing the data in real time, to observe the data collection and to perform self-diagnostics. The research team implemented a cloud-based server that connects to all active devices and ensures data transfer between the device and the server. These files are accessible from any computer connected to the Internet to track the devices. An industry standard encryption method is integrated into the software app developed by the research team to guarantee maximum level of privacy. Moreover, a series of simple yet useful self-diagnostics web-enabled functions, such as the current reporting status of each device, power levels of battery powered devices, and possible data errors, are developed. This software-oriented task will be done in coordination with the equipment testing to ensure that data is captured adequately. Figure 1 below depicts the system architecture that is adopted for this purpose.

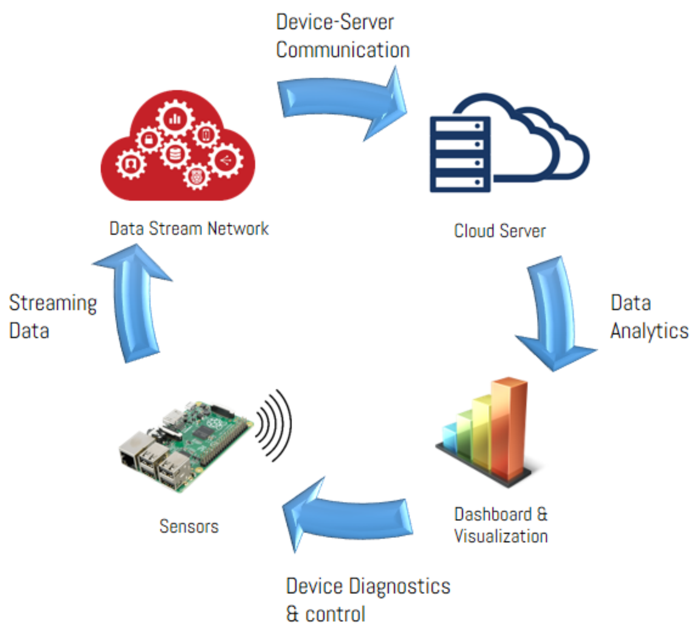


Figure 1 Proposed System Architecture

5.2. Hardware & Software

Raspberry Pi (2008)(2008)(2008)(2008)(2008) is a low cost small sized computer that is compatible with monitors or TVs. It uses a standard keyboard and mouse. Pi supports object-oriented programming languages such as Scratch and Python. It is capable of processing tasks that a desktop computer can do. Furthermore, it is possible to build the Pi so that it can acquire the ability to interact with the environment. Raspberry Pis and similar mini PCs have been employed in various studies in the literature to detect motion (Prasad, Mahalakshmi, Sunder, & Swathi, 2014), measure noise (Mydlarz, Salamon, &

Bello, 2016) and air quality (Cheng et al., 2014), for environmental monitoring (Abraham & Pandian, 2013), and for various other smart city applications.
The Raspbian is an operating system that comes with Raspberry Pi by default. The minimal installation of Raspbian is installed to the sensors. Raspberry Pi 2 Model B, the second generation Raspberry Pi, is used for this project. It has a 900MHz quad-core CPU, 1 GB RAM, 4 USB 2.0 ports, 40 GPIO pins, full HDMI port, Ethernet port, 3.5 mm audio jack, camera interface (CSI), a display interface (DSI), micro SD card slot, and VideoCore IV 3D graphics core. A 16 GB SD card is installed to the sensor. The Raspberry Pi can be powered by a +5.1V micro USB supply. Typically, the model B uses between 700-1000mA depending on what additional gadgets are connected. The maximum power it can use is 1 Amp. With the existing configuration, the sensor can run up to approximately 12 hours on a 10,000mAh battery. One sensor with all the components costs approximately $100-150 depending on the configuration.

5.3. Wi-Fi and Bluetooth Sensors

For Wi-Fi device detection, Aircrack-ng library is utilized to create an access point and sniff the network, and sqlite3 is used as a database to store the data. Aircrack-ng is a complete set of tools to enhance and evaluate Wi-Fi network security. It works mainly on Linux but it is possible to install the library to Windows, OS, and other BSD platforms. The library is able to monitor packet captures and export data to text files. The signal strength (RSSI) of the captured Wi-Fi devices can be used to create a detection zone. With tuning, this creates a detection circle that, when crossed, can trigger the detection system to store the information in SQLite tables. For Bluetooth device detection, the default library for Raspberry Pi (Bluetooth) to detect Bluetooth devices is installed. The scan is executed every second to find available devices nearby. Bluetooth devices do not have the signal strength information.

5.3.1. Wi-Fi Antenna Characteristics

Three different Wi-Fi antennas are evaluated to understand the effects of antenna quality on the received signal strength. Figure 2 shows the experiment setup. Two Raspberry PIs are located 10 ft. apart from each other for this experiment. One of them was programmed to capture probe requests transmitted by wireless devices. The other one was programmed to send its probe requests every second in order to capture enough samples within the study period.

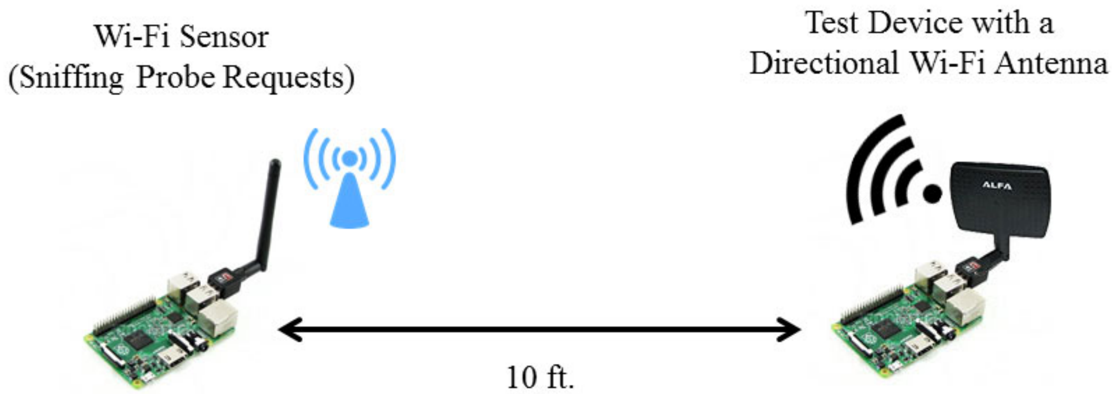


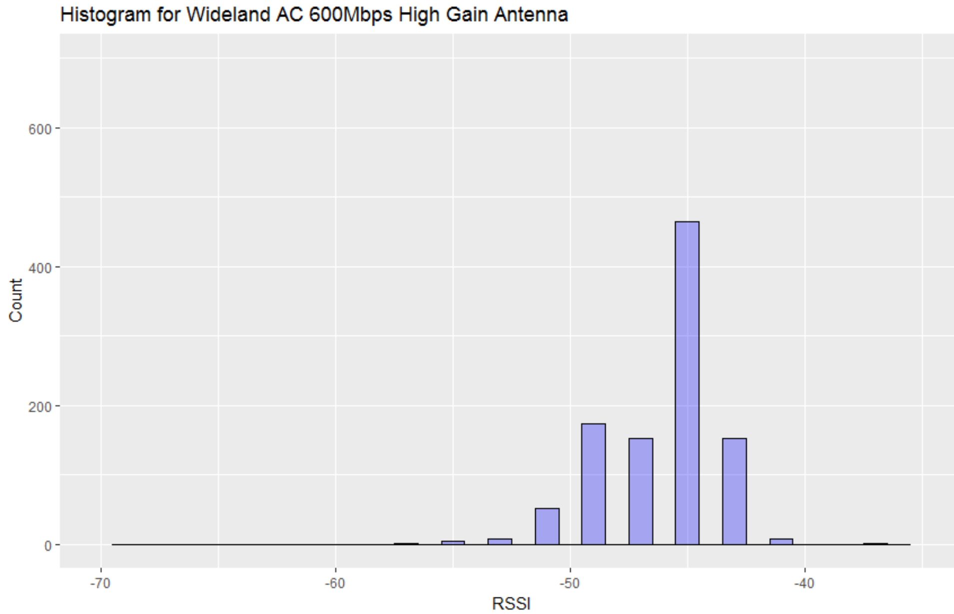
Figure 2: Experiment Setup

Two of the tested antennas are omni-directional, meaning they can transmit/receive Wi-Fi signals in all directions. One of them is a directional antenna, which can only transmit signals in the direction the antenna is facing. The test device sending probe requests was also installed with the same directional antenna to make the signal strength transmitted by the device more robust and noise free. Table 2 below shows the comparison of the received signal strengths (RSSI) by the Wi-Fi sensor with three different antennas.

Table 2. Wi-Fi Antenna Comparison

Type	Sample Size	Min. RSSI	Mean RSSI	Max RSSI	S.D. RSSI
Wideland AC 600Mbps High Gain Antenna (Omni-directional)	1017	-57	-46.1	-37	2.42
BrosTrend 1200 Mbps High Gain (5dBi) Antenna (Omni-directional)	967	-69	-43.6	-37	3.4
Alfa .24HGz 7dBi Antenna (Directional)	884	-69	-44.9	-37	2.9

To better understand the variation of the signal strength, histogram plots of each antenna's received signal intensity are generated in Figure 3. Although Wideland's antenna reached the best signal strength in the experiment, its distribution of received signals is more dispersed than the other two antennas. The other two; BrosTrend's omni-directional antenna and Alfa's directional antenna respectively, performed better regarding consistently receiving the same signal strength for the fixed device placed 10 ft. away from the sensor. Therefore, it may be more appropriate to use one of those two antennas for data collection purposes.


Histogram for Wideland AC 600Mbps High Gain Antenna
600
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200
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Count
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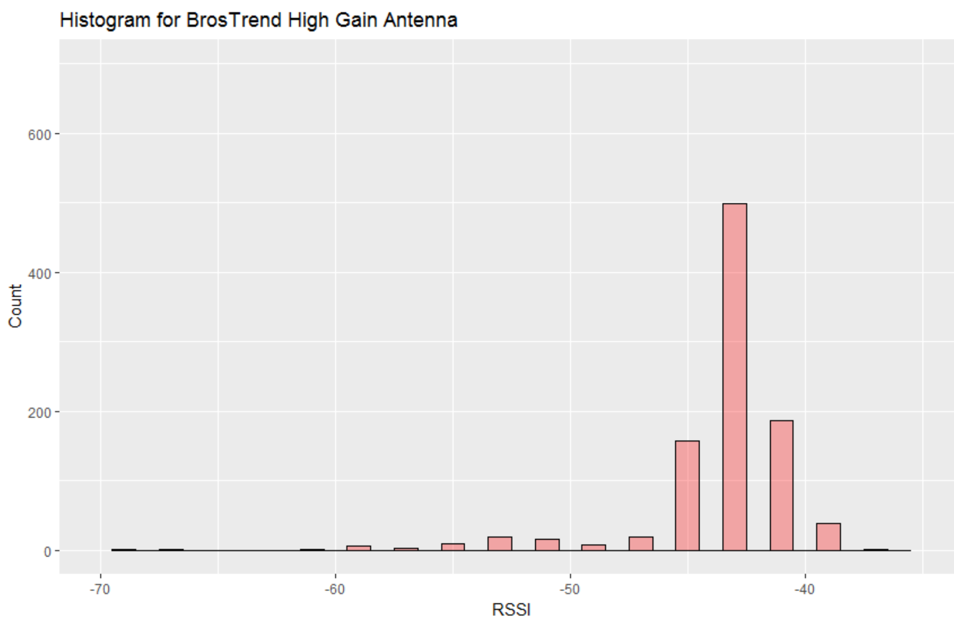
-60
-50
-40
RSSI


Histogram for BrosTrend High Gain Antenna
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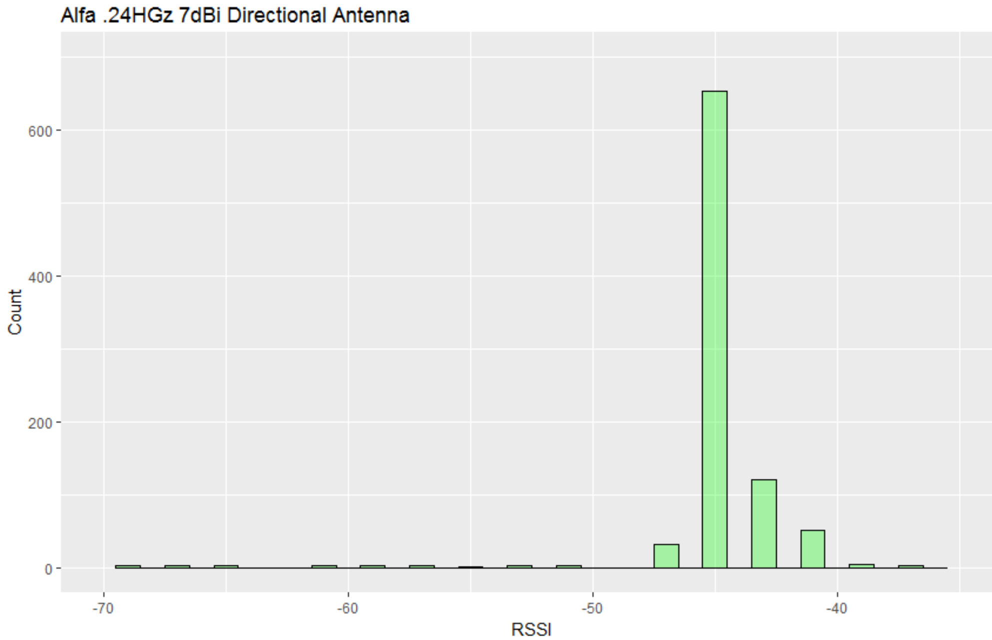


Figure 3: Study of the Detected Signal Strengths

5.4. Air Quality Sensors

The monitoring of Air Quality levels is widely known and established science that started back in the 1980's. With the advances in sensor technology, the solutions utilized for monitoring Air Quality are becoming not only more accurate, but also faster. Sensors are becoming smaller and cost effective. These affordable sensors have also become easily available on the market and many of them are linked to the Internet of Things (IoT) sensing trend. While most of them merely try to provide comparable levels of air quality, some of them can actually achieve the sensitivity of professional or commercial monitors at a much lower cost.

There is an extensive collection of air monitoring sensors available on the market today, from commercial sensors that cost thousands of dollars to IoT enabled devices that cost a few hundred dollars. The properties and capabilities in measuring air quality of these sensors can also differ extensively. In this project, a variety of different IoT enabled sensors are compared to understand what is achievable by using cost-effective sensors. Sensor manufacturers typically do not publish real-world evaluation data and most of the low-cost air quality sensors are not evaluated by organizations that conduct air quality research. The U.S. EPA developed a research initiative to understand basic performance characteristics of low cost O_3 and NO_2 sensors and the results can be found in a report entitled "Sensor Evaluation Report" (Williams et al., 2014). However, the EPA usually conducts laboratory and field-based evaluations of air quality sensors based on the unique design, device developer, popularity and public demand. Although some of the air quality sensors may provide low accuracy and precision, it can still generate comparable results for different locations if it is calibrated to some degree.

The particle sensors can detect the amount of dust in the air. There are two main categories of Particulate Matter. The first one is coarse dust particles (PM10). PM10 particles are between 2.5 to 10 micrometers in diameter. The sources of PM10 include dust, pollen, and mold. The second one is fine particles (PM2.5). PM2.5 particles are 2.5 microns (µ) in diameter or smaller. Fine particles can be generated from all types of combustion, such as motor vehicles, power plants, residential wood burning, forest fires, agricultural burning, and some industrial processes. For PM2.5, the short-term standard (24-hour or daily average maximum level) is 35 micrograms per cubic meter of air (µg/m3) and the long-term standard (annual average) is 15 µg/m3. For PM10, the short-term standard is 150 µg/m3 (there is currently no long-term standard) (EPA, 2012). Table 3 summarizes the comparison conducted by the EPA between low-cost sensors and the commercial MetOne BAM 1020 FEM PM2.5 Monitor. All of the low-cost sensors detected particles via a light-scattering method. The particles entering the sensor scatter light from an internal light source. The scattered light signal is converted by the low-cost sensor to an estimated particle mass concentration. As shown in Table 3, Shinyei PM sensors had moderate agreement with the FEM monitor.

Table 3. Particulate Matter (PM) Sensors Comparison Table -Source: Williams et al. (2014)

Sensor	Sampling Interval	Cost	Data Reported	R^2
Shinyei	1 second	$	µg/m3	0.45 to 0.60
Dylos	1 minute	$	Particle counts	0.63 to 0.67
Airbeam		$	µg/m3	0.65 to 0.66
MetOne	1 minute	$	µg/m3	0.32 to 0.41
Air Quality Egg		$	µg/m3	-0.06 to 0.40

Shinyei Sensors create digital (Lo Pulse) output to PM levels. Lo Pulse occupancy (LPO) time is in proportion to PM concentrations. The output from "P1" is used for detecting particles whose sizes are around 1 micro meter or larger. The standard characteristics of the LPO time vs. the PM concentration output are shown in Figure 4.

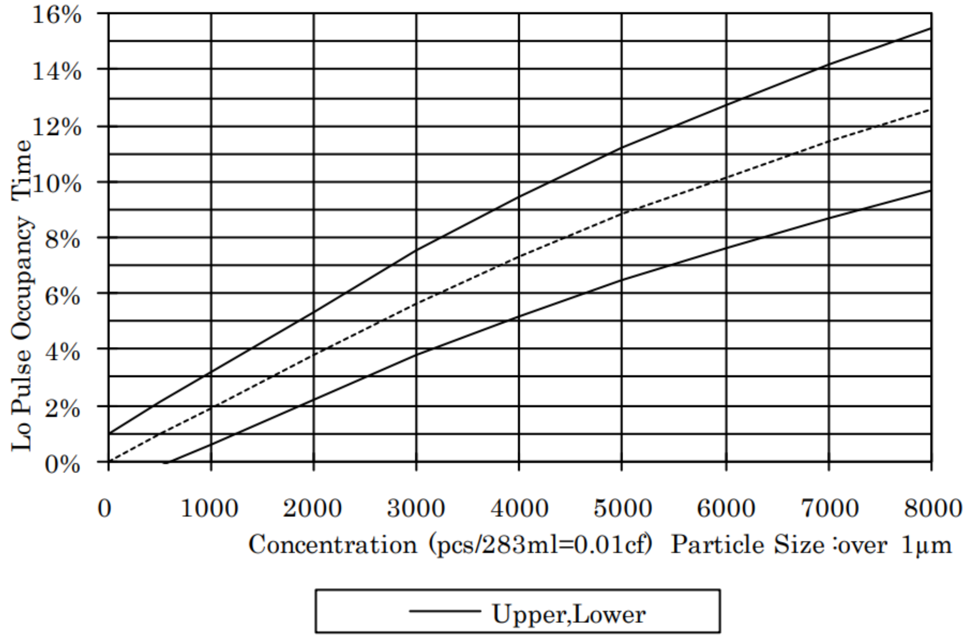


Figure 4: Smoke-Output (P1) Characteristics - Source:Shinyei (2010)

To measure air quality using low-cost sensors, an Analog to Digital (ADC) converter is needed because Raspberry Pi is not capable of reading electrical signals and data from an analog device. Although wiring an ADC to the RPi is quite easy, it is more convenient to connect another micro-controller with a built-in ADC on board to the Raspberry Pi. With such a micro-controller, it would be possible to trigger and control potentiometers and many other analog sensors in real time via a USB connection. The micro-controller can convert the analog readings from the sensor to digital values and send them to Raspberry Pi using the GPIO pins. In this project, the Teensy USB Arduino-based Development Board by PJRC is used. It is a small low-cost circuit board with a microcontroller that offers numerous I/O pins and a USB interface. Figure 5 below illustrates a sample connection schema. In this system, Shinyei Air Quality Sensor sends analog data to Teensy micro-controller (Teensy, 2012). Then, Teensy converts analog data into digital and sends the data to Raspberry Pi via GPIO pins. The micro-controller is powered by one of the USB ports of Raspberry Pi and the air quality sensor is directly powered by the Pi itself.

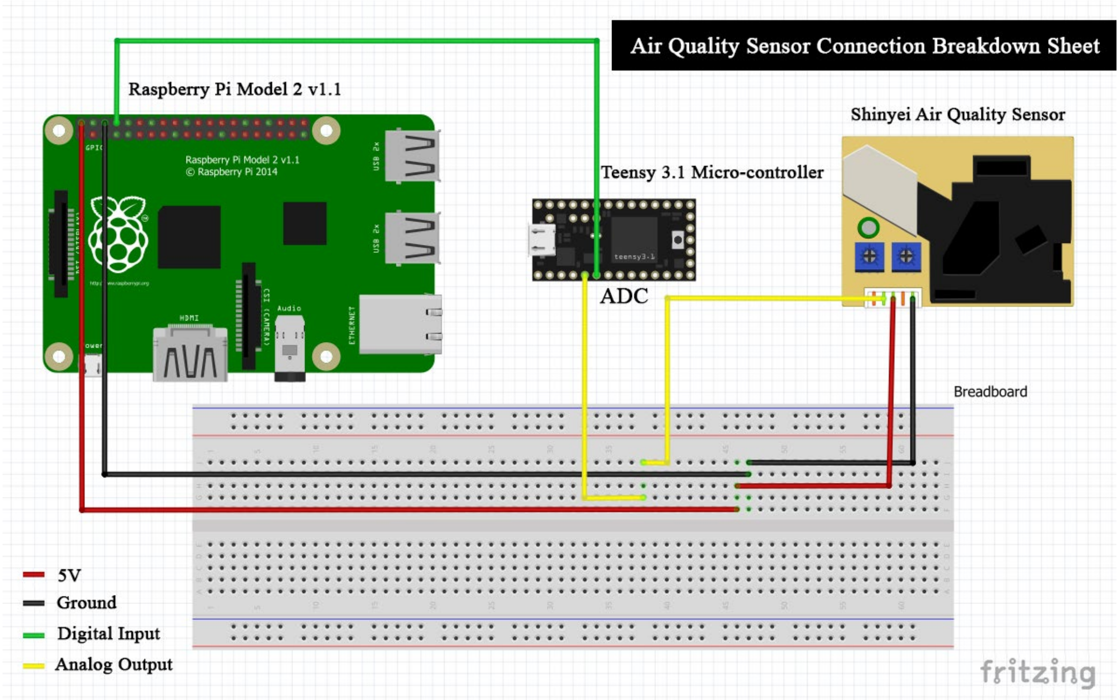


Figure 5. Air Quality Sensor Connection Schema

5.5. Noise Sensors

Inter-IC Sound (I2S) is a serial bus design for digital audio devices. It is used to communicate Pulse-code modulation (PCM) audio data between integrated circuits. PCM is a method which digitally represents sampled analog signals. For instance, audio devices and technologies such as compact disc players (CD), digital televisions, and sound processors utilize I2S technology. It examines audio data separately from clock signals. This separation helps alleviate time-related errors that cause jitter. Typical I2S bus design contains three serial bus lines: a line with two-division multiplexing (TDM) data channels, a clock line, and a word select line. TDM is a method of dividing a single signal into multiple data streams by creating many segments with very short durations. The acoustical intensity is normally not measured; rather, sound pressure level is measured in sound studies. Figure 6A below shows what one cycle of a varying sinusoidal pressure may look like. It also shows the peak value of the signal, the root-mean-square (rms) value and the average value. Figure 6B shows a square wave of unity value.

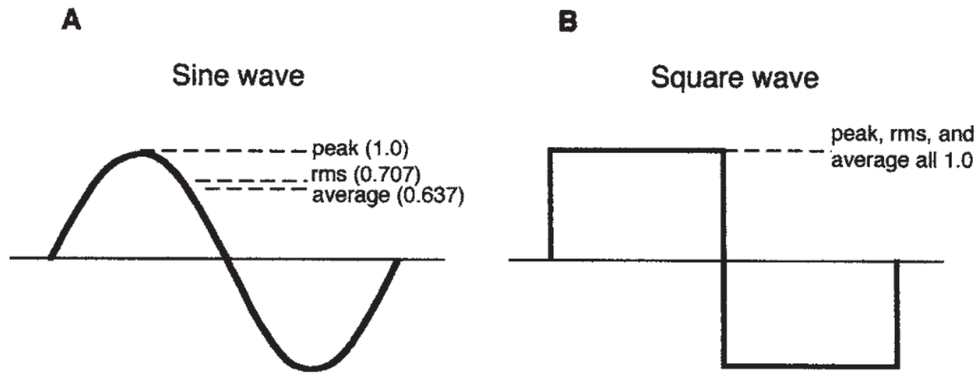


Figure 6: A) Sine Wave B) Square Wave - Source:Eargle (2012)

Due to inconveniences experienced over the years dealing with a large range of numbers, the decibel (dB) scale is invented to provide a reliable scale for understanding a wide range of power values. A great explanation of the basic sound transmission and the dB scale can be found in (Eargle, 2012).

The ICS-43432 is a digital I2S port microphone containing a MEMS sensor, signal conditioning, an ADC converter, decimation and anti-aliasing filters, power management, and 24-bit I2S interface. This microphone can be connected directly to digital processors such as micro-controllers by eliminating the need for an audio codec in the system. The sensitivity tolerance of the ICS-43432 is ±1dB. The functional block diagram of the microphone can be seen below in Figure 7.

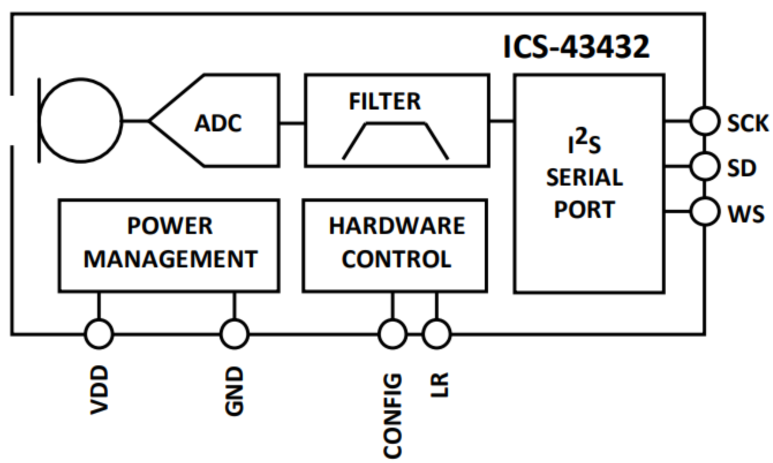
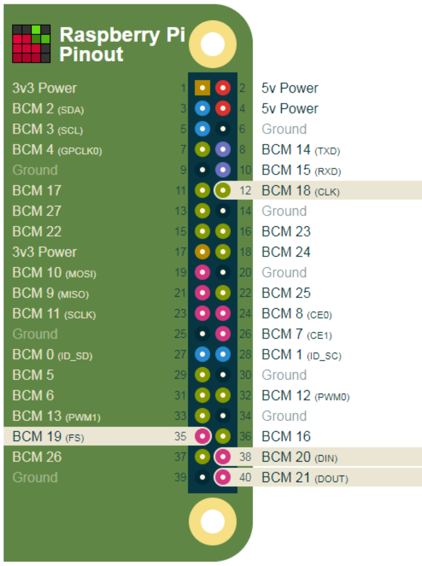


Figure 7. ICS-43442 Functional Block Diagram - Source: InvenSense (2014)



As mentioned, PCM is a digital representation of sampled analog. This digital representation can be understood by a Raspberry PI. Thus, it is possible to add mono or stereo I2S microphones to Raspberry Pi sensors. The PCM connection requires four GPIO pins from the Raspberry Pi, which can be seen in **Error! Reference source not found.** on the right. ICS43432 MEMs microphone pins were connected to the GPIO pins. The microphone pins are labeled as VCC, Gnd, L/R (Channel Selection), SCK, WS and SD. SCK, WS and SD pins were connected to BCM 18, 19 and 20 respectively. The MEMs microphone requires 3.3v to operate and L/R channel is connected to the Raspberry Pi's Ground pin.

Figure 8. PCM Connection – Source: (Johnson)

To make the sensor work, a kernel driver needs to be compiled and several configuration files need to be modified. A detailed documentation of how to compile the drivers and I2S module can be found in this tutorial (Johnson). Due to the time limitations of this project, noise sensors are not calibrated or used to collect data for indoor and outdoor tests. With the basic setting, they can only provide nominal noise levels, which can be used to make noise level comparisons between different locations.

6. EQUIPMENT AND SOFTWARE TESTING

6.1. Monitoring Wi-Fi and Bluetooth Devices

Six different limited field tests with varying lengths from a couple of hours to a couple of months are conducted before an actual application to develop and improve data filtering algorithms. To evaluate and supplement the sensors' crowd count, manual counts are also reported as ground truth data. Table 4 summarizes the conducted field tests for calibration. It should be noted that parameters and inputs to these filtering algorithms need to be tweaked depending on the purpose and the location of the study.

Table 4 Conducted Field Tests

Study Location	Length	Data	# of Locations
Brooklyn I	2 days	2,792	2
Brooklyn II	1 day	1,159	1
Brooklyn III	7 days	10,655	2
Transit Center	2 Months	2,302,000	8
Commercial Building	14 days	22,759	3
School of Engineering	2 hours	1,875	4

Using the data collected in the transit center field test, the busiest gate is selected to further execute data analysis. The collected wireless traces are filtered to have detections from mobile devices only. Figure 9 below shows the comparison of the smartphone brands in the market, reported by Parks Associates (Associates, February 2016), and the brands identified by the sensors in the collected data at a bus stop.

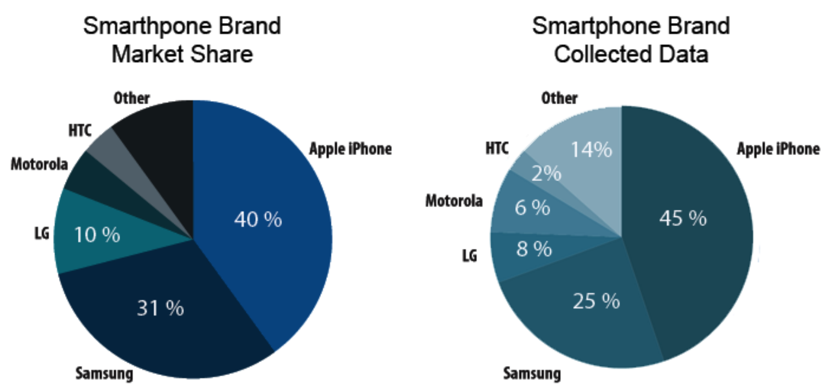


Figure 9 - Smartphone Brand Market Shares – Source: Associates (2016)

The signal strength (RSSI) of the devices can be used to create a detection zone. With tuning, this creates a detection circle that, when crossed, can trigger the detection system to store the information such as detection type (Wi-Fi or Bluetooth), encrypted MAC address, timestamp, and brand in SQLite tables. An illustration of the data that can be collected is shown in Table 5. There are more than 50,000 detected unique mobile devices in the dataset for a 10-week period.

Table 5. Sample Data

Type	Mac	RSSI	Timestamp	Brand
WiFi	...	-77	2017-07-16 11:25:22	Samsung
WiFi	...	-66	2017-07-16 12:18:51	Apple
Bluetooth	...	0	2017-07-16 12:19:23	Nokia
Bluetooth	...	0	2017-07-16 12:22:24	Apple
WiFi	...	-65	2017-07-16 12:24:55	Samsung

6.1.1. Data Pre-Processing

Following the industry practice to ensure privacy, instead of keeping all the digits of the MAC address, only the last three octets (2 digit blocks) are stored to protect the embedded private information. Within the last three of the last five digits are kept and then encrypted with an encryption key and stored on the instrument. This technique delivers an extra layer of protection. It also preserves the uniqueness of MAC addresses for approximately 96% of the cases. The encryption key is randomly generated on a remote server. After the initial key is generated, it is then encrypted again before uploading to the devices on site.

The initial filtering process starts with finding the most occurred device addresses. If a device occurs in the database more frequently than every 10 minutes on average for a 6-hour period, it is removed. The reason behind this initial filtering is to eliminate non-mobile devices captured in the database, devices of the staff, and any other smart device that has not moved during the test time period. The second filter is applied only to the sensors at the selected bus gates to detect devices with signal strengths that are lower than some threshold value. If a device is detected with an RSSI value stronger than -80 dBi at least once, it is retained in the database, otherwise, it is removed. The selection of -80 dBi approximately corresponds to a 15-meter radius proximity to the sensor.

Sensor data were checked and analyzed every week during the data collection period to ensure all sensors were working properly. In addition, data were recovered on a monthly basis.

6.1.2. Indoor Test: Pedestrians in a Bus Terminal

Sensors are deployed in six locations at a transit terminal. Two are placed at the main entrances, and four are located at the busiest gates. The data stored on sensors are collected every week for the first month and every 2 weeks for the following month. One week in which all sensors worked without a problem is selected for further investigation. Developed filtering algorithms are applied to the collected data, and results are reported in this section.

The initial filtering process starts with finding the addresses of the devices that occurred most often. If a device occurs in the database more frequently than every 10 min on average for a 6-h period, it is removed. The reason behind this initial filtering is to eliminate nonmobile devices captured in the database, devices of the staff, and any other smart device that has not moved during the test time period. The second filter is applied only to the sensors at the selected bus gates to detect devices with signal strengths that are lower than some threshold value. If a device is detected at least once with a received signal strength indication value stronger than −80 dBi, it is retained in the database; otherwise, it is removed. The selection of −80 dBi corresponds approximately to a 15-m radius proximity to the sensor. The initial filtering algorithm is applied to the weeklong data to capture the patterns of the number of detected devices on different days. Figure 10 shows the results from Monday to Sunday for the test week. It can be clearly seen that the number of detected devices follows a decreasing trend during the week. The busiest times at this specific entrance point are experienced on Monday. The evening peak period on Friday is flatter, stretching over a longer time period, approximately from 3 to 9 p.m. There are commercial stores near Entrance A; thus, Figure 10 illustrates the number of passengers entering the terminal as well as customers visiting these commercial facilities.

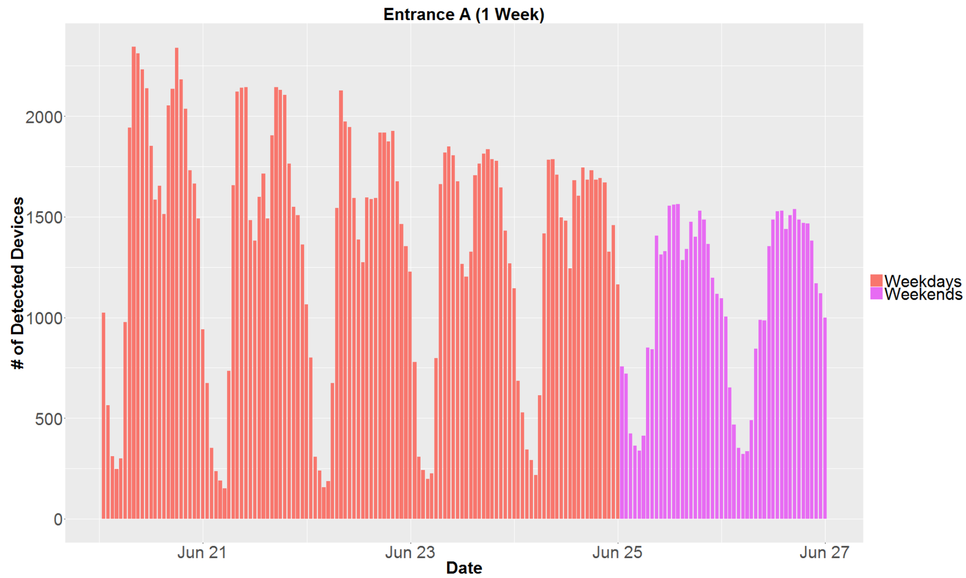


Figure 10: Number of Detected Mobile Devices for a Week

A new filtering algorithm is designed to count discoverable people who are within the detection range of the sensor. It aims to filter pedestrians moving in circles, or going back and forth. The goal here is to address the problem of double counting resulting from such movements. The algorithm creates a cycle block for the first 5 min and stores every detected address in it. It then checks whether the detected MAC addresses in the 6th min can be found in the first 5 min. If a common MAC address is detected, it is removed from the existing minute's count. For the next time period, it creates another 5-min block starting from the 2nd min to the 6th min and checks the MAC addresses detected in the 7th min with this new 5-min block. The moving algorithm code is applied to the data collected at Entrance A of the terminal test location to evaluate the pedestrian traffic at a fixed location. Figure 11 shows the pedestrian count results. Clearly, the distribution of the number of detected devices is similar to that of the pedestrian count data. However, the count data are different than simply the number of devices detected at the scene because the algorithm eliminates the double counts in the data set by consistently checking the recurring devices throughout the moving block.

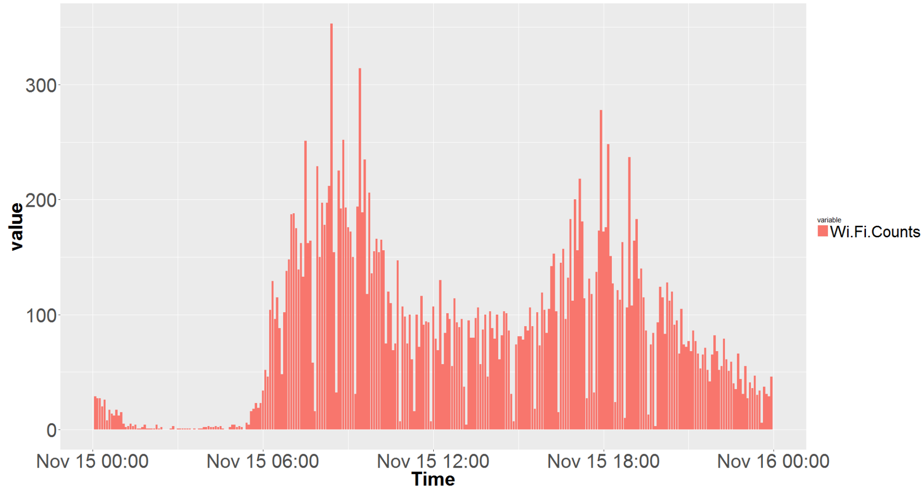


Figure 11: Pedestrian counts for a day at Entrance A

Table 6 shows the pedestrian flows from entrances to the gates. While some of the gates, such as Gate 1 and Gate 2, are heavily used by passengers that enter through, respectively, Entrance B and Entrance A, other gates most likely have passengers originating from other entrances. In addition, Entrances A and B are closer to Gates 1 and 2 than to other gates. There are 37,240 distinct mobile devices detected at Gate 2. Pedestrians using Entrances A and B constitute 26% of all foot traffic at this gate.

Table 6: Pedestrian Flows for 1 Week

	To			
From	Gate 1	Gate 2	Gate 3	Gate 4
Entrance A	960	4487	4	517
Entrance B	6444	5310	81	4

Time-dependent O-D pairs can also be created with the wireless sensor data. Figure 12 shows the temporal distribution of the detected pedestrian intensity traveling from Entrance A to Gate 2 for a week. The gate experienced its busiest period on Tuesday between 4 and 8 p.m. as can be seen in the figure.

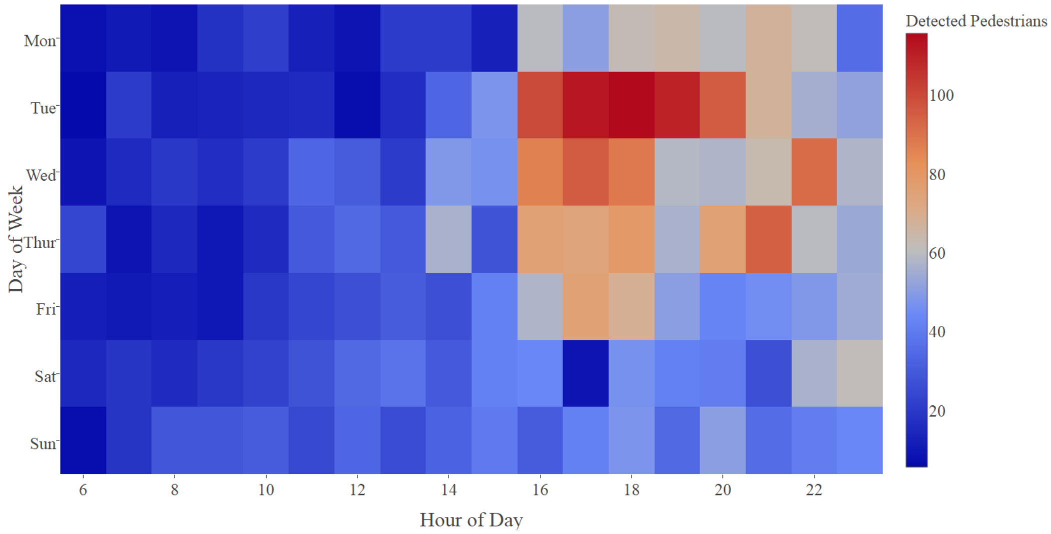


Figure 12: Detected Pedestrians between Entrance A and Gate 2

6.1.3. Outdoor Test: Vehicular Travel Time Collection

The research team also conducted an outdoor test of Wi-Fi and Bluetooth sensors to understand whether they are capable of collecting travel time using the matched detections at different locations on an urban roadway. The sensor locations for this field study are illustrated in Figure 13. Travel time data is collected only for the southbound (SB) direction.

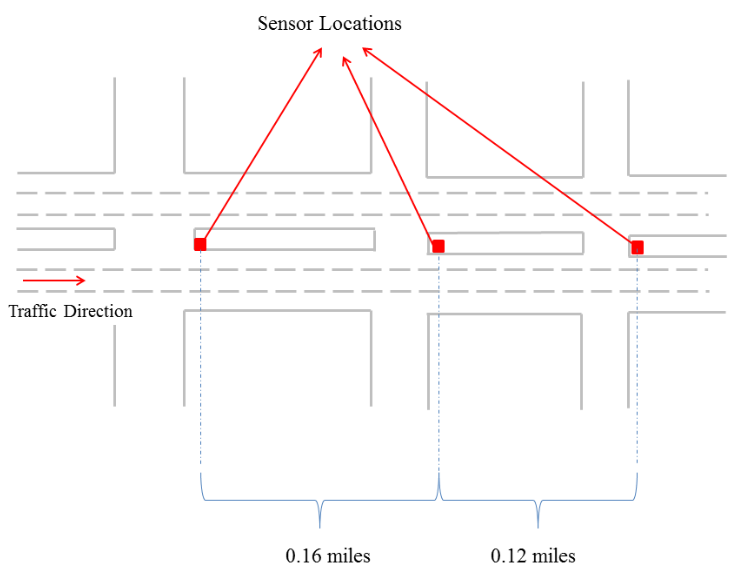


Figure 13: Data Collection Locations

Mobile devices look for available networks in intervals approximately varying from 4-20 seconds. This varying interval makes is harder to detect vehicles traveling at higher speeds. Locations that have interrupted vehicular flows such as signalized intersections provide more time for sensors to pick up devices within vehicles. It is apparent that these sensors should be used for vehicular detection at locations where traffic density is high or stop and go behavior is observed. “Virtual Sensors” which collect data from online traffic sources such as Bing Maps are set up to validate travel times collected by sensors. Figure 14 shows the comparison between travel time which is collected by using virtual and developed sensors. As it can be seen from the figure, travel times collected by the developed sensors are in good agreement with Virtual Sensors.

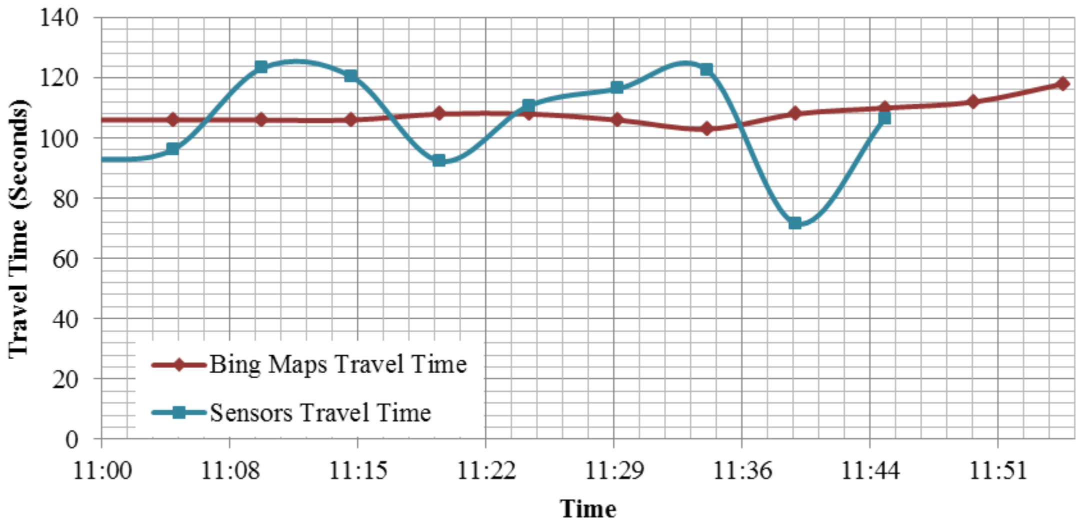


Figure 14: Travel Time Comparison between Virtual and Physical Sensors

During the data collection process, members of the research team walked between sensors 10 times to compute the minimum and maximum walking times to filter out pedestrian detections. From these runs, it was found out that it takes 3 minutes at minimum to walk from the first sensor to the last one. All the detections that are exceeding 3 minutes are removed from the collected data.

6.2. Monitoring Air Quality

6.2.1. Indoor Tests

Most of the air quality tests were conducted indoor to understand the capabilities of the developed low cost sensor. The results were compared to the air quality readings captured from Dylos Air Quality Monitor DC1100 (Figure 15). DC1100 is a true laser particle counter with 2 size ranges 2.5 PM for small and 10 PM for large particles. It is built for monitoring of indoor air quality. It has an LCD screen that shows small and large particle counts with a dynamic bar showing the actual particle readings. DC1100 collects a selection of air to determine how many particles within a defined size range are present in the sample.

Figure 15: Dylos Air Quality Monitor DC1100

Dylos sensor measures particles per 0.01 ft^3. However, the output data must be modified to be directly compared to the EPA standard. Researchers at Drexel University (Uva, Falcone, McClellan, & Ostapowicz, 2009) came up with an estimation algorithm which converts Dylos readings into the EPA's standard. The developed algorithm assumes that all particles are spherical, with a density of 1.65E12 $\mu g/m^3$, the PM2.5 particle radius is 0.44μm and the PM10 particle radius is 2.60 μm. Based on these assumptions, it is possible to approximate the mass of a particle in both PM channels. To calculate the concentration, one needs to multiply the number of particles per volume by the mass per particle.

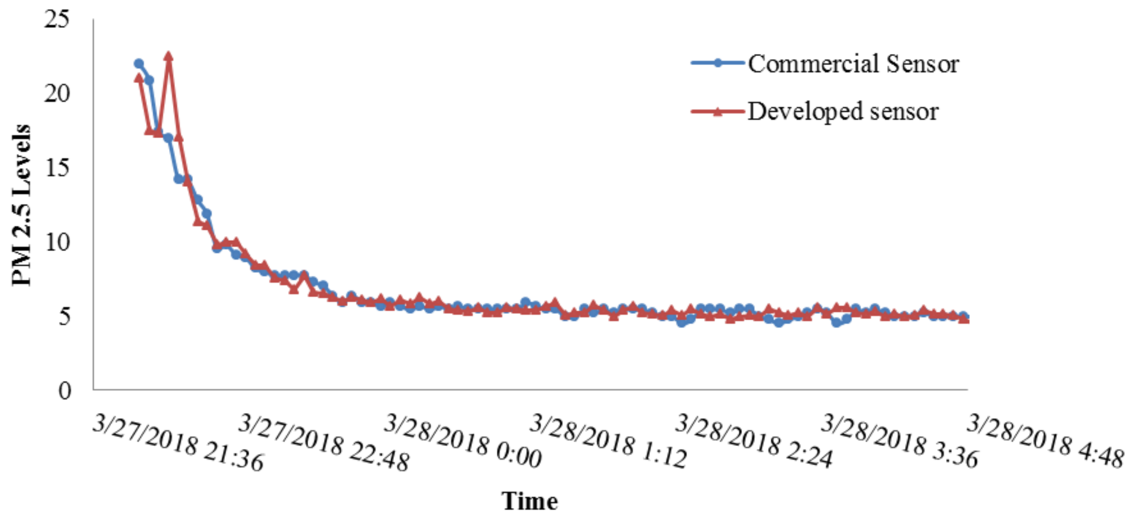


Figure 16 shows the comparison between detected PM2.5 particles (μg/m^3) using both sensors.

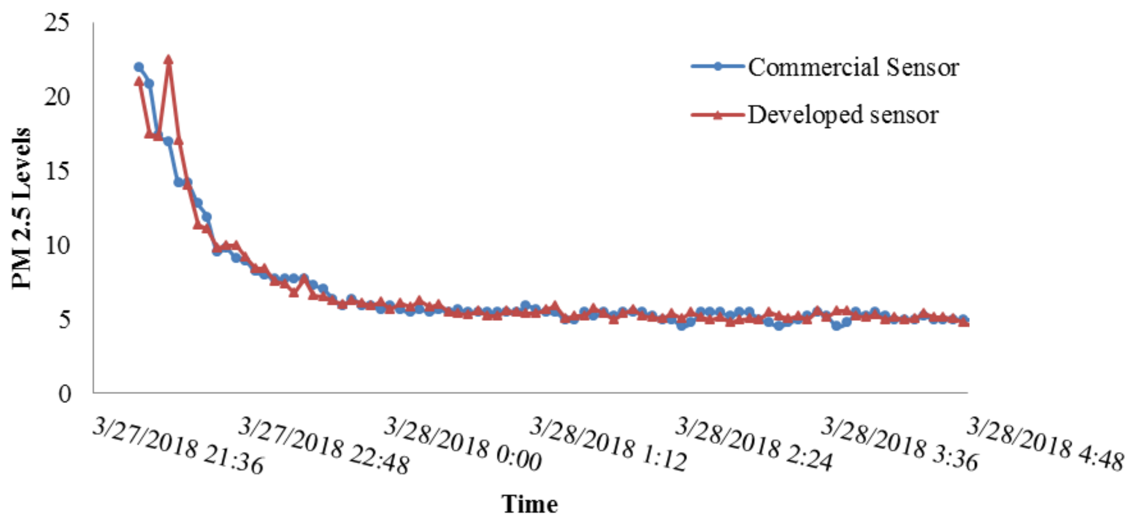


Figure 16: PM2.5 Comparison between Dylos and Developed Sensor

6.2.2. Outdoor Tests

The final step in the development of the air quality monitoring sensor is to compare the readings of the low cost sensor to the air quality readings published online by New York State Department of Environmental Conservation (NYS DEC)[1]. The base station was deployed in Brooklyn and initial tests were conducted in an outdoor environment. Figure 17 shows the final system results. The EPA standard suggests that the average concentration for a particular day should not exceed 35 μg/m^3.

[1] http://www.nyaqinow.net/

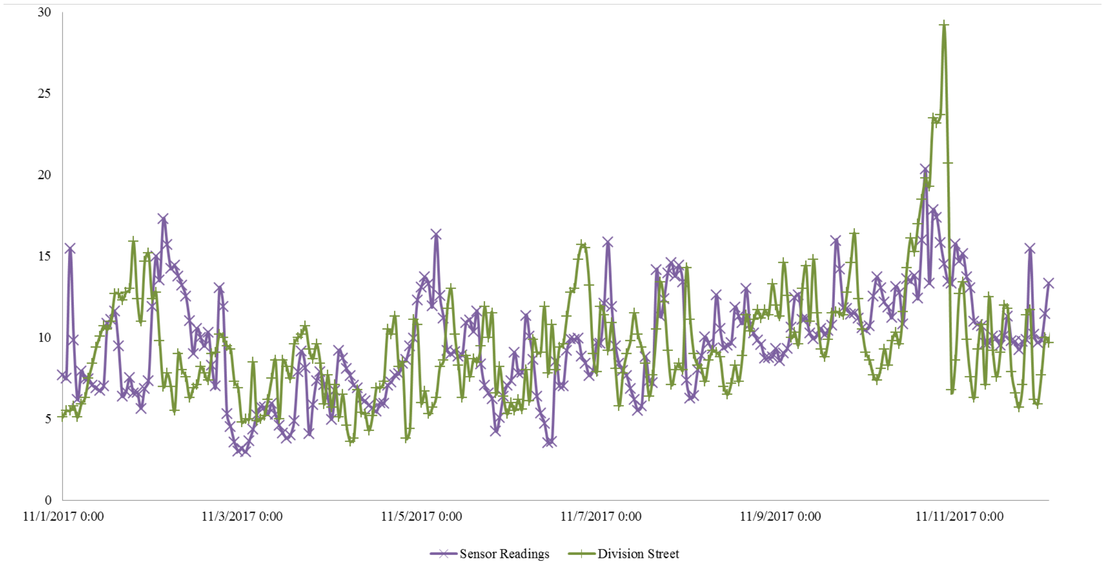


Figure 17: Continuous Data Readings: Developed Sensor vs. NY State Air Monitoring Website

Table 7 also provides PM2.5 statistics computed using 10-day long air quality data.

Table 7: Summary of PM2.5 Levels

Min	1st Quartile	Mean	Median	3rd Quartile	Max	Standard Deviation
2.97	7.35	9.66	9.64	11.66	20.36	3.14

7. CASE STUDY: A FRAMEWORK FOR FUSING BLUETOOTH/WI-FI BASED DATA WITH LOOP DETECTOR DATA TO IDENTIFY SECONDARY CRASHES

7.1. Introduction

Numerous traffic incidents occur on highways daily, resulting in tremendous economic loss, traffic congestion, and safety issues. According to the report of the National Highway Traffic Safety Administration, the cost of traffic incidents was more than 240 billion dollars in 2010 (Blincoe, Miller, Zaloshnja, & Lawrence, 2015). Among all traffic incidents, one type of incident, namely secondary crashes, is of great importance to traffic operation/management agencies. The reason is that secondary crashes induced by early (primary) crashes accounted for almost 20 percent of all crashes and 18 percent of all fatalities on U.S. freeways (Owens et al., 2010). As such, statistical measurements (e.g., frequency) of secondary crashes have been considered as key performance indicators by the Federal Highway Administration.

In order to reduce the number of secondary crashes, a more thorough understanding of when, where, and why these crashes occurred is needed. In practice, almost all crashes were independently reported, and specific information on whether a crash was a secondary crash was not available in crash records. This creates a big challenge in investigating the underlying occurence mechanisms of secondary crashes. Prior to the detailed examination of secondary crashes, we need first to distinguish these crashes from all the others.

Thanks to the contributions of early research, different approaches have been developed to assist with the identification of secondary crashes. For example, fixed spatiotemporal threshold-based approach (Raub, 1997b), queue-based approach(Zhang & Khattak, 2010), etc. were available. However, the performances of existing methods were primarily affected by the subjective thresholds or simplified models to quantify the impact area of a crash. With the advance of sensor technologies, more traffic data has become available that are capable of providing high-accuracy traffic information. The availability of these sensor data led to the development of data-driven approaches for determining secondary crashes. One such approach is the shockwave based method, which estimates crash impact area by analyzing shockwave propagation with data collected from stationary sensors (e.g., inductive loop detectors). Despite the incorporation of traffic information, the spaced detectors often are not sufficient to accurately capture the propagation of shockwaves. For example, if a primary crash occurred between two adjacent loop detectors, it will need additional time for these detectors to sense the change of traffic states. If the impact presents between two sensors, there will be no precise location information about the boundary of the impact area. On the other hand, deploying enough sensors to create short intervals (e.g., 0.1-mile) is not practical due to the cost.

Considering the issues of shockwave based methods and the data obtained from stationary sensors, we proposed a new analysis framework for determining secondary crashes. The proposed framework is based on the shockwave based method, but takes advantage of both detector data and the probe data collected by the developed Bluetooth and Wi-Fi sensor systems. It consists of three major components, including the integration of probe vehicle data and loop detector data, the shockwave based method to capture the impact area of a primary crash, and the improved angle summation algorithm to identify secondary crashes within the impact area of the initial crash. The first component is intended to enhance the data quality. The second component estimates the boundary of the impact area induced by the primary crashes. The third component automatically identifies whether or not a crash is a secondary crash based on the boundary estimated in the second component.

7.2. State-of-the-art Practices

We have examined current practices in identifying secondary crashes. It was found that a few methods have been developed spanning the past two decades. Existing methods are mainly focused on static threshold-based methods, queuing model-based methods, and data-driven methods. Static threshold-based approaches are the simplest methods, which typically use pre-defined temporal and spatial boundaries to depict the impact area of the primary crashes (Raub, 1997a). If a crash was located within the boundary, it is classified as a secondary crash. For example, Tian, Chen, and Truong (2016) defined three types of criteria to identify secondary crashes on interstate highways in Florida. Despite their simplicity, the static thresholds are often not adaptive and cannot address the impact of different crashes under different conditions. Thus this method is prone to both overestimation and underestimation due to the subjectively defined thresholds applied to all crash scenarios.

Another set of studies attempted to develop analytic queuing models to capture the dynamic characteristics of crash impact. These models usually estimated the queue length based on explanatory variables such as crash duration and the number of blocked lanes (Zhan, Gan., & Hadi, 2009). Any crash within the estimated range of the queue is considered to be a secondary crash. For example, Zhan et al. (2009) proposed a linear model using assumed arrival rate, diversion rate, full capacity, lane closures, and the capacity reduction factor from the Highway Capacity Manual (HCM) to calculate the maximum queue length. Theoretically, if models can correctly estimate the progression of the queue, secondary crashes can be determined reliably. However, these models are subject to many issues ranging from the subjective choice of model structures, assumptions, latent explanatory variables, etc. Therefore, their deployment is often limited.

Lately, there is growing practice in developing data-driven approaches for analyzing secondary crashes. These approaches mainly take advantage of the available measurements such as speed and occupancy from fixed, infrastructure-based sensors. Based on the specific procedures to analyze the sensor data, the data-driven method can be further grouped into two classes: speed contour plot-based method and shockwave-based method.

Speed contour plot-based methods use historical speed measurements to capture the incident impact area for identifying secondary crashes (Park & Haghani, 2016; H. Yang, Bartin, & Ozbay, 2013). For example, H. Yang et al. (2013) proposed an algorithm to generate the binary speed contour plot and quantify the influence area of the primary crashes. The Gaussian Mixture Model (GMM) was adopted by Park and Haghani (2016) to determine the reference speed for drawing the binary speed contour plot. These methods collectively considered the prevailing traffic condition and provided better characterization of the actual traffic states before, during, and after crashes. However, their performance will be affected mainly by the spacing of sensors along the roadways. For example, it will be difficult to identify the exact impact area of a minor crash located between two distant detectors.

Meanwhile, shockwave-based methods use traffic flow theory to identify secondary crashes based on the impact area characterized by shockwave propagation (Wang, Xie, Liu, & Ragland, 2016; Zheng, Chitturi, Bill, & Noyce, 2014). If a crash is inside the impact area enclosed by the shockwaves induced by a primary crash, it is deemed to be a secondary crash. For instance, Zheng et al. (2014) used the simplified queuing shockwave and the discharging shockwave to estimate the impact area of a crash. Many assumptions, such as fixed traffic flow rate and density, were required to ensure the validity of the proposed model. However, such assumptions are often unrealistic. Alternatively, several studies have made some modifications. For example, Wang et al. (2016) considered the potential shockwave induced by the incident response crew. Thus the back-of-queue shockwave was estimated as piecewise linear segments consisting of two lines with different slopes. It should be noted that the model is still subject to low accuracy due to non-constant flow rate.

A common challenge associated with aforementioned data-driven approaches is the sensor data coverage. If the density of the sensors is relatively high (e.g., 0.1 mile-interval), one can estimate the impact area of a crash more precisely. However, most of the instrumented sensors on roads are often sparsely distributed (e.g., 1-mile interval). Traffic states between any two sensors cannot be accurately measured. In addition, the high cost of installing and maintaining sensors prevents the deployment of additional detectors to facilitate traffic data collection. Therefore, any incident impact area located between the spaced sensors cannot be well characterized.

Powered by the developed portable sensor systems in this project, one can now gather vehicle location information with high resolution. The time stamps of the detected vehicles at different locations can be used as probes to acquire traffic flow information, and thus offer us a new perspective to explore secondary crashes. By integrating such vehicle information with loop detector data, we introduce a framework to improve the estimation of traffic states and address the issues of current data-driven approaches for secondary crash identification.

7.3. Overview of the Proposed Framework

The efforts of developing the data-driven approach for identifying secondary crashes (See Figure 18 for an illustration of primary crash **A** and secondary crash **B**) mainly focuses on two essential tasks: (a) the quantification of the incident impact area (IIA); and (b) the determination of secondary crashes within the IIA. The first task provides the basis for accurately capturing the spatiotemporal impact of a primary crash. To accomplish the task, we introduce a data fusion framework to integrate a loop detector and the data from the developed sensor systems. Benefiting from the fused data, a piecewise shockwave-based approach was proposed to capture the spatiotemporal IIA of a crash dynamically. Upon the availability of the quantified IIA, the angle summation algorithm is introduced for addressing point-in-polygon (PIP) problem: determining whether a secondary crash presents within the IIA. Figure 19 shows the framework.

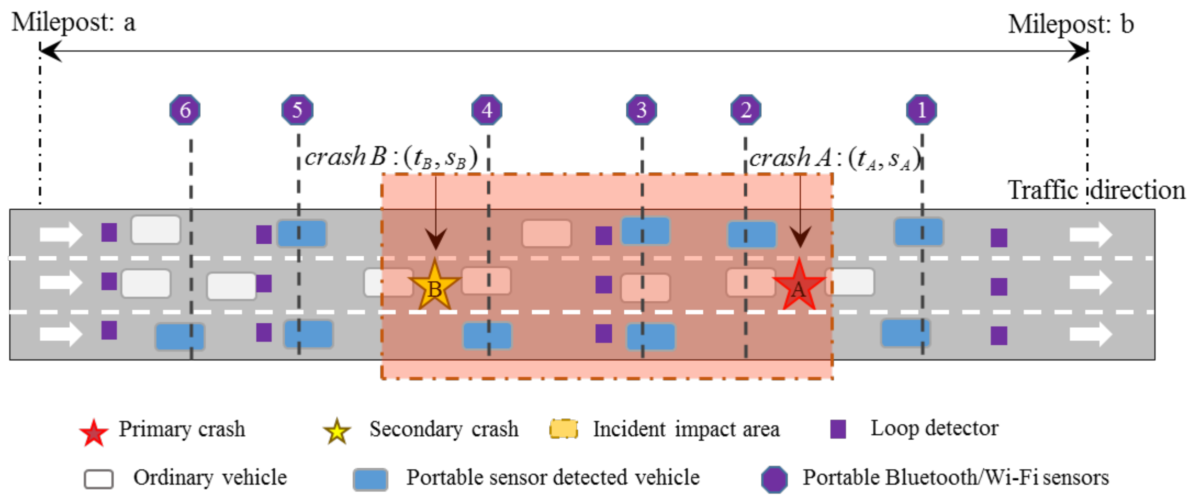


Figure 18: Conceptual illustration of primary and secondary crashes.

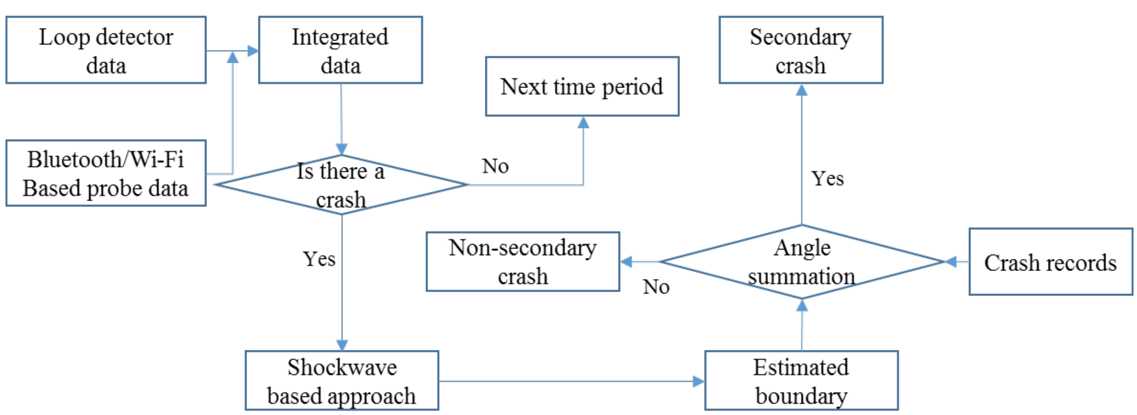


Figure 19: Framework of the proposed methodology.

7.4. Integration of Detector and Sensor Data

Assume there are multiple detectors deployed along a roadway. They are sparsely distributed (e.g., detectors A, B, and C in Figure 20(a)). These detectors record key traffic measurements such as speed, flow, and occupancy based on fixed time intervals (e.g., 5-minute). With the speed measurements, one can quickly generate the speed contour map.

For example, the gray areas in Figure 20(a) denote the uncongested area with high speeds whereas the red areas represent the congested area with low speeds. Other than the detector data, we assume that Bluetooth and/or Wi-Fi detection data are available. These Bluetooth and Wi-Fi data can be considered as probe vehicle data since we can easily locate the vehicles and derive their speed from the time stamps. Let's denote these Bluetooth and/or Wi-Fi detected data as the probe points. Each probe point has the location information as well as the speed information. Depending on the number of deployed sensor systems and the sampling approach, one may obtain the full trajectories of many (or some) vehicle(s) over a time period and space (e.g., the blue lines and points shown in Figure 20(a)). If the full trajectories are available for many vehicles, the time-space diagram derived based on them can be used to highlight the change of traffic states. For example, the triangle area highlighted by the red dash lines in Figure 20(a) can clearly show the changes of traffic states. Compared with the congested area highlighted by the speed measurements of the loop detectors, we can see that many areas should not be considered as the congested states. This is due to the limitation of the speed contour map that fulfills a cell (a roadway segment between two sensors over a time interval) with the same speed. If the space between two detectors is large, a constant speed cannot represent possible traffic state changes on each segment.

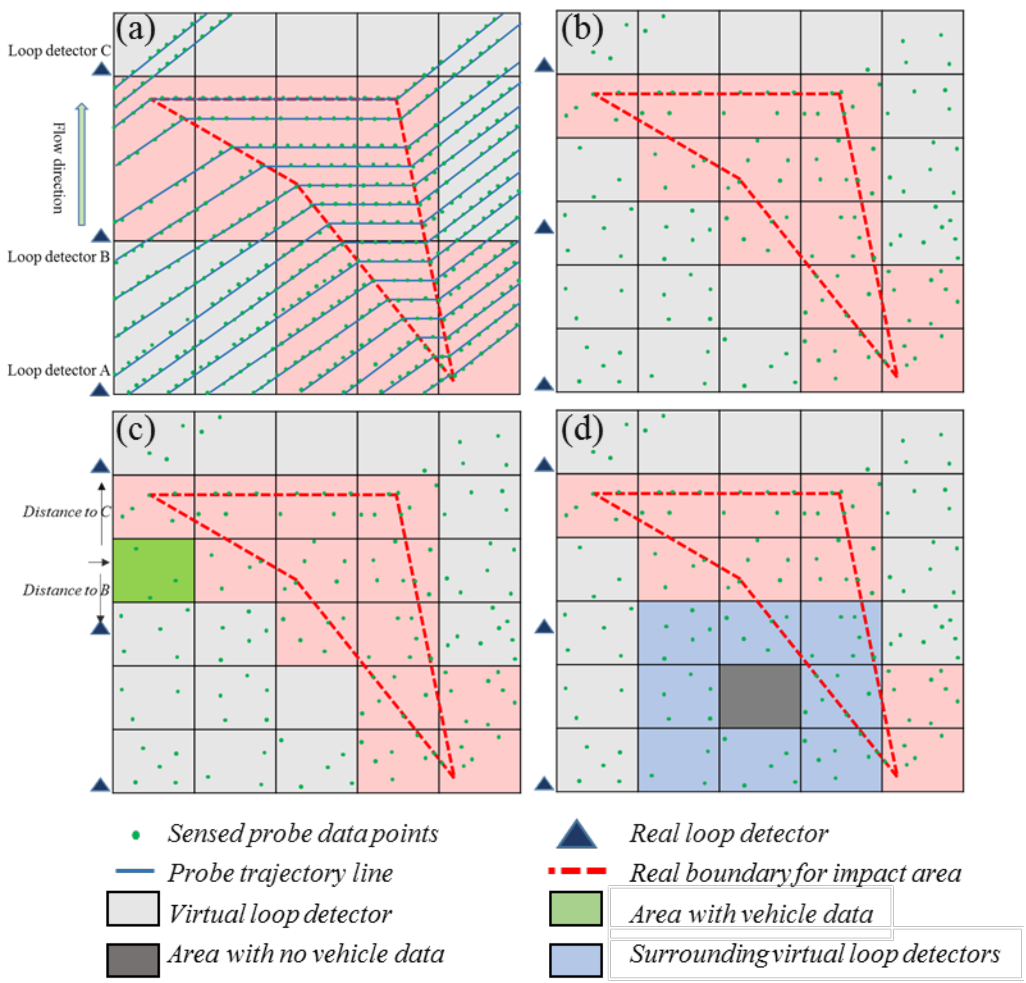


Figure 20: Integration of loop detector data and sensed vehicle data.

With the sensed vehicles, it is possible to probe the traffic conditions between two loop sensors. The more sensed vehicles, the better, but it will require the deployment of many sensors. Herein we assume a more general case where only a few probe points are available due to the limited number of sensor deployments in practice. Similar to Figure 20(b), sampled probe points can be added to the original speed contour plot. Since we do not know the vehicle identity of each point, the time-space diagram cannot be constructed. Instead of deriving a time-space diagram, these probe data will be fused with the Bluetooth/Wi-Fi sensor data. The segment between two detectors will then be split into shorter segments. This helps us construct smaller cells for the speed contour plot. As shown in Figure 20, a stationary loop detector observes and records key information such as speed and occupancy. The blue lines are the probe trajectory lines, while the green dots are the detected vehicles. The speed contour map is drawn based on the speed obtained from the traditional loop detectors A, B, and C (blue means uncongested area, and red denotes congested area). Then, virtual loop detectors are initially generated based on the distance to the traditional loop detectors. In the first loop, virtual loop detectors and detected trajectory points are combined with the values of the virtual loop detectors both upstream and downstream. In the second iteration, a virtual loop detector with no vehicle trajectory points located is integrated using the speed values of the surrounding virtual loop detectors based on the bi-cubic interpolation mechanism.

The detailed steps to integrate loop detector data with the probe trajectory data are presented below:

Step 1: Loop detector records the critical information like occupancy, volume, and speed. The speed V in virtual loop detector shown in Figure 20(b) are scaled and calculated according to the following equation:

$$V = \frac{d_1}{d+d_2} \times V_{up} + \frac{d_2}{d_1+d_2} \times V_{down} \tag{1}$$

where d_1 and d_2 represent the distance between the original loop detector data and the current virtual loop detector. V_{up} and V_{down} denote the speed of the virtual loop detectors in the upstream and downstream.

Step 2: Fuse the detected vehicle trajectory points with the loop detector data. For those virtual loop detectors that are just at the location of an actual loop detector, use the original loop detector data.

Step 3: Calculate the mean value of speed of all detected vehicle trajectory points associated with a virtual loop detector, and update the value of current loop detector with the equation:

$$V = a_1 \times V_{up} + a_2 \times V_{down} + (1 - a_1 - a_2) \times mean\left(V_{prob}\right)$$
$$a_1 = \frac{c \times d_1}{d_1 + d_2}$$
$$, \tag{2}$$

$$a_2 = \frac{c \times d_2}{d_1 + d_2}$$

where c represents the influence parameter of the original loop detector data.

Step 4: For those virtual loop detectors without the detected vehicle points, integrate the loop detector data points based on the following equation:

$$h(x,y) = \sum_{i=0}^{3} \sum_{j=0}^{3} a_{ij} x^i y^j \tag{3}$$

All the surrounding virtual loop detectors are used to calculate the coefficients a_{ij} based on their positions and speed values. Suppose the speed values and their derivatives f_x, f_y, f_{xy} are known at 4 corners (0,0), (0,1), (1,0), and (1,1) of the unit square. The derivatives at a point (x,y) can be expressed by the following equation:

$$h_x(x,y) = \sum_{i=1}^{3} \sum_{j=0}^{3} a_{ij} i x^{i-1} y^j \tag{4}$$

$$h_y(x,y) = \sum_{i=0}^{3} \sum_{j=1}^{3} a_{ij} j x^i y^{j-1} \tag{5}$$

$$h_{xy}(x,y) = \sum_{i=1}^{3} \sum_{j=1}^{3} a_{ij} i x^{i-1} j y^{j-1} \tag{6}$$

Thus, all above 16 equations for 4 corners (0,0), (0,1), (1,0), and (1,1) can be used to calculate the coefficients a_{ij}, where x direction denotes the time, and y direction represents the distance, and i and j each represents the length of a cell in each direction, respectively.

7.5. Shockwave-based Approach

According to the shockwave theory shown in Figure 21 the two red lines will intersect and compose a triangle which depicts the impact area of congestion. The slopes of the two red lines in the triangle are calculated using the following equation:

$$\Omega_{ab} = \frac{Q_a - Q_b}{K_a - K_b} \tag{7}$$

This is based on the relationship between flow and density. The upper line of the triangle is assumed to be entirely congested, and thus its slope is zero.

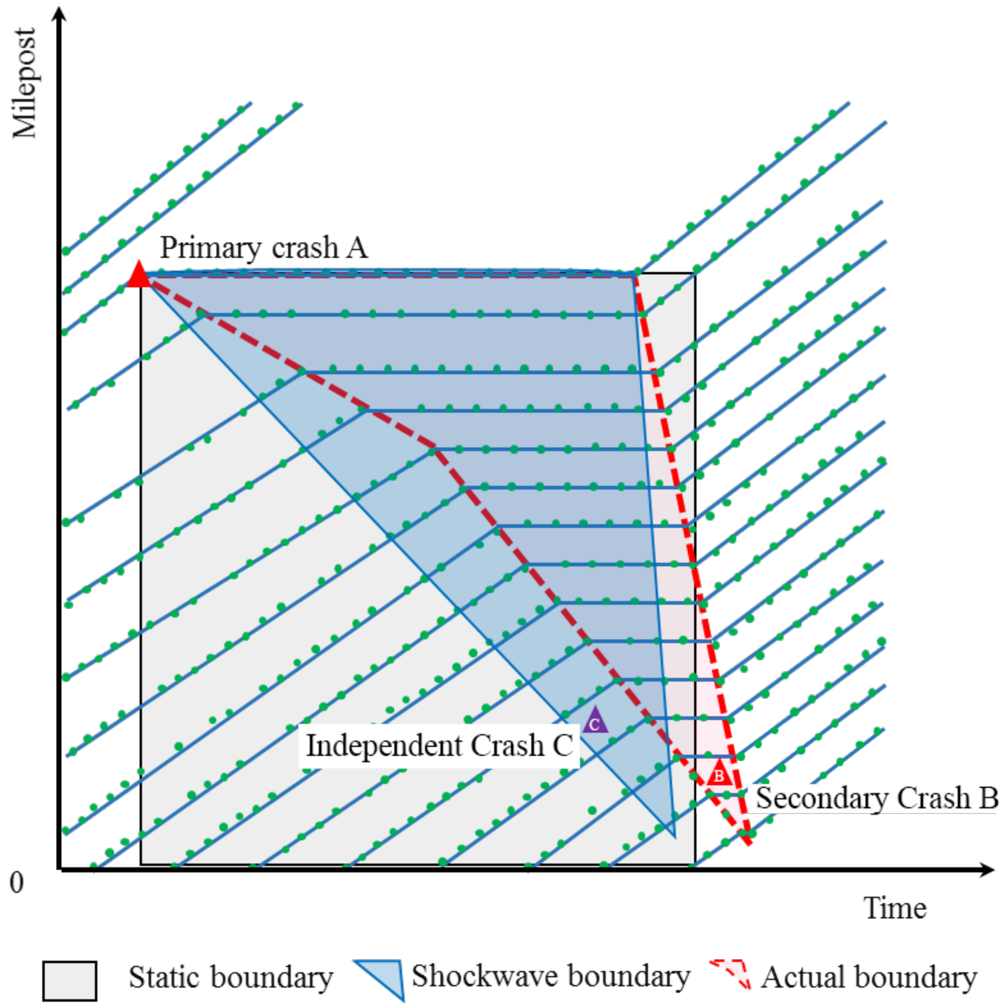


Figure 21: Shockwave estimation.

However, the shockwave-based method only considers the simple triangle polygon shape, which may not fit the actual complex traffic scenario. For example, the independent crash C is misclassified as a secondary crash of primary crash A. Thus, we propose the multi-stage shockwave estimation method.

As shown in Figure 22, the small cell represents the virtual loop detector and its value of the speed after the data fusion algorithm. The first stage starts with the primary crash, and the shockwave propagation speed at the backward and the forward positions are calculated. Based on the detailed virtual loop detector data and according speed information, the primary crash is identified, and the speed V_{PC} at the primary crash with certain parameter P is used to calculate the state change parameter $V_{PC} \times P_1$ for determining the position of the real new state change in the following stage.

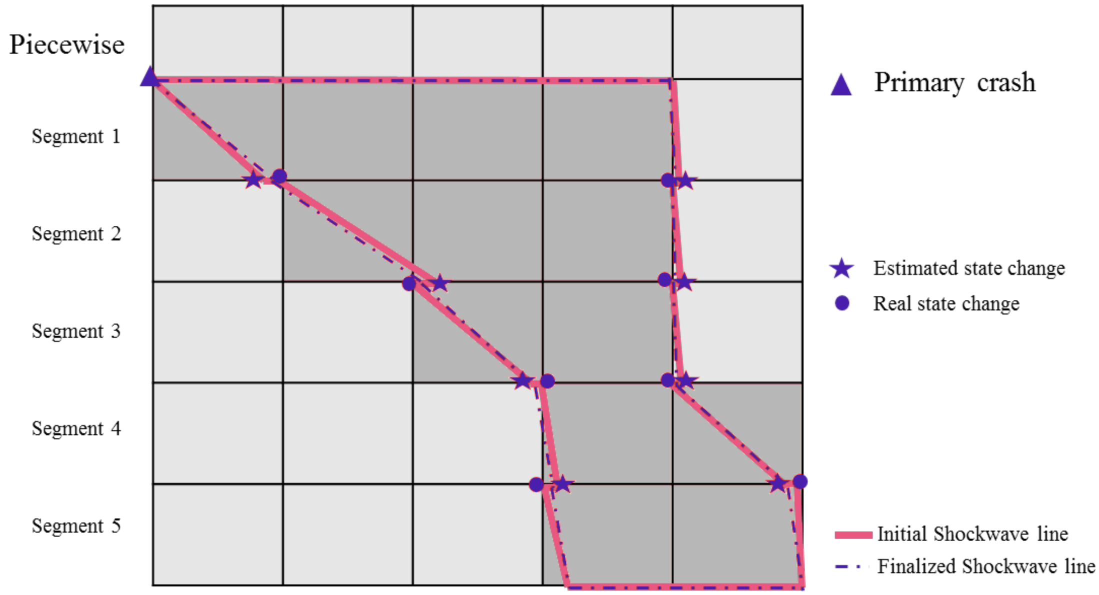


Figure 22: Multi-stage shockwave-based algorithm.

The red stars represent the estimated stage change positions of the virtual loop detectors, and the red circles represent the real stage change positions for the virtual loop detectors. By connecting all the red circles and stars, the gray line which is the initial shockwave line could be obtained. Then, the linear regression algorithm is applied to achieve the final shockwave lines (the red dotted lines).

7.6. Automated Identification of Secondary Crashes

The impact area of the primary crash is depicted using the polygon estimated in the previous section. Thus, the crash points located in the polygon like the triangular shape are identified as secondary crashes. To automatically identify the secondary crash method, the modified angle summation algorithm is used in this study.

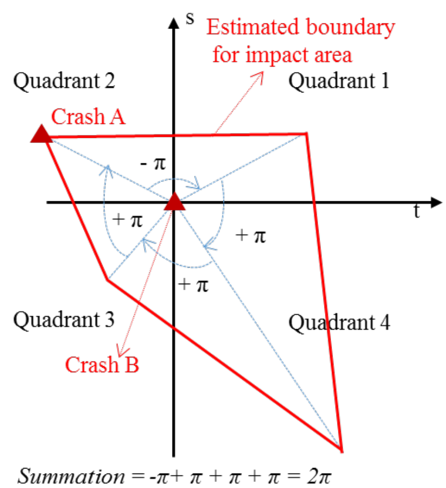


Figure 23: Modified angle summation algorithm.

In this study, we introduced the modified angle summation algorithm to determine whether a point is in the polygon as shown in Figure 23. The primary crash and the identified secondary crash are marked by the red triangles. The estimated boundary for impact area has three vertexes. By comparing the vertexes in the clockwise direction, the angle is summed based on the following criteria: If the final summation of the value is π, then the point is within the boundary of the polygon; if the final summation of the value is 0, the point is not inside the polygon; if the final summation of the value is 2π, the point is inside the polygon. The pseudo code for the modified angle summation method is given below.

Algorithm 1. Pseudo Code for modified angle summation algorithm

```
Input: Crash information {C_t, C_s}, estimated boundary segments
 composed by pairs of vertexes {P_i, P_i+1}
For each segment do:
        Calculate the angle summation ω
                If P_i is below P_i+1
                    ω=ω+π
                elseif P_i is above P_i+1
                    ω=ω-π
                elseif P_i is in the opposite quadrant of P_i+1
                    ω=ω+2π
                End if
End for
If ω=0
                C is identified as NSC
   Else
                C is identified as SC
End if
```

8. CONCLUSIONS & DISCUSSION

This research study consisted of the deployment of a low-cost integrated multi-sensor system designed for data-driven performance evaluation of urban transportation networks and related environmental impacts. The research team developed a portable sensor system and tested their performance in monitoring multiple elements of transportation networks, including air quality, noise, humidity, temperature, pedestrian movement patterns and vehicular traffic.

The sensors were used to record and analyze pedestrian movements in a transit terminal. The initial filtering of the data showed that capturing recurring patterns of the passengers in the terminal is probable. The peak periods and busiest hours can also be detected at sensor locations. This information makes it easier to estimate passenger demand at a transit terminal. However, the results from the initial filtering algorithm represent only the number of detected devices and should not be used as actual pedestrian counts. The flows between sensors indicated that certain entrances are more heavily used to reach specific gates. Although pedestrian flows provide an indicator of how the entrances are used, there are more than two entrances and four gates at this terminal. Therefore, more sensors should be installed in the future to locate the most heavily used entrances and the corresponding gates. In conclusion, it is suggested that the wireless data be used with great care and the well-tested filters must be used to clean the collected data.
Substantial progress has been made on the preliminary screening system for particulate matter in ambient air using low cost multi-sensors in this project. The first fabricated version of the system can be improved with some additions, such as reducing power consumption, conducting more tests for calibration and validation of PM2.5 readings, and deployment of a greater number of sensors.

During the course of this research, the research team has learned a great deal about developing portable and integrated multi-sensors, the problems inherent in the current data collection methodologies, and calibration-validation of the collected data. The development of these sensors and some of the technical details were explained in detail in this report, and the team hopes that it will be useful to other teams developing similar sensors for research.

There are of course limitations of these procedures that deserve mention. Short living network addresses, nonmobile devices that transmit intermittent probe requests, devices that are detectable at a low frequency, extreme weather conditions, and power problems can reduce the accuracy of the data collected by developed sensors. However, the main contribution here is to alleviate the inaccuracies originating from the noise inherent in the collected data points. Most of the proposed algorithms aim to remove low-quality detections, eliminate periodic and cyclic behavior, and improve the detection performance of the devices.

While not all stated deliverables have been met at this point, we have delivered additional results beyond the initial goals. A framework to use the Bluetooth and/or Wi-Fi sensor data for identifying secondary crashes was proposed. These sensor data can be fused with conventional loop detector data to help estimate traffic state changes, especially for the long section between two sets of loop detectors. If more sensors were deployed along the section, more vehicles could be detected and matched by multiple sensors that help collect more probe points. This will facilitate the estimation of the speed for each short section defined by the virtual sensors and thus estimate the propagation of the shockwaves more accurately. It will also provide a more thorough understanding of when, where, and why these crashes occurred in order to reduce the number of secondary crashes.

Using these analytical capabilities for processing massive traffic data and fusing sensor data, the research group will also customize and enhance two new tools for data analysis as future work:

- **ParkView**: An application using computer vision algorithms for detection and identification of vehicles, especially parked trucks and illegally parked and double-parked vehicles. This tool has been under development for the last two years by Professor Ozbay's group, and this project will be an ideal opportunity to field-test it.
- **TruckAnalytics**: A data analytics and visualization app being developed for the processing, analysis, visualization and reporting of the data captured by video, noise and emission sensors. The main functionalities of this tool have been developed by the research group for the last several years, and they will be enhanced as part of this project, as described in the "Statement of Work" section of this proposal.

Identification of a number of key pilot locations should be made in close consultation with NYCDOT and based on previous records of parking violations available from the NYC Open data web portal (https://nycopendata.socrata.com).

This project demonstrates the economic feasibility of the deployment of a large number of multi-sensor systems in the city with the ultimate goal of using multi-sensor data for data-driven decision-making.

9. DISSEMINATION OF RESEARCH RESULTS

In addition to this report, research results from this study have been published in the following journal articles:

Shlayan, N., A. Kurkcu, and K. Ozbay. Exploring pedestrian Bluetooth and WiFi detection at public transportation terminals. *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC),*, IEEE, 2016. pp. 229-234.

Kurkcu, A., and K. Ozbay. Estimating Pedestrian Densities, Wait Times, and Flows with Wi-Fi and Bluetooth Sensors. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2644, 2017, pp. 72-82.

Ozbay, K., N. Shlayan, H. Nassif, A. Kurkcu, S. Demiroluk, M. D. Maggio, and H. Yang. Real-Time Estimation of Transit OD Patterns and Delays Using Low Cost-Ubiquitous Advanced Technologies. 2017.

Kurkcu, A., and K. R. Kaan Ozbay. Investigating Transit Passenger Arrivals using Wi-Fi and Bluetooth Sensors. 2017. *12th ITS European Congress*

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