Estimating Pedestrian Densities, Wait Times, and Flows with Wi-Fi and Bluetooth Sensors

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Monitoring nonmotorized traffic is gaining more attention in the context of transportation studies. Most of the traditional pedestrian monitoring technologies focus on counting pedestrians passing through a fixed location in the network. It is thus not possible to anonymously track the movement of individuals or groups as they move outside each particular sensor's range. Moreover, most agencies do not have continuous pedestrian counts mainly because of technological limitations. Wireless data collection technologies, however, can capture crowd dynamics by scanning mobile devices. Data collection that takes advantage of mobile devices has gained much interest in the transportation literature as a result of its low cost, ease of implementation, and richness of the captured data. In this paper, algorithms to filter and aggregate data collected by wireless sensors are investigated, as well as how to fuse additional data sources to improve the estimation of various pedestrian-based performance measures. Procedures to accurately filter the noise in the collected data and to find pedestrian flows, wait times, and counts with wireless sensors are presented. The developed methods are applied to a 2-month-long collection of public transportation terminal data carried out with the use of six sensors. Results point out that if the penetration rate of discoverable devices is known, then it is possible to accurately estimate the number of pedestrians, pedestrian flows, and average wait times in the detection zone of the developed sensors.

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 are collected. In recent years, several studies have been reported in the literature on automating pedestrian detection or counting to explore economic and reliable methods (*1–5*). These researchers reviewed the available automated pedestrian counting technologies, such as infrared and thermal sensors (*6*). 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 (O-D), travel time, wait time, and flow information for some subset of 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 (*7*). This type of traffic detection system can be supplemented by traditional sensing technologies to improve crowd monitoring systems (*8*).

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, 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 used in various applications and data collection processes in the literature.

To be able to manage transportation systems efficiently, information about nonmotorized traffic is required. However, decision makers and transportation officials in the United States have not yet extensively examined nonmotorized traffic (*9*). In addition, most agencies lack comprehensive pedestrian counts mainly because of technological limitations. Some of these challenges can be explained as follows:

- Unlike motorized vehicles, pedestrians do not travel in fixed lanes or paths and they make unpredictable movements.
- Pedestrians sometimes travel very close to each other, creating platoons, and some sensors have difficulty counting individuals in the group (*3*).
- The number of locations for which pedestrian data are needed is exponentially higher than is the number needed for monitoring vehicular traffic.

Although the FHWA Traffic Monitoring Guide 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 (*10*). According to FHWA's guide, calibration and validation procedures should be implemented to ensure that pedestrian counts are within the bounds of acceptable accuracy. Table 1 illustrates the available technologies and costs adapted from that guide; the table is updated with the addition of relevant information about wireless sensors. The proposed sensors cost approximately $100, including additional parts such as Wi-Fi and Bluetooth USB antennas.

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TABLE 1 Available Pedestrian Counting Technologies

	Technology	Pedestrian Detection	Cost
Permanent	Wi-Fi and Bluetooth sensors	○	$
↑	Pressure sensor	○	$$
	Radar sensor	○	$–$$
How long?	Seismic sensor	○	$$
	Video imaging: automated	○	$–$$
↓	Infrared sensor: active or passive	●	$–$$
Temporary or short term	Video imaging: manual	○	$–$$$
	Manual observers	●	$$–$$$

NOTE: ○ = what is technologically possible; ● = a common practice; $, $$, and $$$ indicate relative cost per data point.
SOURCE: FHWA (*10*). 2013.

Most of the common pedestrian monitoring technologies mentioned in the table 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 each particular sensor's range. Tracking pedestrians may be achieved with the use of video imaging and matching the same pedestrians but is not preferred because of 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 relies on some assumptions about the crowd and conditional factors, depending on the site of the study.

In this study, methods on how to anonymize, filter, and aggregate traces of pedestrians and how to fuse additional data sources to enhance existing filtering and counting algorithms are discussed. The proposed methods are evaluated with various data collection scenarios. After the evaluation period, developed techniques are applied to a 2-month-long collection of public transportation terminal data and the results are reported.

BACKGROUND

Bluetooth technology is the global wireless standard enabling the communication between smart devices using radio transmissions. The key properties of Bluetooth are robustness, low power, and low cost (*11*). Although not all Bluetooth devices are discoverable, in general, it has been reported that 5% to 12% of devices are discoverable via Bluetooth (*12*). When the user is looking for other devices to connect to with Bluetooth, the device will be active and visible to all other devices on the network. Developed sensors can detect only those devices that are actively looking for other Bluetooth devices or are already connected to another device via Bluetooth.

Wi-Fi is a technology defined in the IEEE 802.11 standard that allows electronic devices to connect to a wireless local area network with the use of radio bands. Whenever devices try to connect to a wireless local area network, they send out a probe request. A probe request is a special frame that asks for information from either a specific access point or all access points in the area. By sending a probe request, the wireless device is making an active scan of networks. Probe requests contain the MAC address of the sender; the service set identifier, which is the network name; and the received signal strength indication.

To ensure the maximum amount of anonymity, data collection systems that will use signals from Wi-Fi- and Bluetooth-enabled mobile devices should not store personally identifiable data; therefore, MAC addresses collected by sensors should not be associated with specific users. In some studies in the literature, the electronic identifier of the mobile device of the detected agent is converted into an encrypted hash code. MAC addresses that are not matched are deleted at the site (*7*). In others, it has been stated that privacy concerns for the end users are a nonissue when the data are collected through Bluetooth. The MAC addresses were kept anonymous without being directly tied to individuals (*1, 13, 14*). In a 2010 research study by the Texas Transportation Institute, a routine was added to Bluetooth data collection software to encrypt collected MAC addresses. This step was taken to ensure that actual device addresses are not stored anywhere, but rather a random set of characters is used (*15*). In this paper, a similar technique is proposed for the encryption to ensure maximum privacy while maintaining persistent records. The code that grabs the MAC address from probe requests checks only the last three octets. Instead of keeping all digits of the MAC address, to protect the embedded private information, only the part that contains the last six digits is read. For example, if the MAC address of a device is MM:MM:MM:SS:SS:SS, only SS:SS:SS is kept. After the last six digits are retrieved, that information is then encrypted with an encryption key and stored on the instrument. This technique provides an extra layer of protection. It also keeps the MAC addresses unique for approximately 98% of the detected devices. The encryption key is first randomly generated on a remote server. After the initial key is generated, it is then encrypted again before being uploaded to the devices on site. Moreover, it is proposed that for most of the field applications, individual data points be aggregated and deleted on site depending on the type of data collection. For example, to obviate the need to keep even highly anonymized and encrypted individual data points, sensors will keep the aggregated counts only if they are calibrated for counting.

Earlier efforts found in the transportation literature dealing with the determination of individual movements focused mostly on Bluetooth-based detection. The work presented by Ahmed et al. is one of the first to use Bluetooth detection for vehicle monitoring (*16*). The contribution of this work is the deployment for the first time of a very low cost and low power device–software combination for transit-related O-D estimation applications. Kostakos used Bluetooth devices to trace passenger journeys on public buses and derive passenger O-D matrices (*17*). Bullock et al. deployed a Bluetooth tracking system at the new Indianapolis International Airport in Indiana to measure the time for passengers to transit from the nonsterile side of the airport (presecurity), clear the security screening checkpoint, and enter the walkway to the sterile side (*18*). Hamedi et al. investigated the quality of vehicle probe data using new traffic surveillance devices based on Bluetooth technology (*19*). Their results showed that this technology is a promising method for collecting high-quality travel time data that can be used for evaluating other sources of travel time and intelligent transportation systems applications. Haseman et al. also used Bluetooth probe data from multiple field collection sites to quantify delay and to assess diversion rates at a rural Interstate highway work zone along I-65 in northwestern Indiana (*20*).

Malinovskiy et al. presented a study of pedestrian detection using Bluetooth at two separate sites (*7*). They investigated the feasibility of using Bluetooth technology for pedestrian studies and found that it can provide useful information for pedestrian travel behavior. Barceló et al. used travel time data captured by Bluetooth sensors to estimate time-dependent O-D matrices in simulation tests (*13*). Lees-Miller et al. tried recovering the path of a vehicle by using Bluetooth detection data (*21*). The proposed approach was able to reconstruct vehicle trajectories outperforming a simple deterministic strategy by 30% to 50%. Michau et al. showed that the position of the detectors is of great importance and the wireless signals are easily weakened by physical conditions as well as weather (*22*). The detection process of a Bluetooth device can be described as a cycle during which the sniffer will transmit messages on a different range of frequencies and wait for devices to pick up the messages. Therefore, it was concluded that Bluetooth devices have to be in a discoverable mode for about 10 s in the detection zone to detect them (*22*). Laharotte et al. provided some insights on how Bluetooth data can be used for vehicular flow forecasting (*14*). Their filtering algorithm reconstructs traffic states at a network scale with nonparametric pattern recognition techniques with a *k*-nearest-neighbors procedure. Their prediction of the network traffic state with a *k*-nearest-neighbors approach showed convincing results with 31 days of data.

Integration of Wi-Fi systems with Bluetooth sensors can be found in recent studies dealing with real-time data collection and monitoring of pedestrian networks. Lesani and Miranda-Moreno investigated the advantages and the feasibility of a Wi-Fi data collection system as an alternative and a supplement to Bluetooth technology (*23*). They found that the detection rate for Bluetooth is as low as 2.0%, and the combination of Wi-Fi and Bluetooth systems showed promising results. Hourly travel time estimation errors were about 3.8%. The average and median prediction errors of pedestrian flows were 15% and 9%, respectively. Weppner et al. (*24*) and Weppner and Lukowicz (*25*) used Bluetooth scanners to count the number of devices in a fixed region. Nicolai and Kenn presented a method to discover the relationship between detected Bluetooth devices and the ground truth data (*26*). Kalogianni et al. used a passive Wi-Fi scanning method to sense the movements of students, employees, and visitors on a university campus (*27*). They investigated what kinds of patterns can be captured by Wi-Fi monitoring and how people use the buildings on the campus. The results pointed out that passive Wi-Fi monitoring is an effective way to identify building usage and movement between buildings. Bonne et al. developed a low-cost crowd counting system based on a single-board computer with the addition of an LED to provide a status indicator and an Android cell phone as an operator (*28*). Fifteen devices were deployed at a music festival and four on a university campus. They concluded that tracking visitors at mass events can be achieved with the use of Raspberry Pi sensors at a very low cost. Abedi et al. used a commercial sensor with the capability of scanning Bluetooth and Wi-Fi addresses simultaneously (*8*). They compared the standards for both technologies concerning architecture, discovery time, signal strength, and popularity of use. The results showed that Wi-Fi has a shorter discovery time, the distance from the sensor can be estimated on the basis of the signal strength, and Wi-Fi is accepted as the more appropriate standard compared with Bluetooth for pedestrian data collection. Abedi et al. evaluated antenna characteristics and concluded that the bigger antenna captures more data, but may not be useful for small scales of monitoring because of overlapping detection areas (*8*). Schauer et al. used Wi-Fi and Bluetooth sensors to estimate crowd densities and pedestrian flow at a major German airport (*29*). Additional studies can be found in the literature that deal with pattern mining in tourist attraction visits (*30*), the Bayesian approach to detect destinations (*31*), and location popularity and visit patterns (*32*).

Although almost all of these applications used similar data sets, only a few developed their own sensors and comprehensive techniques for removing erroneous detections (*33*). In addition, measures other than pedestrian movement and O-D data were not investigated. In this study, sensors developed by the research team to collect Wi-Fi and Bluetooth traces are used to improve scenario-based filtering algorithms and accurately report measures such as pedestrian counts, wait times, and time-dependent O-D patterns.

RESEARCH METHOD

It is possible to detect the proximity of personal electronic devices with Wi-Fi and Bluetooth when they are actively looking for other devices. Wireless sensors can detect not only the mobile devices around them but also the nonmobile devices, access points, and other networks disseminating their presence to the network. Therefore, it is critical to build efficient algorithms to filter the raw data captured by the sensors. In this paper, four filtering algorithms are developed to accurately refine wireless traces. The initial filter will remove the devices that are far away from the sensors and the nonmobile devices in the captured data. After this initial cleaning, pedestrian counts, flows, and wait times can be calculated with the, respectively, moving blocks, flow, and wait time filters. Figure 1 shows the flowchart of the algorithms applied to the collected traces and their results.

Virtual Sensors—Bus Time

A web scraper is also developed to retrieve real-time bus schedules and delays for the corresponding bus lines from the transit authority's web application. It behaves as a virtual sensor to track bus departure times and delays (*34*). This information will be used in the evaluation of wait times to remove the erroneous detections efficiently and to calculate maximum acceptable wait times at the stations.

Pedestrian Sensors

Hardware

Raspberry Pi is a low-cost, small computer that is compatible with monitors or televisions (*35*). 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 one can expect a desktop computer to do. In addition, it is possible to build the Pi so that it will have the ability to interact with the environment. As reported in the literature, the Raspberry Pi and similar mini PCs have been used to detect motion (*36*), measure noise (*37*) and air quality (*38*), and monitor the environment (*39*) as well as for various smart city applications (*40–42*). The developed sensor can be seen in Figure 2.

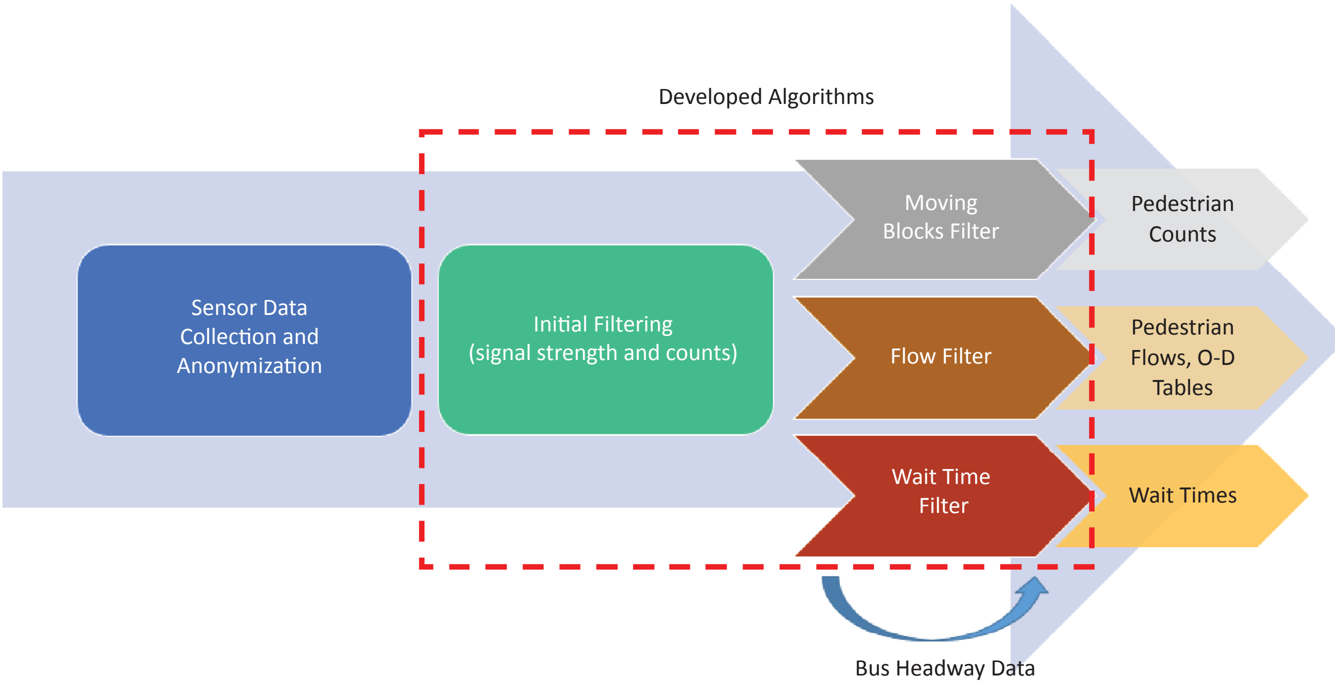
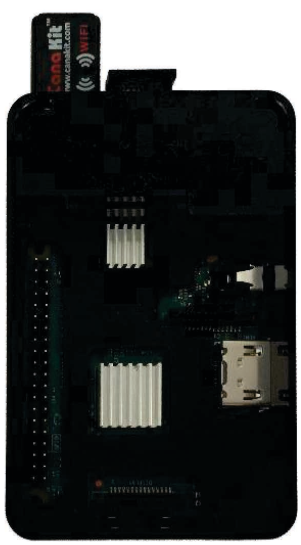


FIGURE 1 Proposed method for data analysis.

Software

Installation of Raspbian, the Linux operating system, is minimal, and the system comes with the Pi's SD card installed. The Aircrack-ng library is used to create an access point and sniff the network, and SQLite3 is used as a database to store the data. The signal strength (received signal strength indication) of the devices can be used to create a detection zone. With tuning, a circular detection circle is created that when crossed, can trigger the detection system to store the information in SQLite tables.

(a)



(b)

FIGURE 2 Raspberry Pi.

Data-Filtering Algorithms

Seven trial field tests with varying lengths, from a couple of hours to a couple of weeks, are conducted before an actual field test to develop and improve the data-filtering algorithms. To evaluate and supplement the sensor's crowd count, manual counts that are done to be collected as ground truth data are also reported. Table 2 summarizes the conducted field tests. Parameters and inputs to these algorithms need to be tweaked, depending on the purpose and the location of the study.

Initial Filtering of Data

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,

TABLE 2 Conducted Tests

Study Location	Length	Data	No. of Locations
Brooklyn I	5 days	7,792	3
Brooklyn II	1 day	2,159	2
Brooklyn III	5 days	9,755	2
Transit center	1.5 h	1,102	2
Commercial building	14 days	22,759	3
Student center	1 h	1,266	3
School of engineering	2 h	1,875	4

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.

Moving Blocks—Counting Crowds

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 visualization of this method can be seen in Figure 3*a.* The moving block algorithm successfully removed a significant amount of noise in the count data during the field tests. However, it is prone to errors at the beginning and the end of the study because of the limited block availability. The counts become more reliable with a 5-min warm-up and a cool-down period. The algorithm's performance in accurately counting pedestrians is heavily dependent on the ratio of people with discoverable devices.

Estimation of Pedestrian Flows

Flow data can be captured by finding overlapping anonymized and encrypted MAC addresses between two sensors. Figure 3*b* shows the flow estimation algorithm. For each record, the time it took an individual to go to one sensor from another is calculated from the data. The distances between the sensors are known, and irregular travel times can be filtered out with the use of the walking speed. The data points are removed if the calculated speed does not fall within the 95th percentile confidence interval. It is assumed that pedestrians have large interindividual differences, and the desired speed of an individual follows a Gaussian distribution with mean 1.2 m/s and standard deviation 0.3 m/s (*43*).

Wait Time Calculation

The time difference between the first and the last occurrence of anonymized and encrypted MAC addresses is stored in a temporary table. These data do not need to be saved and can be deleted on completion of the calculations for 5-min or 15-min periods. Figure 3*c* visualizes the proposed filtering algorithm. Individual pedestrian wait times are calculated for each hour and are assigned to hour slices depending on the first detection time. With the real-time bus data, the longest headway between two buses is found for respective gates. Therefore, pedestrian wait times that are longer than that value and shorter than 30 s are removed from the temporary table for further analysis.

EXPERIMENTAL RESULTS OF FILTERING ALGORITHMS

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.

Initial Filtering

The initial filtering algorithm described above is applied to the week-long data to capture the patterns of the number of detected devices on different days. Figure 4*a* 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 4*a* illustrates the number of passengers entering the terminal as well as customers visiting these commercial facilities.

Figure 4*b* shows the number of detected devices for Wednesday. The busiest hour is between 7 and 8 a.m., with 2,126 detected devices. The patterns of the device detection more or less remain the same for the weekdays. The different patterns on Sunday can be explained by buses having less frequent service times and a lower number of riders and by some commercial stores being closed at the terminal.

Moving Block Algorithm Results

Two indoor field tests with high foot traffic are conducted to test the moving block algorithm; Figure 5 shows the results. An observer counted pedestrians present by the sensor for at least an hour at 5-min intervals for each test. Although manual counts are accepted as ground truth, these counts are subject to the usual human errors, especially in cases in which the count time is noted. This situation can be improved by having a video feed of the study location providing more accurate pedestrian counts. Field tests were conducted in a campus environment, and the penetration rate of discoverable devices was assumed to be 100%. Results revealed that the accuracy of the total count was 97% in the first test and 92% in the second test. However, the variation in counts after 2:30 p.m. in the second field test was not captured as can be seen from Figure 5. One potential explanation for this difference can be the devices with wireless features turned off. It is also possible that some of the pedestrians may be double counted by the sensor. The variables that the algorithm used remained the same in both cases.

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 6 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.

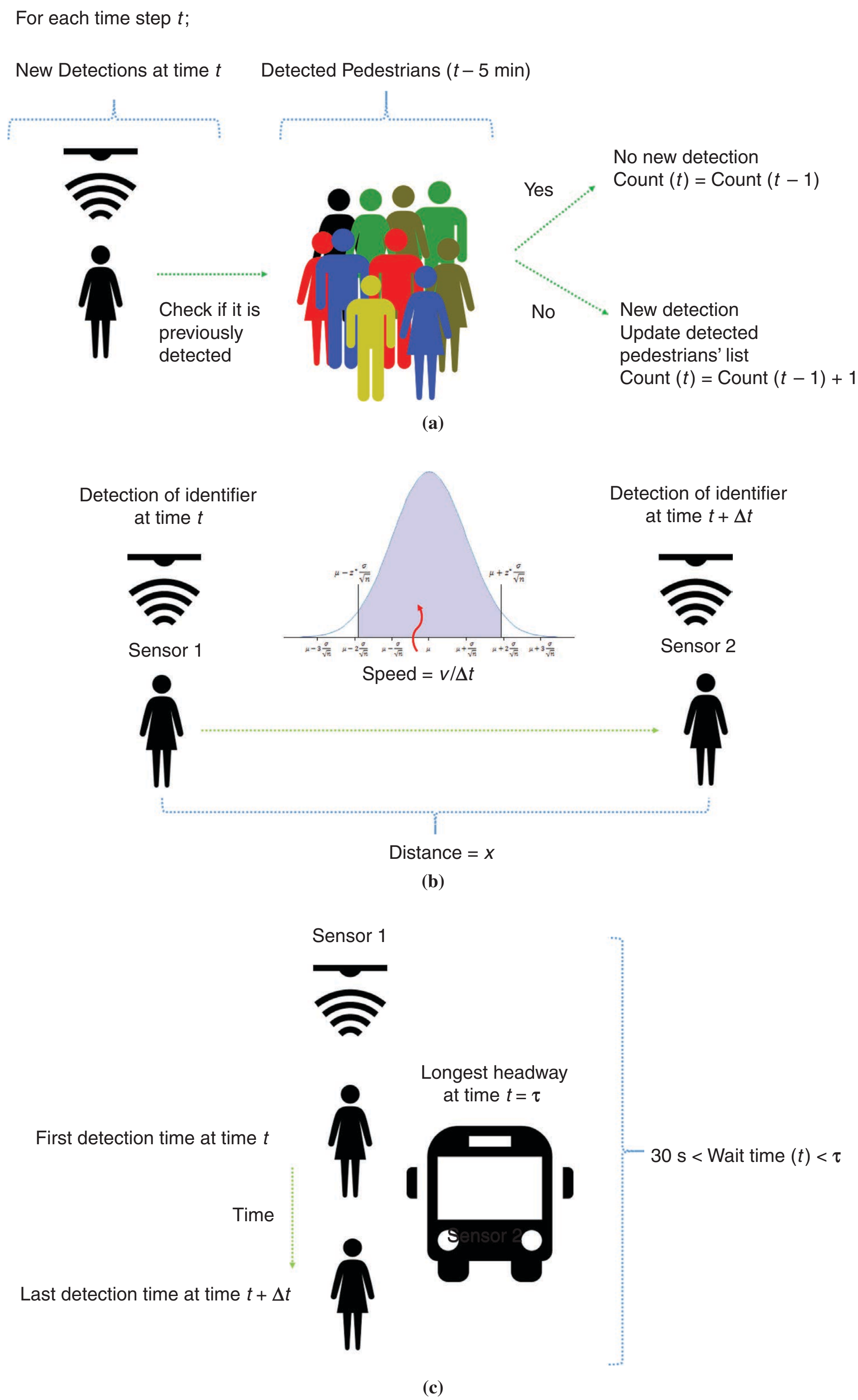


FIGURE 3 Proposed filtering algorithms: (*a*) moving block algorithm, (*b*) estimation of pedestrian flows, and (*c*) wait time calculation.

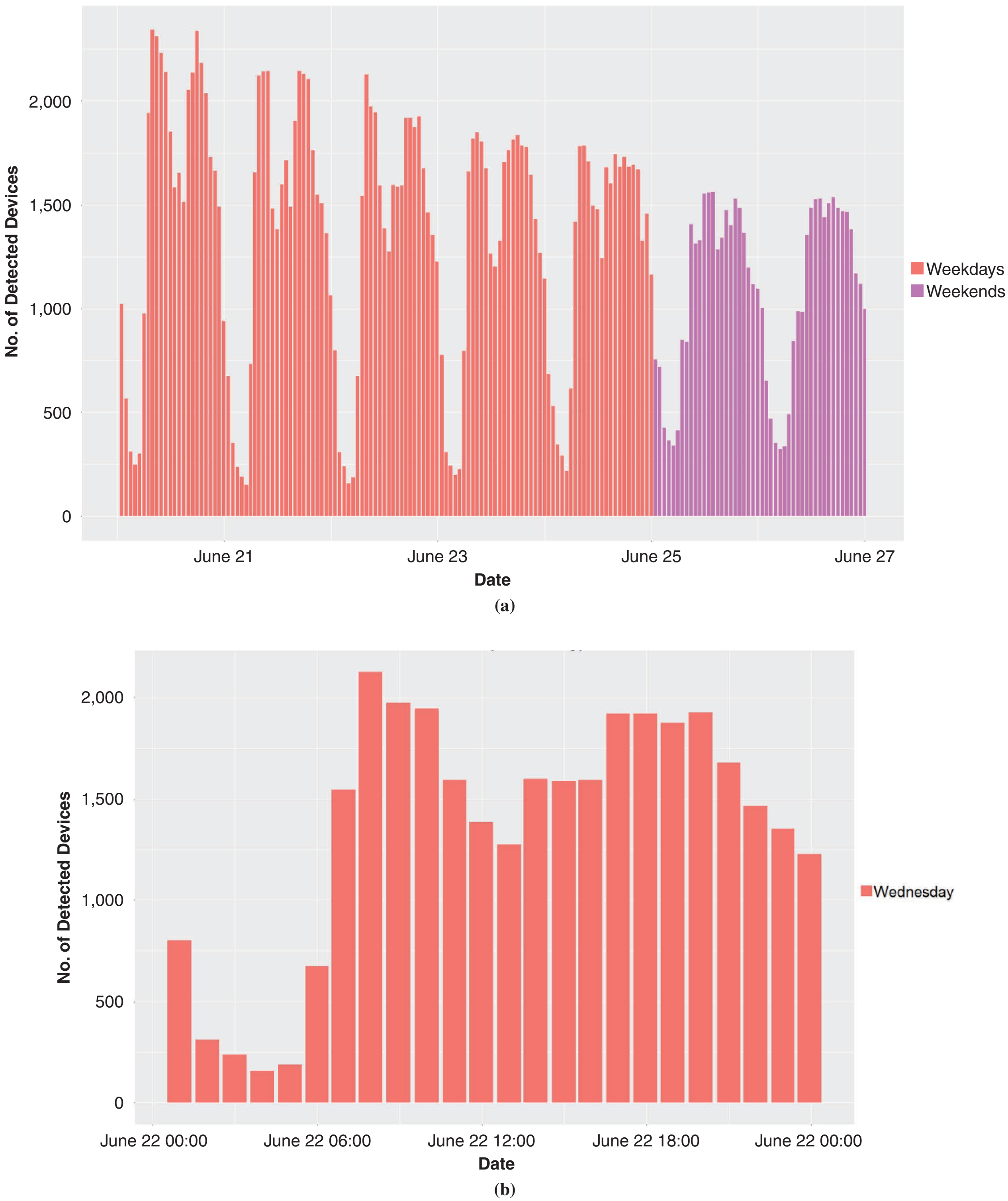


FIGURE 4 Number of detected devices: (*a*) detected mobile devices for a week and (*b*) detected devices for a day.

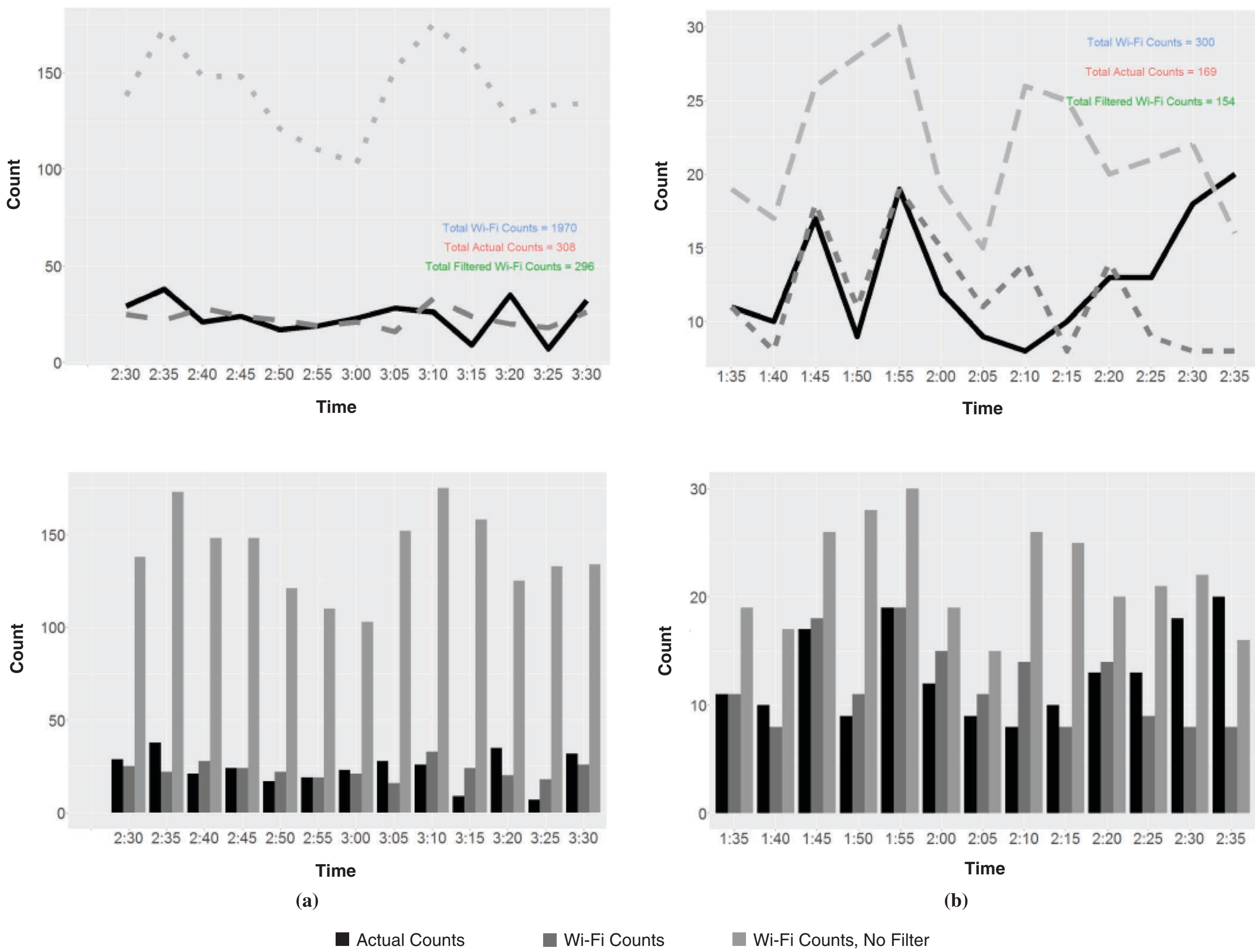


FIGURE 5 Moving block algorithm results.

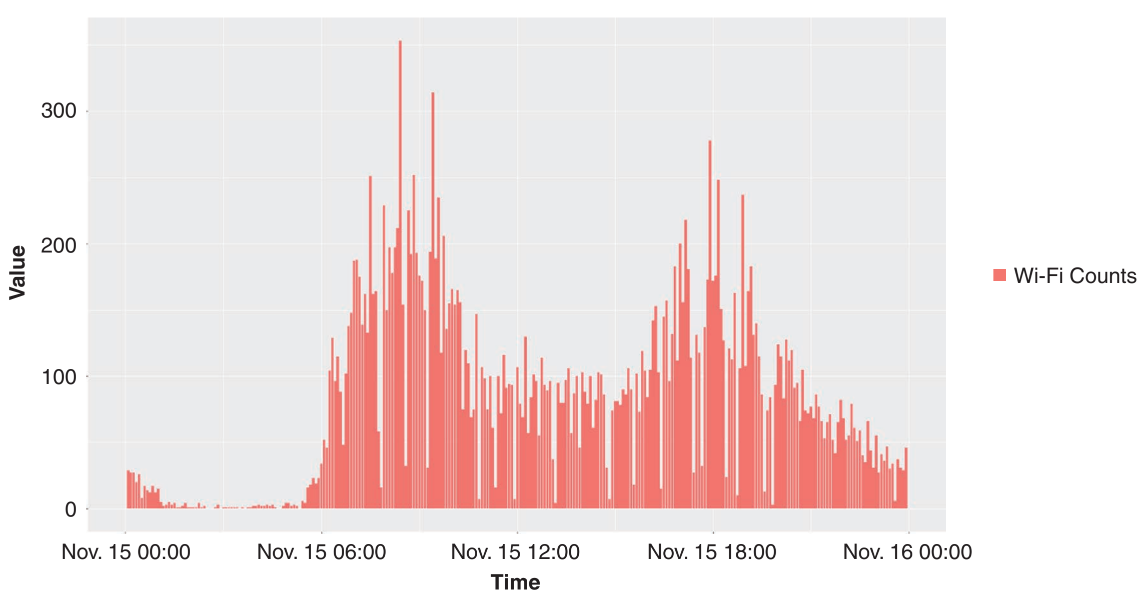


FIGURE 6 Pedestrian counts for a day at Entrance A.

TABLE 3 Pedestrian Flows for 1 Week

From	To Gate 1	Gate 2	Gate 3	Gate 4
Entrance A	960	4,487	4	517
Entrance B	6,444	5,310	81	4

Pedestrian Flows

Table 3 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.

Time-dependent O-D pairs can also be created with the wireless sensor data. Figure 7 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.

Wait Times

Wait times at the gates are studied by comparing them with actual bus schedules by the code described in the previous section. Figure 8 visualizes wait times for each detected device. The horizontal bars reflect the wait times, and the vertical lines in red and green show the scheduled and actual bus departures, respectively. The actual bus departure information is collected with the use of the virtual sensor algorithm explained in the section describing the method. Departure delays up to 5 min are experienced at this gate. Buses also may arrive at their gate earlier than the departure time and open their doors for boarding. Therefore, it is more accurate to create a 5-min buffer zone around the scheduled departure times. Even though successive filters are applied to the data, there are still some outliers that may decrease the accuracy of the calculated wait times. For example, the detected devices p1001 and p1004 leave the platform at about 8:13 a.m. after the bus departs at about 8 a.m. Device p1001 comes to the stop at about 8:00 a.m., and p1004 comes to the stop at about 8:08 a.m. These data points should be excluded to calculate wait times more accurately.

CONCLUSIONS AND FUTURE WORK

This paper presents the algorithms developed to filter and aggregate the data collected by Wi-Fi and Bluetooth sensors and explains how to fuse an additional data source to improve the estimation of wait times. The developed methods are applied to a 2-month-long collection of data carried out in a transit terminal. The sensors are located at the two main entrances as well as at four passenger gates. There are of course limitations of these procedures that deserve mention. Short living network addresses, nonmobile devices that transmit intermittent probe requests, and devices that are detectable at a low frequency can reduce the accuracy of the developed algorithms. However, the main contribution here is to alleviate the inaccuracies originating from the noise inherent in the collected wireless traces. All of the proposed algorithms aim to remove low-quality detections, eliminate periodic and cyclic behavior, and improve the detection and counting performance of the devices.

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

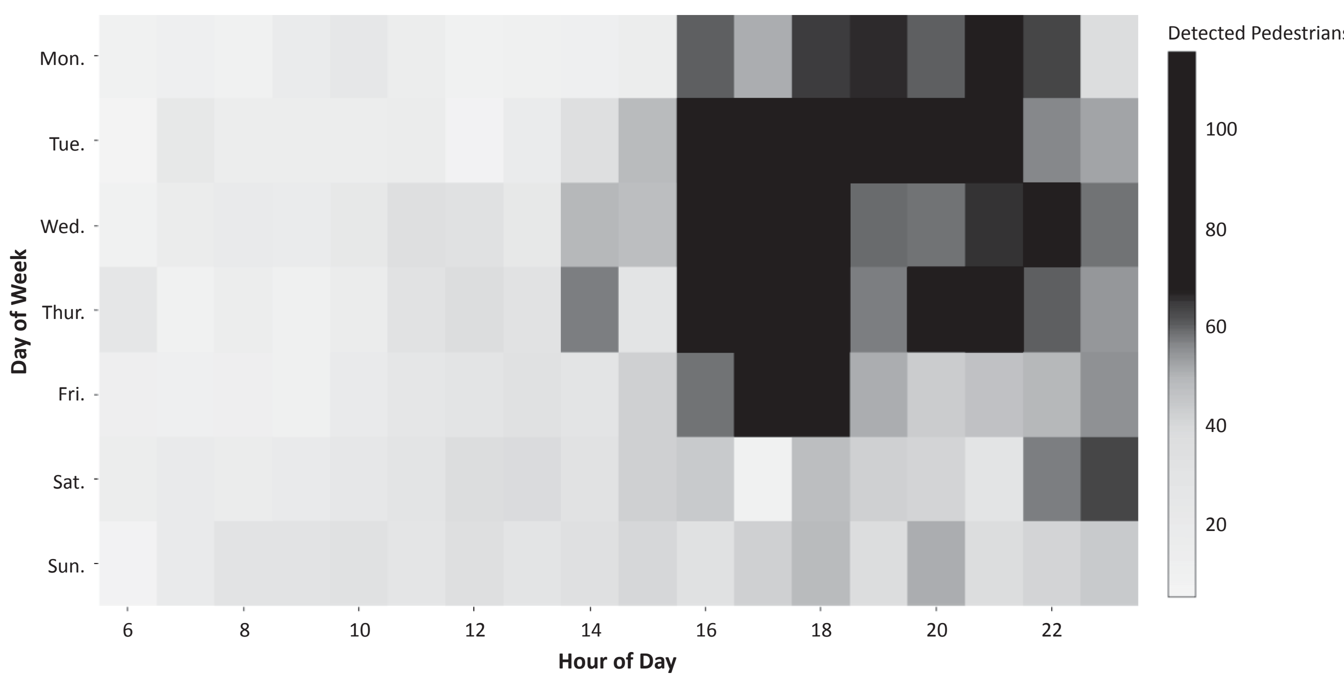


FIGURE 7 Detected pedestrians between Entrance A and Gate 2.

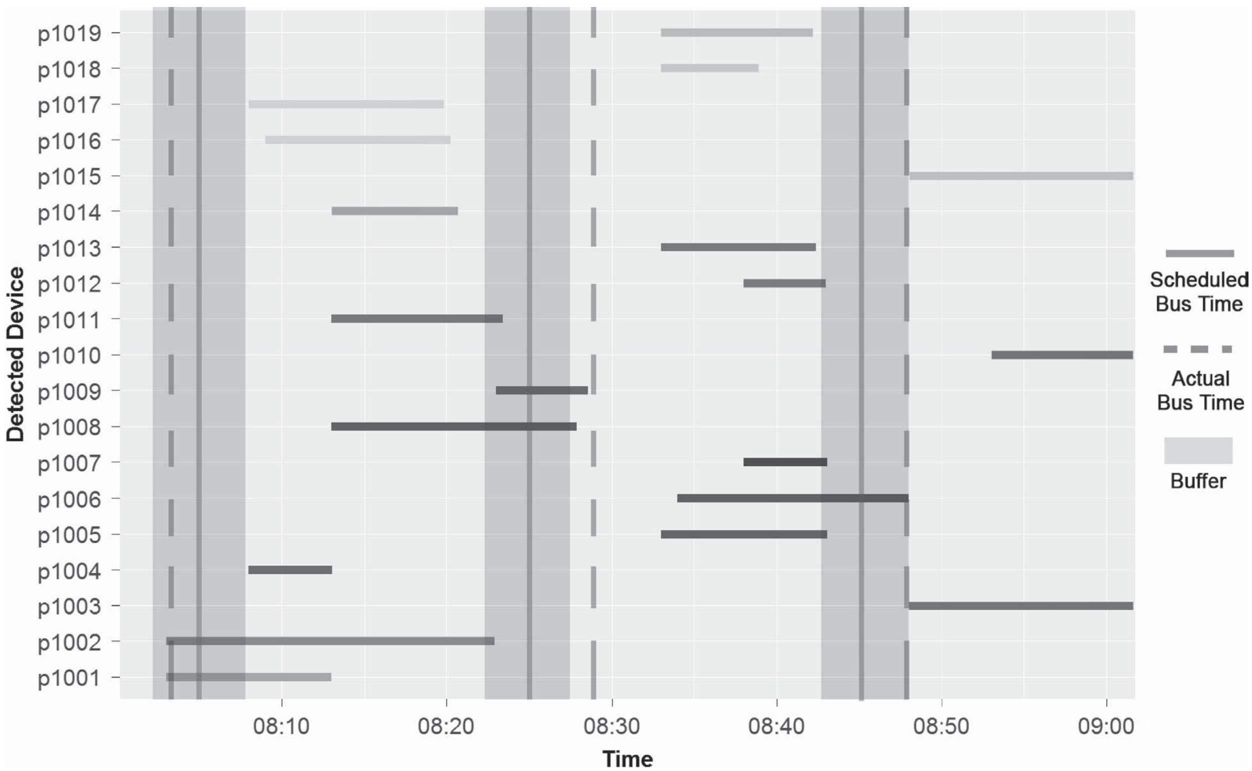


FIGURE 8 Wait time visualization.

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 moving block algorithm can provide more accurate representation of the pedestrian counts at fixed sensor locations because it can efficiently eliminate the double counts and nonmobile devices. Results from field tests showed that the moving blocks algorithm can reach approximately 90% accuracy with the availability of data 5 min before and after the study period if the discoverability rates of the devices are close to 100%. If this location- and time-specific penetration rate is known for other study sites, the moving block filter can be used to factor in the Bluetooth and Wi-Fi samples to account for total pedestrian counts. The flows between sensors indicated that some 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. In a future study, these results, which are based on 1 week, should be supplemented with additional long-term data to ensure that seasonal variations are represented.

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