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Analysis and Use of Wi-Fi data for Signal State Identification

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Abstract

Efficient planning, operation and management of transportation facilities require extensive data regarding the traffic demand, patterns and conditions prevalent in the transportation network. Conventional data collection techniques such as loop detectors bear practical limitations such as limited accuracy and applicability, especially in mixed traffic conditions. Since use of smart phones has gained prominence in the recent times, crowd sourced data using Bluetooth and Wi-Fi technologies is perceived to be a reliable alternative for traffic data collection. This eases the rigorous data collection process by considerably reducing the investments on labor, time and other resources. Significant research has been carried out in the extraction and analysis of traffic data from Bluetooth sensors. Changes in privacy settings of smartphones has necessitated the devices to be put on "Discoverable" mode for passive data collection thereby resulting in drastic drops in market penetration rates. Unlike their Bluetooth counterparts, Wi-Fi protocol just requires the Wi-Fi to be switched on for passive data collection, thus resulting in higher penetration rates. This paper presents a preliminary analysis of data extracted from Wi-Fi sensors and the use of it for extracting the signal state information.

Keywords: Traffic data collection; Wi-Fi sensors; Descriptive statistics; Signal timings.

1. Introduction

Accurate, reliable and real-time information on the state of traffic prevalent on the network at any given time is necessary for planning, maintenance and operation of any transportation facilities. Data collection techniques to extract these traffic related data has evolved with time. Manual counting of vehicles was the earliest of the approaches. This

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was automated gradually with the introduction of various types of detectors like pneumatic tubes, magnetic detectors, inductive loop detectors, microwave, infrared and other electromagnetic wave based detectors. Out of these, inductive loop detectors are most commonly used for collection of traffic data like volume which is indicative of the demand and pattern of traffic; and occupancy which is indicative of the prevalent traffic state. Loop detectors are invasive to the pavement. Also, like most other detectors, they are less efficient for mixed traffic conditions having a wide diversity in terms of vehicle classes and lack of lane discipline. Extraction of trip characteristics like travel time, delay and origin and destination is much more challenging and require extensive surveys like license plate survey, household survey, road side survey etc. These surveys are resource intensive in terms of labor, time and money. Thus, it is of utmost importance to find cost effective, less resource intensive and scalable alterative traffic data collection techniques, especially for mixed traffic conditions.

Conventional data collection techniques include use of location-based sensors such as inductive loops, magnetometers, radar, infrared sensors etc. and then tracking solutions like GPS. Out of these, video-based image processing, and GPS are two possible solutions that can work under mixed traffic conditions. The problem with image processing technique is the need for extensive network of cameras and high-end computing requirements rendering it expensive. The usage of GPS based probe vehicles for traffic data collection has privacy concerns and thus only public transport vehicles are commonly used as probes. Such a small sample of vehicle population may not adequately represent the traffic stream.

One field which has been growing as rapid, if not more, as that of the traffic growth is the information technology (IT) sector. Taping into the vast possibilities of the IT field, the usage of IT in traffic data collection has been on the rise. Over the past couple of decades, the usage of mobile phones and other electronic devices with various short-range communication protocols like Bluetooth and Wi-Fi has gained prominence. Devices can be uniquely identified using Media Access Control (MAC) ID under these protocols. This has opened a new horizon for crowd sourced passive traffic data collection. With the MAC IDs being uniquely broadcasted by the devices, it is just needed to passively record those MACS IDs along with timestamp. Tracking the MAC IDs along a network with the help of multiple sensors would yield relevant trip information like travel time, origin-destination, etc.

Bluetooth has been the more commonly used short range communication protocol for traffic data collection and extensive studies have been reported with regard to collection, extraction and analysis of traffic data using Bluetooth sensors (Haghani et al. 2010 and Martchouk et al. 2011). However, in the recent years, the market penetration of Bluetooth sensors has reduced because of the improvements in privacy settings in most of the mobile phones. For the devices to be passively detected, the privacy improvements necessitate the Bluetooth device to be put on "Discoverable" mode in addition to switching on the Bluetooth. However, unlike Bluetooth, Wi-Fi requires the devices to have just the Wi-Fi switched on for passive MAC ID collection. This study presents the collection, processing and analysis of data obtained from Wi-Fi MAC ID matching technique to extract meaningful traffic related parameters. In addition to just giving travel time and origin and destination information, there can be many other traffic related data concealed in this data. The present study tries to explore these possibilities and presents one such application for the identification of signal state at an intersection using Wi-Fi sensor data.

The reminder of this paper is structured as follows. Section 2 presents a review of the literature pertaining to traffic data collection in general and traffic data collection using Bluetooth and Wi-Fi sensors in particular. Section 3 discusses the data collection methodology adopted in this study. Section 4 presents the analysis of the Wi-Fi data and discusses the significant findings. The paper concludes by presenting in Section 5 a methodology to extract signal state from Wi-Fi sensor data.

2. Review of literature

Owing to the vitality of traffic data collection in various traffic engineering applications, researchers have tried to continuously come up with newer and better alternative data collection practices to ease the data collection process and make it less resource intensive. Klein et al. (2006) and Leduc (2008) presented an overview of the various traffic data collection methods starting from manual counts to videography-based traffic data collection. These included different types of detectors like the pneumatic tubes, inductive loop, magnetic loops and other intrusive and non-intrusive data collection methods. Probe vehicle-based data collection like floating car method was also attempted for traffic data collection (Robertson and Hummer (1994)). The probe vehicle had to travel along the corridor to extract travel time and speed. Quiroga and Bullock (1998) presented the use of GPS devices in these probe vehicles to collect vehicle trajectories. Hunter et al. (2006) presented a methodology to extract travel time using GPS equipped probe vehicles. Hao et al. (2012) and Di-hua et al. (2017) studied the estimation of signal timings using GPS based intersection travel times. Radio Frequency Identification (RFID) based techniques were attempted for traffic data collection (Sringiwai et al. (2010)) and reported an accuracy of 85%. A major limitation of RFID based, and GPS based traffic data collection is the marginal penetration and privacy concerns. Image processing based Automatic License Plate Recognition (ALPR) systems have also been attempted to obtain traffic data like travel time, origin-destination and speed. Yasin et al. (2009) demonstrated the use of ALPR system for real time estimation of travel times. License plate readability during night times and during adverse weather conditions have been a major hurdle for traffic data collection using ALPR, in addition to it, being an expensive alternative.

Most of the conventional data collection techniques discussed above had one or more limitations like higher capital, operation and maintenance costs, privacy concerns, limited sample size, inability to work under heterogeneous traffic and adverse weather conditions. This had resulted in the search for innovative data collection sensors. One such passive data collection technique attempted by researchers was Bluetooth and Wi-Fi sensor-based traffic data collection. These techniques are passive in nature and are very cost effective. When switched on, the devices broadcast their unique Media Access Control (MAC) IDs. Researchers have used re-identification of MAC IDs with the help of Bluetooth sensors to extract different meaningful traffic parameters. Haghani et al. (2010) presented the estimation of travel time using MAC ID matching technique. Other applications of Bluetooth data were also explored in literature which include assessment of variability of freeway travel times (Martchouk et al. (2011)), compliance to speed limit at work zones by Wasson et al. (2011), route choice behavior estimation (Hainen et al. (2011)) and estimation of origin-destination pairs (Barceló et al. (2012)). But, the changes in security features of smart phones has resulted in the reduction of penetration of Bluetooth devices, since they have to be put in discoverable mode in addition to turning on Bluetooth for them to be detected (Shiravi et al. (2016)). Mathew et al. (2016) investigated the usability of Bluetooth sensors for travel time estimation under Indian heterogeneous traffic conditions. The penetration rate varied between 7 to 10 % and the matching rate was found to be about 4%. The increase in usage of smartphones had led to the rise in popularity of Wi-Fi protocol. Also, Wi-Fi based techniques needs only the Wi-Fi to be turned on, which may lead to more detections. Thus, the usage of Wi-Fi sensors for traffic data collection gained prominence (Shiravi et al. (2016) and Hoogendoorn et al. (2016)).

It is evident from the literature that Bluetooth and Wi-Fi sensor-based data collection provides a cost effective and scalable alternative for data collection. Though the applicability of Bluetooth for traffic data collection has been explored comprehensively, the usage of Wi-Fi sensors for traffic data collection still needs detailed study. This paper presents an analysis of travel time data obtained from Wi-Fi sensors under heterogeneous conditions. Also, methodology to extract traffic signal state from Wi-Fi sensor data is also presented.

3. Data collection and processing

The study area selected was a straight stretch along Rajiv Gandhi IT expressway, Chennai, from First Foot-over Bridge (13°00’14.0’’N, 80°14’50.8” E) to Tidel Park Intersection (12°59’15.9” N, 80°15’05.0”E). Wi-Fi sensors were deployed at 4 locations along the stretch. **Error! Reference source not found.** shows satellite view of the study location. Table 1 and
Table 2 gives the details of the same.

Table 1: Description of Location of Sensors

S. No.	Location Name	Description
1.	Foot Over Bridge 1near MadyaKailash (FOB1)	Midblock Section with 3 lane dual carriageway and service lanes on both sides
2.	2ndAvenue near Indira Nagar Railway Station (2nd Ave)	T intersection with 3 lane dual carriageway and service lanes on both sides
3.	Tidel Intersection near Tidel Park (Tidel)	Four-legged Intersection with 3 lane dual carriageway meeting 2 lane dual carriageway (ECR) and service lanes on both sides

4.	Thiruvanmiyur	Mid-block section with 2 lane dual carriageway

Fig. 1 Study corridor showing Wi-Fi sensor locations

Table 2 Description of segments

S. No	Study Segments	Description	Length (km)
1	Link 1	FOB1 to 2nd Ave	1.07
2	Link 2	2nd Ave to TIDEL	0.70
3	Link 3	TIDEL to Thiruvanmiyur	0.34

Wi-Fi data were collected at FOB1, 2nd Avenue and Tidel for a period of 55 days (17-05-2018 to 12-07-2018) and at Thiruvanmiyur for a period of 42 days (31-06-2018 to 12-07-2018). The Wi-Fi data collected included unique MACIDs of various devices passing through the location of Wi-Fi sensor along with the time stamp (in EPOCH time) and signal strength with which it was detected.

In order to extract penetration rate, matching percentage etc. and to validate the analysis carried out on Wi-Fi data, videography technique was employed to collect field data. Cameras were installed, and videos were recorded at the four locations for the same period simultaneously to capture actual traffic volume, signal timings and turning movements. Due to non-availability of any automated image processing solutions, the classified volume count data required was extracted by writing a python script and assigning dedicated keys to store time stamp for each vehicle class and turning movement.

The collected data was processed prior to analysis, to remove the possible noise. The noise could be attributed to Wi-Fi enabled devices carried by pedestrians or static devices of the neighborhood area. Heuristic based approaches were adopted to clean the data. For example, if the time spent by a device at a location (difference of last detection and first detection by the sensor) was more than 1.5 times maximum possible travel time, it was considered as a static device and removed.

4. Data analysis and results

Preliminary analysis of the filtered data was performed to understand the penetration capability of the Wi-Fi sensor, matching rate to obtain travel time information, and descriptive analysis and pattern analysis of travel time.

4.1 Penetration Rate

To carry out penetration analysis, Wi-Fi data at one of the installed locations (2nd Ave) for a peak 30minutes period on a weekday morning was chosen. Number of unique MAC IDs detected for this location and period was found to be 4226 detections. Corresponding actual traffic volume passing the point was extracted from video manually and was found to be 6056 vehicles. This leads to a penetration rate of 69.77%. However, this does not directly translate to the number of vehicles as this can include multiple Wi-Fi devices associated with a particular vehicle.

4.2 Matching Rate

To obtain the travel time between two points using this, sensor has to be installed at both locations and the MAC IDs need to be matched. This matching rate was also found out by comparing the matching number with the actual traffic volume traversing between the locations. FOB1 to 2nd Ave and 2nd Ave to Tidel for a peak period of 30minutes on a weekday morning were chosen and the actual number of vehicles that traversed these sections were extracted from video data. Results obtained are tabulated in Table 3. It can be seen that matching rate is 7.37 % for segment 1 (FOB1 to 2nd Ave) and 8.02% for segment 2 (2nd Ave to Tidel).

Table 3 Matching percentage for different pair of locations

Segment	Actual traffic volume (from video data)	Total matched Wi-Fi MAC Ids	Matching percentage
FOB1 to 2nd Ave	2524	187	7.37%
2nd Ave to Tidel	3290	264	8.02%

4.3 Travel time analysis

Travel times were extracted using the MAC ID matching technique by taking the difference of timestamp of last recorded timestamp at location B and last recorded timestamp at location A for every matched MAC address. Fig. 2 shows a sample variation of 15-minute mean travel time data traversing segment 1 (FOB1 to 2nd Ave). Since the travel time data was observed to contain a lot of noise due to pedestrians, static devices and other outliers, the raw travel times obtained were cleaned for outliers using modified Z score, as discussed below.

A conventional Z-test finds the difference between each observation and the sample mean. This value is then divided by the sample standard deviation and compared to a critical value to determine if a point should be considered as an outlier. However, these values are highly influenced by extreme data points, which may lead to under-detection of outliers. The Modified Z-Test remedy this problem by using the median when calculating the deviation of each point (Iglewicz and Hoaglin (1993)). Fig. 3 shows the same data after applying the outlier removal. It was observed that plot was uncluttered with two explicit peaks during morning and evening peak hours.

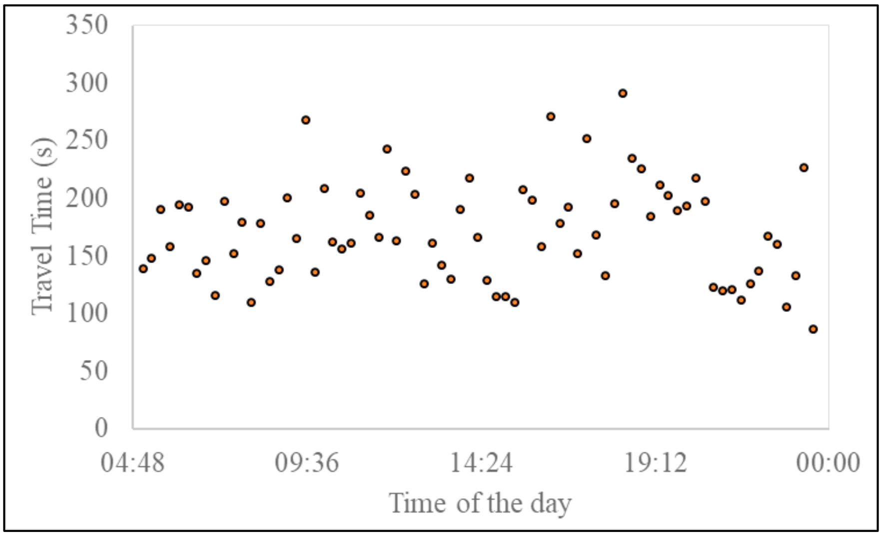

Fig. 2. Variation of mean travel times at Segment 1 (FOB1 to 2nd Ave) before outlier removal

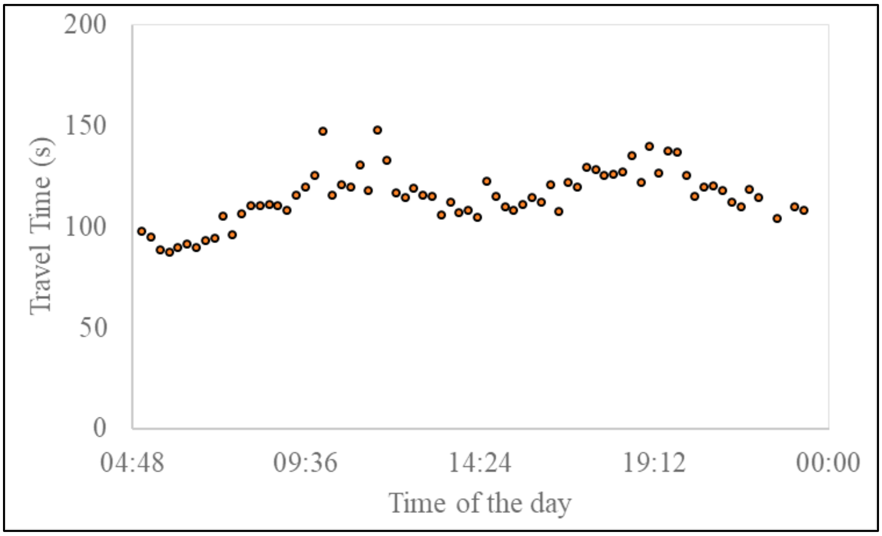

Fig. 3. Variation of mean travel times at Segment 1 (FOB1 to 2nd Ave) after outlier removal

The travel time values thus obtained after the outlier removal process were analyzed further to understand it better. Preliminary analysis included checking the descriptive statistics and is discussed next.

4.3.1 Descriptive statistics of travel time

Descriptive statistics includes the measurement of central tendency and variability or spread of the data. These statistics include mean, median, and mode as measures of central tendency and standard deviation, variance, the minimum and maximum values and Inter Quartile Range (IQR) as measures of variability. Box plots are best way to represent these descriptive statistics and are used in this analysis.

Fig. 4 presents boxplots showing measures of descriptive statistics like mean, median, 25th percentile and 75th percentile and IQR for segment 1. It is evident that travel time (mean) and its variability (Inter Quartile Range) are higher during morning (08:00 to 11:00) and evening peak (17:00 to 20:00) periods. Though the mean travel time is lower during the late evening period (21:00 to 00:00), the variability in travel time is high. This may be because of the lesser sample size during this period. The late-night trips (01:00 to 04:00) had the least average travel times. Fig. 5 shows similar plot for segment 2. In addition to travel times being higher, the variability in travel time is also higher in this section, mostly due to the congestion at Tidel park intersection.

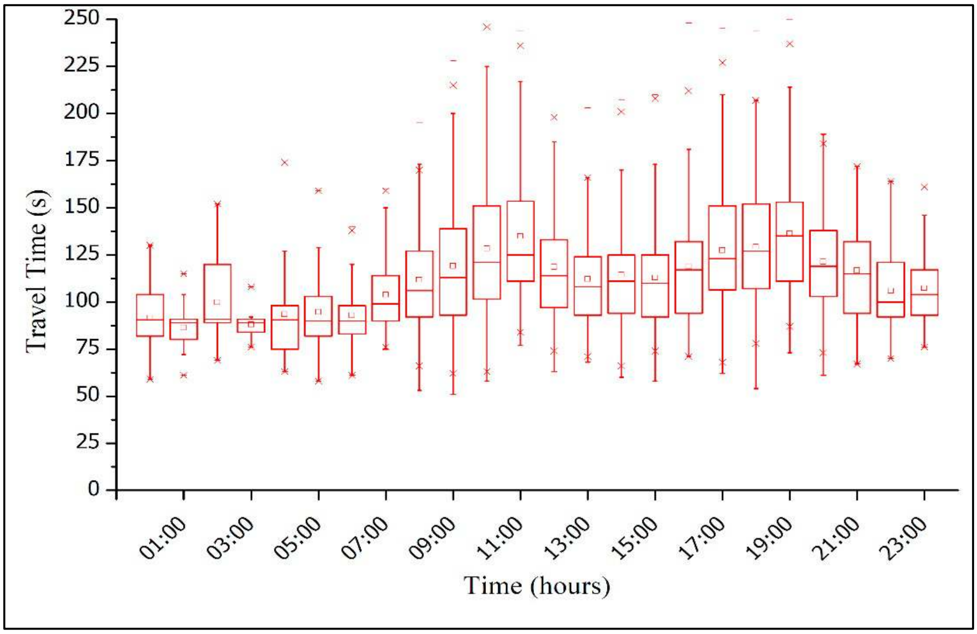

Fig. 4. Box plots for travel time at segment 1 (FOB1 to 2nd Ave)

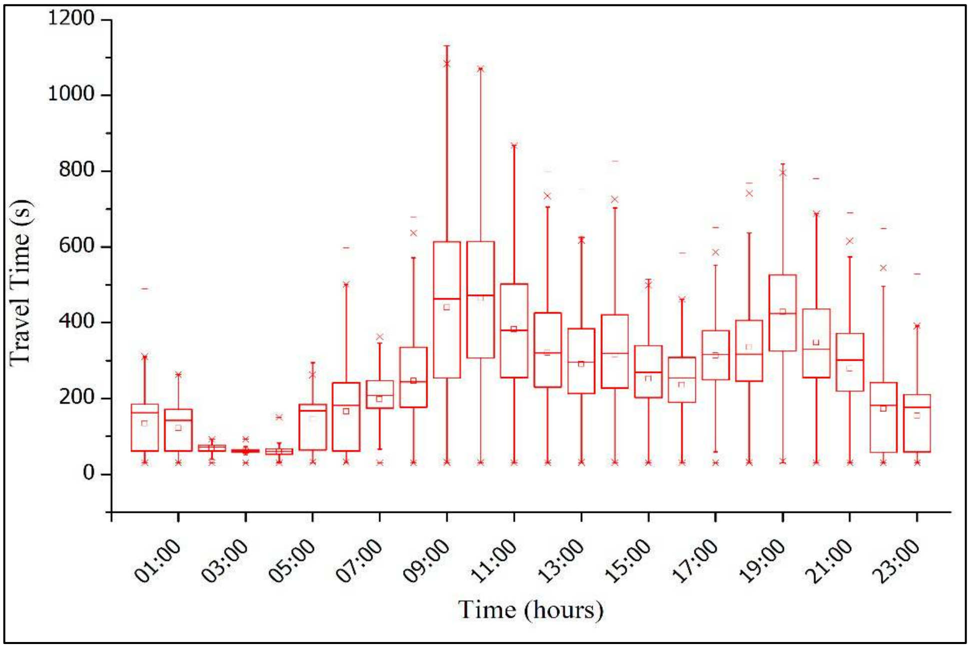

Fig. 5. Box plots for travel time at segment 2 (2nd Ave to Tidel)

4.3.2 Pattern analysis

Analysis was done to understand weekly, daily and hourly variations of travel time and discussed below. For weekly analysis, same day of multiple weeks were analysed. Fig. 6 and Fig. 7 compares the travel time patterns for two Mondays and Sundays respectively. It is evident from the plots that the two Mondays share a similar travel time pattern within the day and the two Sundays also have similar travel time pattern. It can be inferred that there is considerably difference between the travel time pattern on weekdays (say Monday) and weekends (say Sunday).

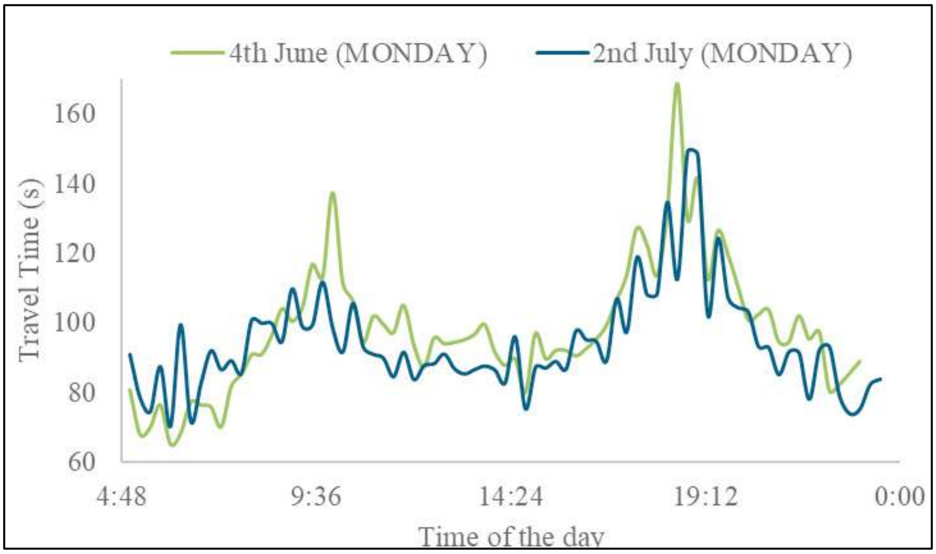

Fig. 6. Comparison of Travel Time pattern for two Mondays

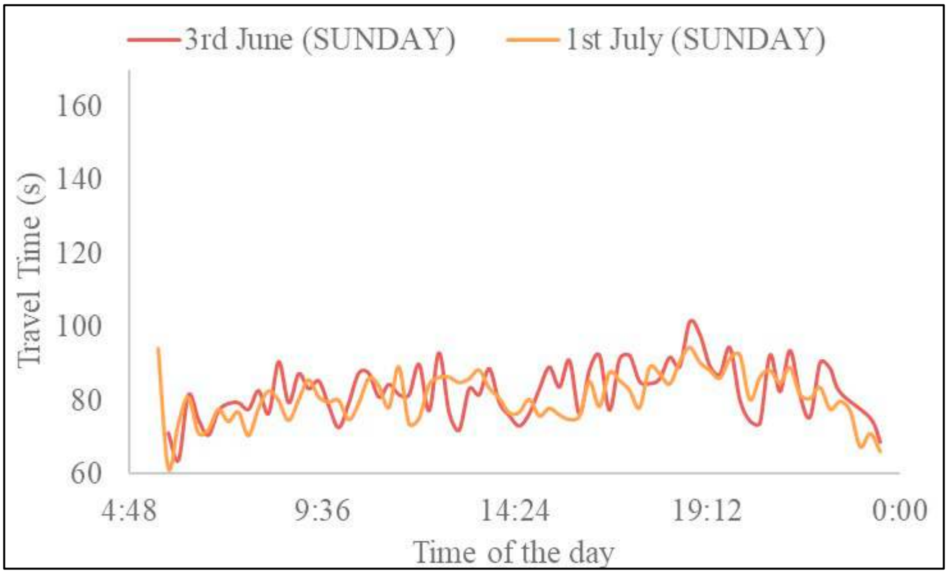

Fig. 7. Comparison of Travel Time pattern for two Sundays

To analyse daily patterns, fifteen minutes average travel times were plotted against time of day for a period of one week for both the segments. Fig. 8 shows data for seven days from 31st May 2018 to 06th June 2018. It can be observed that, for weekdays, two distinct peaks indicative of morning and evening peaks exist whereas for weekends (02-06-2018 and 03-06-2018), no such distinct visible peaks exist and a mean travel time in the range of 50 to 200 seconds is there throughout the day. Fig. 9 shows similar plot for segment 2 and in comparison, to segment 1, for segment 2, sharper distinct peaks can be observed for weekdays, indicative of more distinct morning and evening peaks. Travel times are more for this segment due to presence of major intersections at both ends.

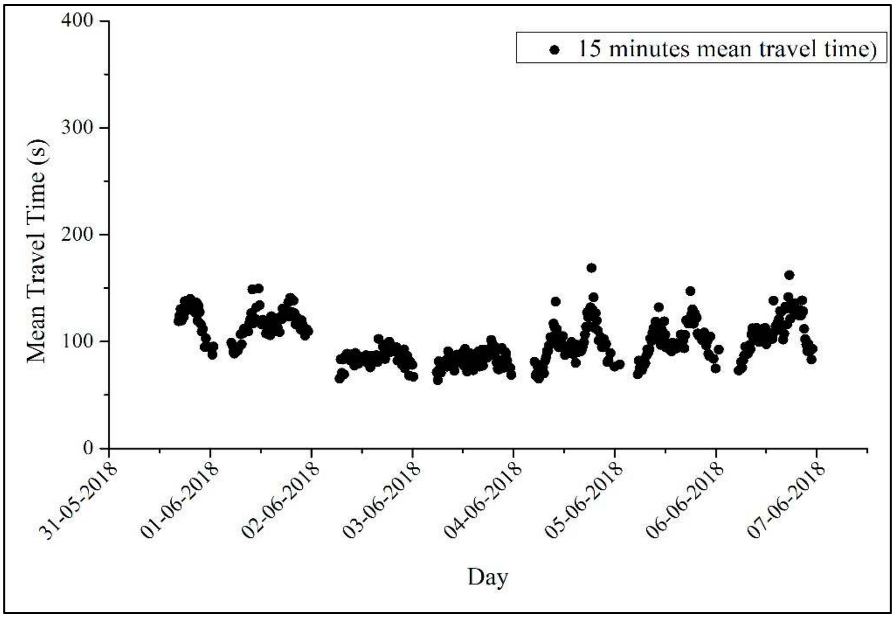

Fig. 8. Daily variation of travel time for Segment 1(FOB1 to 2nd Ave)

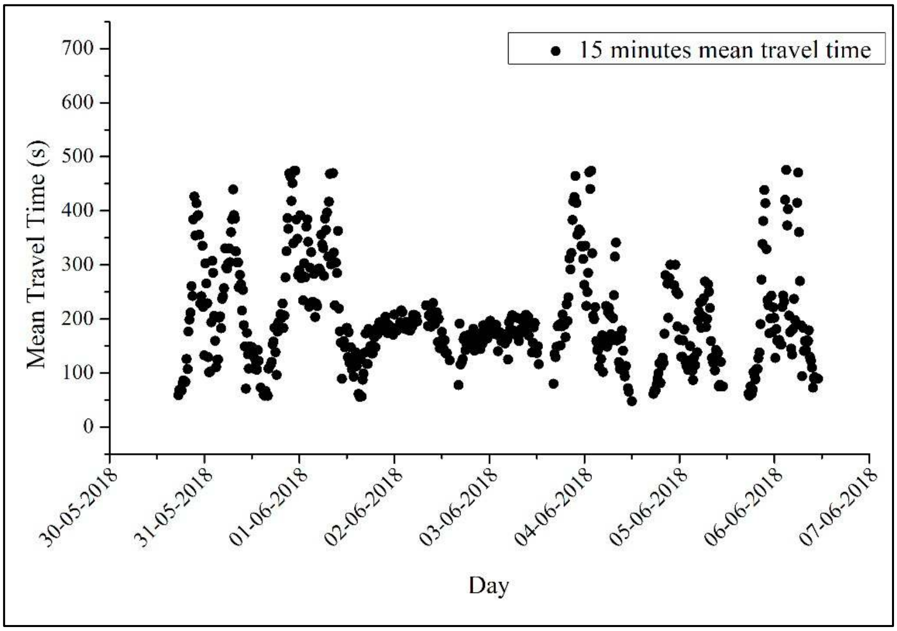

Fig. 9. Daily variation of travel time for Segment 2 (2nd Ave to Tidel)

For hourly variation, mean hourly travel times on a weekday were plotted depicted the travel time variation every hour as shown in Fig. 10 and Fig. 11. Based on these plots, four basic time of day categories can clearly be defined as morning off-peak (00:00-06:00), morning peak (08:00-11:00), evening peak (17:00-21:00) and afternoon peak (12:00-15:00).

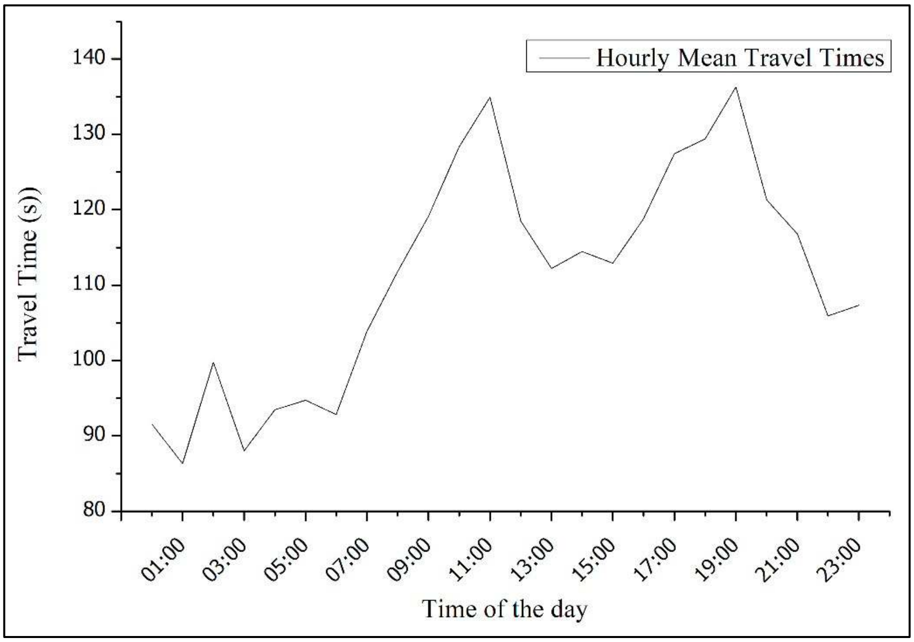

Fig. 10. Hourly variation of travel time for Segment 1 (FOB1 to 2nd Ave)

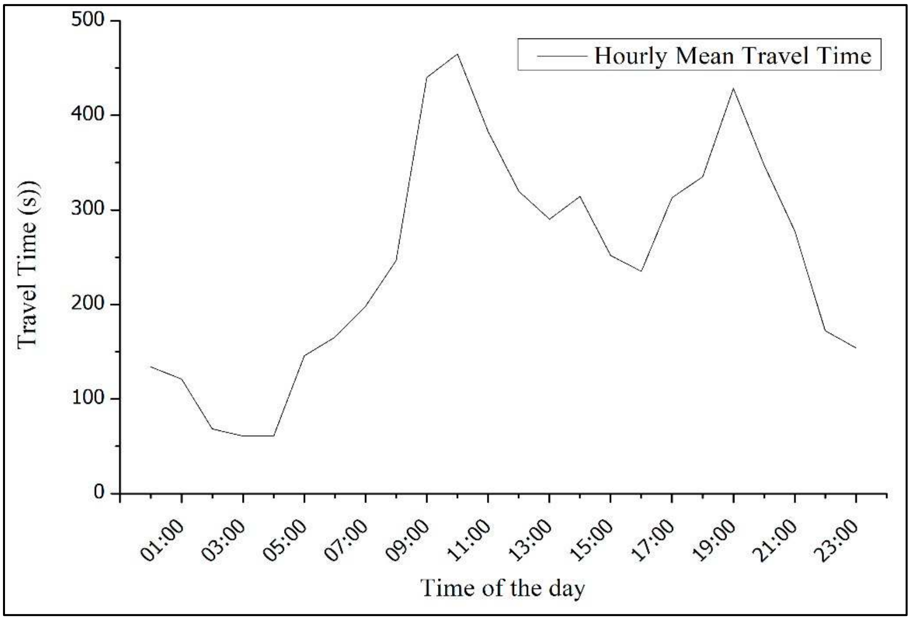

Fig. 11. Hourly variation of travel time for Segment 2 (2nd Ave to Tidel)

5. Signal state identification using wi-fi sensor data

Varying of signal phase sequence and duration of each signal indication in accord with the existing traffic volume by traffic police is prevalent in most of the signalized intersections in India. But, knowledge of signal timing parameters is essential for understanding the traffic state, in predicting travel time, delay, queue length etc. This necessitates the need to automatically identify the signal display in real time. Extraction of signal timings using GPS data was reported in literature (Hao et al. (2012) and Di-hua et al. (2017)). Such an estimation of start and end of signal state and its duration using Wi-Fi based travel time information was attempted in this study.

To start with, N-curve plots using cumulative number of last detections were made for a period of 15 minutes to understand the data and a sample plot is presented in Fig. 12. It can be observed that there is a significant difference between red and green phase data. Based on this, it was decided to use the time difference between successive last detections as an indicator of the signal indication. Fig. 13 shows a sample plot of difference between successive detections against time for a period of 15 minutes. It can be seen that there is clear pattern showing time at which the graph peaks indicating the start of red phase. Duration from this time to the next detection, which will happen at the start of next green, was expected to yield the approximate duration of red phase. The detailed estimation of start and end of red phases along with the phase duration for all the individual cycles is presented in Table 6. Actual signal timing was noted down from video recordings manually and are used as the ground truth values. Table shows the ground truth values of red starting, ending and duration against what was obtained using the procedure proposed above.

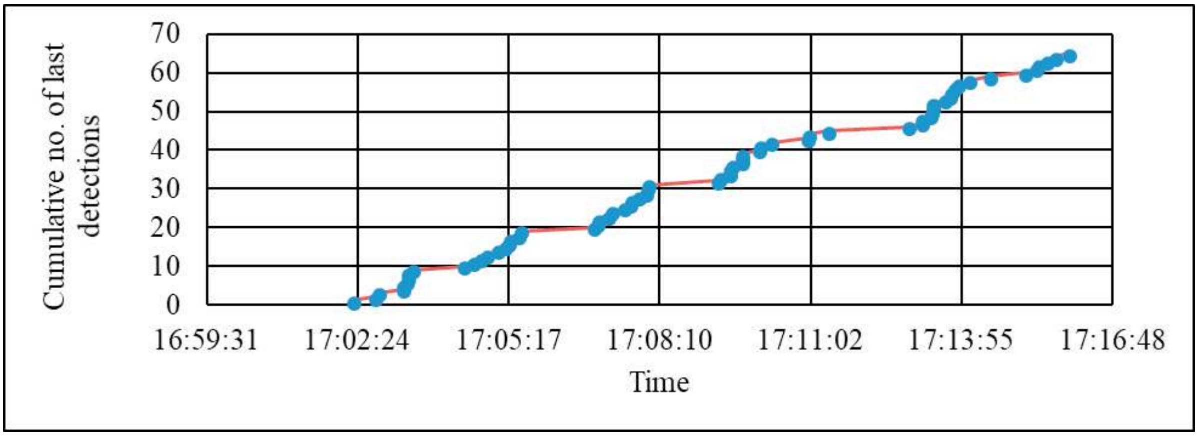

Fig. 12. Cumulative number of last detections versus time

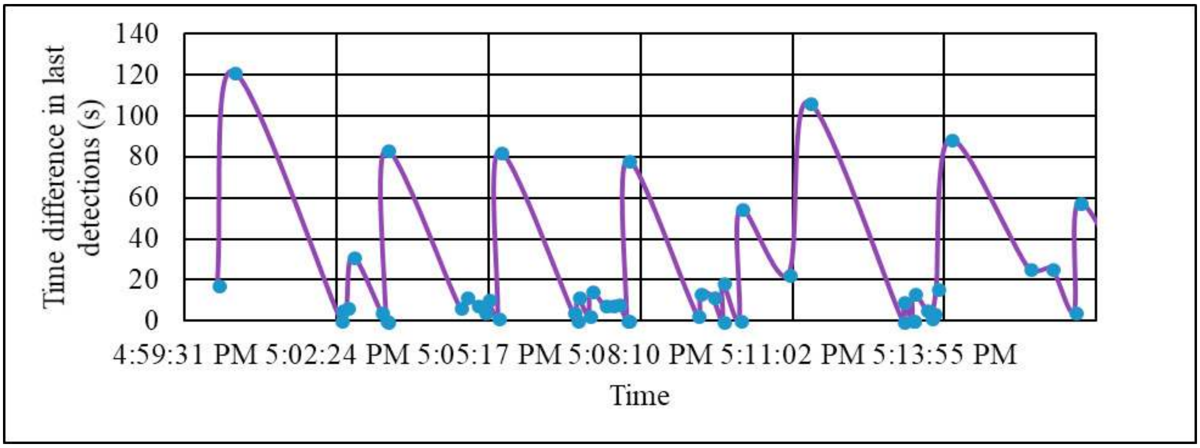

Fig. 13. Time difference between last detections at 2nd Avenue

Table 4 Comparison of extracted signal timings from Wi-Fi data with field signal timings

	Data from Video			Data from Wi-Fi Data			Comparison of Video and Wi-Fi results		
Cycle number	Start time (Red)	End time (Red)	Red phase length	Start time (Red)	End time (Red)	Red phase length	Error in red phase duration	Error in start time	Error in end time
1	17:01:07	17:02:17	0:01:10	17:00:26	17:02:28	0:02:02	0:00:52	0:00:41	0:00:11
2	17:03:27	17:04:32	0:01:05	17:03:20	17:04:44	0:01:24	0:00:19	0:00:07	0:00:12
3	17:05:48	17:06:45	0:00:57	17:05:29	17:06:52	0:01:23	0:00:26	0:00:19	0:00:07
4	17:07:32	17:09:12	0:01:40	17:07:55	17:09:14	0:01:19	0:00:21	0:00:23	0:00:02
5	17:11:31	17:13:01	0:01:30	17:11:21	17:13:08	0:01:47	0:00:17	0:00:10	0:00:07
6	17:14:16	17:15:30	0:01:14	17:14:02	17:15:31	0:01:29	0:00:15	0:00:14	0:00:01
7	17:16:32	17:17:06	0:00:34	17:16:28	17:17:26	0:00:58	0:00:24	0:00:04	0:00:20
8	17:18:41	17:20:16	0:01:35	17:18:35	17:20:24	0:01:49	0:00:14	0:00:06	0:00:08
9	17:21:24	17:22:36	0:01:12	17:21:13	17:22:19	0:01:06	0:00:06	0:00:11	0:00:17
10	17:23:26	17:24:11	0:00:45	-	-	-	-	-	-
11	17:25:47	17:26:28	0:00:41	17:25:28	17:26:33	0:01:05	0:00:24	0:00:19	0:00:05
12	17:27:27	17:28:08	0:00:41	17:27:13	17:28:10	0:00:57	0:00:16	0:00:14	0:00:02
13	17:29:07	17:29:48	0:00:41	17:28:40	17:29:15	0:00:35	0:00:06	0:00:27	0:00:33
14	17:30:40	17:32:26	0:01:46	17:30:19	17:32:37	0:02:18	0:00:32	0:00:21	0:00:11
15	17:33:20	17:35:00	0:01:40	17:33:07	17:35:03	0:01:56	0:00:16	0:00:13	0:00:03
16	17:35:53	17:37:35	0:01:42	17:35:55	17:36:24	0:00:29	0:01:13	0:00:02	0:01:11
17	17:38:37	17:39:06	0:00:29	17:38:10	17:39:12	0:01:02	0:00:33	0:00:27	0:00:06
18	17:39:20	17:40:24	0:01:04	17:39:33	17:40:06	0:00:33	0:00:31	0:00:13	0:00:18
19	17:41:18	17:42:55	0:01:37	17:41:19	17:43:01	0:01:42	0:00:05	0:00:01	0:00:06
20	17:43:51	17:45:45	0:01:54	17:44:41	17:45:52	0:01:11	0:00:43	0:00:50	0:00:07
21	17:47:03	17:48:42	0:01:39	17:47:37	17:48:23	0:00:46	0:00:53	0:00:34	0:00:19
22	17:49:48	17:51:12	0:01:24	17:49:12	17:50:12	0:01:00	0:00:24	0:00:36	0:01:00
23	17:51:57	17:53:16	0:01:19	17:52:05	17:54:08	0:02:03	0:00:44	0:00:08	0:00:52
24	17:53:57	17:55:46	0:01:49	17:54:45	17:55:50	0:01:05	0:00:44	0:00:48	0:00:04
25	17:56:42	17:57:54	0:01:12	17:56:45	17:58:18	0:01:33	0:00:21	0:00:03	0:00:24
26	17:58:39	18:00:33	0:01:54	17:58:51	18:00:00	0:01:09	0:00:45	0:00:12	0:00:33
					Average error		0:00:28	0:00:19	0:00:18

It can be seen from Table 4 that 25 out of 26 cycles were captured based on this method using Wi-Fi based travel time information. The average error in estimating red phase duration and start and red of red phase for a total of 25 cycles in one hour from the actual duration in field was found to be less than 30 seconds, showing this as a promising method to capture the signal settings.

6. Summary and conclusion

A feasible and cost-effective data collection technique is essential to obtain a comprehensive traffic data required for traffic control and management studies. One such method that is recently coming up is the use of Wi-Fi sensors for traffic data capture. This paper collected data using Wi-Fi sensors placed near roadside locations, which can collect the time stamp and MAC ID of devices inside the vehicles giving valuable information about how the vehicles are moving. The data collected will have outliers due to static devices and pedestrian movement making quality control an essential part. The current study used a modified z-test for outlier removal. Preliminary analysis of the proportion of Wi-Fi devices detected by Wi-Fi sensors (called as penetration rate) and the proportion of getting re-identified at two locations (called as matching rate) were analyzed. It was found that the penetration rate was around 70% and matching rate around 8%. Compared to previous studies which used Bluetooth sensors, these are high rates, revealing the potential of Wi-Fi sensor as a traffic data source. Detailed analysis on the data included studying the weekly, daily and hourly variations of travel time to identify any possible pattern. It was found that weekdays and weekends follow different patterns with distinct peaks observed on weekdays. Signal state estimation was also performed using the cleaned Wi-Fi data. The signal timings extracted from Wi-Fi had close agreement with field signal timings and an average error of less than 30 seconds was observed implying a reasonably high degree of precision.

One among the many possible applications of Wi-Fi based travel time data is explored in this study. Estimation of other relevant traffic measures such as identification of delay patterns, construction of vehicle trajectories, and finding the platoon dispersion proportion may be considered for future.

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