WiTraffic: Low-cost and Non-intrusive Traffic Monitoring System Using WiFi

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Abstract—The traffic monitoring system is an imperative tool for traffic analysis and transportation planning. In this paper, we present WiTraffic: the first WiFi-based traffic monitoring system. Compared with existing solutions, it is non-intrusive, cost-effective, and easy-to-deploy. Unique WiFi Channel State Information (CSI) patterns of passing vehicles are captured and analyzed to effectively perform vehicle classification, lane detection, and speed estimation. A machine learning technique is adopted to train vehicle classification models and efficiently categorize vehicles. An Earth Mover’s Distance (EMD)-based vehicle lane detection algorithm and vehicle speed estimation mechanism are proposed to further utilize WiFi CSI to identify the lane in which a vehicle is located and to estimate the vehicle speed. We implemented WiTraffic with off-the-shelf WiFi devices and performed real-world experiments with over a week of field data collection in both local roads and highways. The results show that the mean classification accuracy, lane detection accuracy for both local road and highway settings are around 96%, and 95%, respectively. The average root-mean-square error (RMSE) of the proposed CSI-based speed estimation method on a highway was 5mph in our experimental settings.

Index Terms—WiFi CSI; Traffic monitoring systems

I. INTRODUCTION

The traffic monitoring system refers to a set of technologies that are designed to collect traffic data on the roadway usage, e.g., the number and characteristics of vehicles. It plays a vital role in analyzing the transportation system and establishing plans for future transportation needs [1]. It is an imperative tool for many state Departments of Transportation (DOTs) to achieve various purposes, e.g., determination of road improvement plans, evaluation of the efficiency of road network, assessment of economic benefits, assistance in new development plans, and so on [2].

Numerous traffic monitoring systems have been developed. These systems can be largely classified into three categories: in-road-based, over-road-based, and aerial-sensor-based approaches. In-road-based systems require to sawcut the pavement and embed sensors in the pavement of the roadway. Those sensors include inductive loop detectors [3], and magnetometers [4]. However, installing sensors is very time and labor-intensive, and the operation of those sensors is intervened by roadway surfacing or pavement deterioration. Over-road-based approaches install sensors (e.g., video cameras [5], ultrasonic sensors [6]) either above the roadway or alongside the roadway. These systems are usually costly and easily affected by weather conditions. Aerial-based approaches [7] utilize satellites or aircrafts to capture road images, and extract traffic information via image processing. These solutions, however, suffer from spatio-temporal limitations.

WiFi Channel State Information (CSI) represents channel properties of wireless communication links that describe how signals are transmitted from a transmitter to a receiver. Recently, various CSI-based applications have been developed, e.g., human activity recognition [8][9][10][11], and localization [12][13] manifesting the versatility of WiFi CSI. In this paper, we present the design, implementation, and evaluation of the first WiFi CSI-based traffic monitoring system called WiTraffic and demonstrate that the limitations of existing traffic monitoring systems are addressed utilizing the rich context information contained in WiFi CSI.

More specifically, we illustrate that WiFi CSI can be used to create a multifaceted traffic monitoring system that is capable of performing vehicle counting, classification, lane detection, and speed estimation. Distinctive CSI patterns of passing vehicles are captured and analyzed to fulfill various functions of the traffic monitoring system. A machine learning technique is employed to train vehicle classification models based on the unique CSI values of different vehicle types. The classification models are utilized to perform effective vehicle categorization. Additionally, motivated by the observation that each lane has a unique distribution of CSI data, a novel vehicle lane detection algorithm is developed that characterizes the distribution of the CSI data per lane, and performs lane detection based on the comparison of the probability distributions of CSI using the Earth Mover’s Distance.

Compared with existing traffic monitoring systems, the
proposed system is non-intrusive, easy-to-deploy, portable, and inexpensive. Especially, in comparison with RF-based vehicle detection systems [14][15] that utilize the received signal strength indicator (RSSI) to detect vehicles, the rich information of CSI allows for more fine-grained analysis of signals at the levels of frequency-selective fading and independent spatial paths enabling vehicle classification beyond simple vehicle detection. In addition, while the RSSI could fluctuate to a few db at the same location [16], CSI is more stable and robust to the complex environments [17]. All it’s required to deploy the proposed system is a off-the-shelf WiFi access point (Internet Connection not necessary) and a WiFi device (such as a laptop) that receives WiFi signals from the access point (Figure 1). With this system, anyone can easily deploy a traffic monitoring system anywhere and perform traffic monitoring at a low cost, potentially addressing the cost issue for many state DOTs to deploy a large number of traffic monitoring systems on rural highways. The contributions of this paper are summarized as follows.

- The first WiFi-based traffic monitoring system is developed.
- Various functionalities of a traffic monitoring system, i.e., vehicle detection, classification, lane identification, and speed measurement are developed based on WiFi CSI.
- A machine learning technique is applied to achieve highly accurate vehicle classification.
- A novel vehicle lane detection mechanism is developed based on the unique CSI distributions of vehicles on different lanes.
- More than a week of real traffic data were collected from local roads and highways, and extensive real-world experiments were conducted to evaluate the performance of the proposed system.

This paper is organized as follows. In Section II, preliminaries are presented to review CSI and to define basic terms that are used in this paper. Section III describes an overview of the proposed system followed by the details of the system components. In Section IV, the system implementation details are explained. Section V evaluates the performance of the proposed system, and in Section VI, the related work is presented. We conclude in Section VII.

II. PRELIMINARIES

The orthogonal frequency division multiplexing (OFDM) modulation scheme has been adopted to implement the physical layer of the current WiFi standards. It divides the channel into subcarriers, and data is transmitted over these subcarriers. Using this channel division mechanism, OFDM addresses the frequency selective fading caused by the multipath effect. CSI characterizes signal strengths and phases of these OFDM subcarriers. More specifically, a received WiFi signal is modeled as the following [18].

\[ y = H \cdot x + n, \]

where \( x \), \( y \), and \( n \) are the transmitted signal, received signal, and channel noise, respectively. A matrix \( H \) represents the frequency response of each subcarrier for all streams, i.e., there are \( m \times n \) streams if there are \( m \) receiver antennas, and \( n \) transmitter antennas. Thus, the dimension of matrix \( H \) is \( m \times n \times w \), where \( w \) denotes the number of subcarriers. For example, matrix \( H \) for a certain stream is represented as a vector of subcarrier groups:

\[ H = [H_1, H_2, ..., H_w], \]

where \( H_i \) denotes the \( i \)-th subcarrier group that represents both the amplitude and phase information as follows.

\[ H_i = |h|e^{jp}, \]

where \(|h|\) and \(p\) represent the amplitude and phase, respectively. The key idea is that by exploiting the amplitude and phase information of subcarrier groups, small changes in the channel usually caused by multipath effects are effectively captured.

![Image](image.png)

Fig. 2. Illustration of multipath effects caused by a passing vehicle.

The multipath effect caused by passing vehicles, i.e., signals reflected from the ground and the vehicle body, is utilized to perform vehicle classification. For example, as shown in Figure 2, the line of sight (LoS) signal is degraded due to the vehicle body; paths \( p1 \) and \( p2 \) are reflected from the ground, and path \( p3 \) is reflected from the vehicle body. Considering the application-specific characteristics of an outdoor environment that has significantly lower signal reflections compared with typical indoor environments with many obstacles, an weighted average of 30 CSI groups in the frequency domain is utilized not only to compensate for the small-scale fading effect, but also to minimize the computational overhead [19]. This effective CSI is formally defined as follows.

\[ CSI_{eff} = \frac{1}{K} \sum_{k=1}^{K} w_k \cdot |H_k|, \]

where \( w_k \) is the weight of the \( k \)-th subcarrier, and \( K \) is the number of subcarriers. Here \( w_k_f = f_k / f_0 \), where \( f_k \) is the frequency of the \( k \)-th subcarrier, and \( f_0 \) is the center frequency.

Normalized effective CSI is converted into the 'radio-strength-dependent one' to more accurately capture the unique CSI values of vehicles, especially to distinguish vehicles that are on different lanes exhibiting different power levels of CSI depending on the distance from the transmitter. Consequently, CSI power is defined based on effective CSI and AGC (Automatic Gain Control - obtained from the NIC) as follows.
CSI power is used as the main feature for vehicle classification and lane detection. It is experimentally observed that CSI power effectively represents the unique CSI patterns of passing vehicles on different lanes. Figure 3 displays the waveforms of CSI power for a passing motorbike, a passenger vehicle, and a truck.

III. SYSTEM DESIGN

In this section, an overview of the proposed system is presented followed by the details of its components.

A. Overview

The system architecture of WiTraffic is depicted in Figure 4. WiTraffic has three main system modules: Data Collection, CSI Analysis, and Model Database. The Data Collection module collects raw CSI data in a sliding window, removes noise in the collected data, and detects a passing vehicle based on the noise-removed data. The CSI Analysis module implements the functions of a traffic monitoring system, i.e., vehicle classification, lane detection, and speed estimation, by performing analysis of the filtered CSI data. The results of data analysis are incorporated into the models in the Model Database to improve the performance of WiTraffic.

B. Noise reduction

CSI data generated by commodity WiFi NICs are inherently noisy due to dynamics of transmit power levels, transmission rates, and internal CSI reference levels. For accurate vehicle classification, such noise needs to be effectively removed. The Butterworth low-pass filter is well known for its effectiveness to reduce noise of CSI data \([10]\). We adopt the Butterworth low-pass filter to remove the noise of collected raw CSI data. We tested the filter with different cut-off frequencies to find the best configuration and observed that with a normalized cut-off frequency of 0.05rad/s, the noise was effectively reduced. Figures 5 and 6 plot measurements of original CSI data and filtered one for a passenger vehicle and a truck, respectively. It is illustrated that the noise is effectively removed after applying the Butterworth low-pass filter. It should be noted that if we adapt the cut-off frequency depending on the traffic environment, it is expected that WiTraffic will perform better. We leave the algorithm development for this dynamic selection of the cut-off frequency as future work.

C. Vehicle Detection and Classification

Once noise of CSI data is successfully reduced, the vehicle detection component of the Data Collection module starts to run to detect a passing vehicle based on the filtered CSI data. Since passing vehicles cause high variance in CSI data (Figures 5 and 6), a simple threshold-based detection method is developed, rather than developing a machine learning algorithm to minimize the system complexity. More specifically, a CSI power sample \(c_i\) measured at time \(t_i\) is compared with threshold \(\Delta d\). The optimal threshold is experimentally determined in Section V-B. We selected the threshold such that the false positive rate is minimized while the vehicle detection accuracy is maximized. Given the selected threshold,
if the current CSI sample value drops below the threshold, CSI values in the corresponding sliding window are input to the CSI Analysis module to proceed with vehicle classification, lane detection, and speed estimation.

![Fig. 5. Filtered CSI power for a passenger vehicle.](image1)

![Fig. 6. Filtered CSI power for a truck.](image2)

Note that vehicle detection and vehicle classification are two different functions of the proposed system, i.e., once a vehicle is detected, vehicle classification is performed to determine the vehicle type. Rich information extracted from CSI data is used to train vehicle classification models, and vehicle classification is performed in accordance with the models. More specifically, we employ the C-Support Vector Machine (C-SVM) [20] to train our vehicle classification models. In this paper, we create two models, i.e., for passenger vehicles, and for freight trucks. It is easy to extend the models for more sophisticated vehicle classification (e.g., SUVs, pickup trucks, mini-vans, etc.), which we leave as our future work. Features of filtered CSI data that represent passing vehicles are extracted and input to the support vector machine to generate the models.

![Fig. 7. Probability distribution of CSI values for a passenger vehicle on Lane 1.](image3)

![Fig. 8. Probability distribution of CSI values for a passenger vehicle on Lane 2.](image4)

That each lane has a distinctive probability distribution of CSI data because of varying distance from the transmitter that determines the received signal strength. To capture the distribution of CSI data (for a certain vehicle type), CSI values are divided into 20 equal-sized bins. Figures 7 and 8 display the results for a passenger vehicle on different lanes that exhibit distinct probability distributions of CSI data. A lane model for each lane is constructed by incorporating a large amount of ground-truth CSI data that are validated with video data. This lane model is individually defined for each vehicle type since different probability distributions are obtained for different vehicle types.

More specifically, assume that a vehicle of type \( v \) is determined. Let a vector \( C_v = \{c_1, c_2, ..., c_n\} \) be the CSI power of the detected vehicle. Each CSI sample \( c_i \) of vector \( C_v \) is then mapped to a bin \( b_{i,v} \) defined for each lane denoted by \( l \), i.e., a value within the range \([0, 20]\), is associated with the CSI sample, more formally, \( \lfloor \frac{c_i}{(20)} \rfloor \rightarrow b \). This operation is repeated for all ground truth data to create, calibrate, and consolidate the lane model.

Once lane models are created, the lane detection module detects in which lane a vehicle is located. More specifically, when a vehicle passes through the line of sight path between the receiver and the transmitter, the module compares the probability distribution of CSI values of the passing vehicle with the lane models defined for each lane (and for this particular vehicle type), and determines the lane model that is ‘closest’ to the probability distribution of the passing vehicle. To perform this distribution dissimilarity test and detect the vehicle lane, we employ the Earth Mover’s Distance (EMD) [21]. The EMD is a measure of dissimilarities between two probability distributions. Conceptually, each bin corresponds to a pile of “earth”. The cost \( f(a, b) \) is defined such that a unit cost is required to move one unit of earth from bin \( a \) to bin \( b \). The EMD measures the minimum cost to convert a histogram to a target histogram. Thus, lower EMD means that the two distributions are more highly correlated, indicating that the vehicle is on this particular lane. The vehicle lane detection accuracy based on this EMD metric will be evaluated in Section V-E.

To train our classification models, we used separated sets of data for training and testing. For training, five features of CSI data were used: (1) root mean square (RMS), (2) median absolute deviation (MAD), (3) mean, (4) first quartile, and (5) third quartile, based on the observation that a passing vehicle creates high variance in CSI data. As shown in Table I, the values of these features for passenger vehicles and trucks in both local roads and highways are distinctively different indicating usefulness of these features to achieve high accuracy in vehicle classification. In particular, to select the best parameters, i.e., \( C \) and \( \gamma \), the cross-validation technique was used [20].

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<tr>
<th>Feature Test Results</th>
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**D. Vehicle Lane Detection**

Once vehicle classification is completed, WiTraffic identifies in which lane a vehicle is located. The key intuition is...
CSI data are further utilized to estimate the vehicle speed, basically implementing all essential traffic monitoring functions based on WiFi CSI. The key idea is simple: the number of CSI samples collected while a vehicle passes through the line-of-sight path between transmitter and receiver is used as an indicator for estimating the speed of the vehicle. We observe that when the line-of-sight path is interrupted, the CSI power substantially decreases. Consequently, in order to estimate the vehicle speed, the first step is to find the beginning \( c_b \) and end \( c_e \) of the CSI time series that represent the time period for which the vehicle is blocking the line-of-sight path (Figure 9). To find \( c_b \), a similar threshold-based approach is used. Suppose that the vehicle was detected at \( t_i \), i.e., \( c_i \) was smaller than the threshold. We then estimate that \( t_i \) is \( c_b \). Now, to determine \( c_e \), a small time window \( \Delta t \) is defined. Starting from \( t_i \), the degree of variations in the CSI time series in a time window between \( t_j \) and \( t_k \) is iteratively calculated using the mean absolute deviation (MAD) denoted by \( \delta_{jk} \). If \( \delta_{jk} \) is smaller than a predefined threshold, \( t_j \) is marked as the end of the vehicle passing activity. Consequently, the total number of samples between \( t_i \) and \( t_j \) are counted, which is denoted by \( N_s \). This total number of samples is used as the main feature for training our vehicle speed model, i.e., a speed model is built using a set of pairs \( (N_s, \text{ground} \_ \text{truth} \_ \text{speed}) \) for each vehicle type.

IV. SYSTEM IMPLEMENTATION

We used off-the-shelf hardware to implement the proposed system. The Dell Precision M4400 integrated with Intel 5300 WiFi NIC was used as the receiver. This laptop had the 2.5GHz Intel Core Duo processor with 8GB of RAM and ran Ubuntu 14.04.01 with kernel version of Ubuntu-3.13.0-32.57. We used the TP-Link TL-WR7500 WiFi router as the transmitter which operated in the 802.11n AP mode with 2.4GHz frequency and 20MHz bandwidth. The modified WiFi NIC driver developed by Halperin et al. [22] was adopted to collect raw CSI data at the sampling rate of 1,000 packets per second.

The laptop and router were deployed on the roadside as shown in Figure 10. In order to collect the ground truth data to build the models for vehicle classification, lane detection, and speed measurement, two USB cameras, ELP 2.0mp, were connected to the laptop and collected video data. In addition, the Bushnell velocity speed gun was also installed to collect the ground truth vehicle speed data. More than a week of real-world field data were collected to prepare a data set for a large number of passenger vehicles and trucks for the system evaluation of Wi-Traffic.

Given created models, the proposed system was evaluated in two different roadway environments. Figure 10 depicts the two test scenarios: the local road (left) and the highway (right). The local road was selected as our test site to understand the system accuracy under complex environments in which there are pedestrians, bicycles, trees, buildings, and so on. In fact, as it will be shown in Section V, the accuracy for the highway was higher compared with that for the local road primarily due to this complexity.

V. EXPERIMENTAL RESULTS

This section evaluates the performance of WiTraffic. The optimal window size and threshold are experimentally determined. Based on the determined window size and threshold, accuracy of vehicle detection, vehicle classification, vehicle lane detection, and vehicle speed estimation is evaluated.

A. Selection of Window Size

It was observed that CSI values of a vehicle change significantly when a vehicle crosses through the line-of-sight path between the transmitter and receiver. Thus, the window size needs to be determined based on the vehicle body length. The body length of a general passenger vehicle is around 4.5m. According to the Federal Highway Administration (FHWA) [23], the maximum body length of commercial motor vehicles, trucks, is about 40m. Assuming that the vehicle speed is typically between 15mph (6.7m/s) and 75mph (33.5m/s), the maximum time required for a vehicle to cross the line-of-sight path is between 0.13s and 1.19s, according to the vehicle body length statistics. Considering the maximum possible time, the window sizes of 0.05s, 0.1s, 0.2s, and 0.3s were evaluated.

The classification accuracy for passenger vehicles and trucks in the local road with varying window sizes is depicted in Figures 11 and 12. The results for passenger vehicles show that the accuracy increased slightly between the window sizes of 0.05s and 0.1s, and decreased thereafter. The reason for the decreased accuracy is that a larger window contains more CSI values, and thus more irrelevant data are included that affect the classification process. In case of trucks (Figure 12), the
that is used to detect a vehicle. Recall that when measuring CSI value drops below $\Delta d$, a vehicle is detected. In this section, we perform experiments to understand the effect of the threshold and select appropriate thresholds for both the local road and the highway. Figures 15 and 16 depict the effect of the threshold for the local road and the highway, respectively. As shown in both figures, larger thresholds resulted in higher false positive rates. In other words, CSI values dropped below the threshold even though there was no passing vehicles since the threshold was set too high. Thus, when the threshold was lowered, the accuracy increased and the false positive decreased. Interestingly, the accuracy, however, started decreasing at certain threshold and started to decrease. This result indicates that if the threshold is too small, some vehicles that do not cause much variation in CSI values are not detected. Consequently, we selected the thresholds for both the local road (0.1125) and the highway (0.0425) that maximize the accuracy while minimizing the false positive rates. In particular, the threshold for the highway was set a bit smaller than that for the local road because of the faster vehicle speed on the highway.

### C. Vehicle Detection Accuracy

Having determined the appropriate window size and the threshold, this section evaluates the vehicle detection accuracy. More specifically, the accuracy was measured for 400 passing vehicles in both the local road and the highway environments. Figures 17 and 18 depict the accumulative average of the detection accuracy for the local road and the highway, respectively. It was observed that the average detection accuracy reached 93% and 95% for the local road and the highway, respectively. Despite the faster vehicle speed on the highway, the accuracy for the highway was greater than the local road due mainly to obstacles around the local road. Another observation was that the accumulative average accuracy reached its peak value more rapidly in the highway environment. The reason is similarly attributed to the noise.
caused by obstacles like houses and trees around the local road.

D. Vehicle Classification Accuracy

![Figure 19](image1)  
![Figure 20](image2)

Fig. 19. Classification accuracy for local road.  
Fig. 20. Classification accuracy for highway.

Once a vehicle is detected, classification is performed to categorize the vehicle type. Similar to the experiments for the detection accuracy, the classification accuracy was measured for 400 passing vehicles. The same window size and threshold were used for this experiment. Figures 19 and 20 depict the accumulative average of the classification accuracy for the local road and highway, respectively. WiTraffic quickly converged to the peak classification accuracy of 92% and 96% for the local road and the highway, respectively. It was observed that the complex environment around the local road not only influenced the vehicle detection accuracy but also the classification accuracy, resulting in the slightly lower classification accuracy for the local road compared with the highway. It was also observed that WiTraffic reached the peak classification accuracy more rapidly in the highway environment.

E. Vehicle Lane Detection Accuracy

![Figure 21](image3)  
![Figure 22](image4)

Fig. 21. Lane model for Lane 1 (local road).  
Fig. 22. Lane model for Lane 2 (local road).

In this section, the vehicle lane detection accuracy is evaluated. For this experiment, we generated lane models for a passenger vehicle. A lane model is individually defined for each lane. Figures 21 and 22 depict the two lane models for Lane 1 and Lane 2 of the local road, respectively. As shown, the two lane models exhibit clearly different distributions of CSI values. More specifically, it was observed that CSI values of a vehicle on the lane that was closer to the access point (Lane 2) dropped more sharply compared with the other lane (Lane 1).

Figures 23 and 24 depict the two lane models for Lane 1 and Lane 2 of the highway. Similar to the results for the local road, distinctive distributions were observed for the two lanes. It is worth to mention that we obtain different distributions for different vehicle types because of unique vehicle body lengths and shapes, and it can be easily extended that lane models for other types of vehicles are established for higher lane detection accuracy.

![Figure 23](image5)  
![Figure 24](image6)

Fig. 23. Lane model for Lane 1 (highway).  
Fig. 24. Lane model for Lane 2 (highway).

![Figure 25](image7)

Fig. 25. Lane detection accuracy for local road and highway.

The generated models were used to evaluate the vehicle lane detection accuracy. Figure 25 depicts the average lane detection accuracy for a passenger vehicle in both lanes. Regardless of lanes, the average lane detection accuracy was about 90% in both the local road and the highway. It was observed that the average detection accuracy for Lane 2 (95.34%) was about 3.5% higher than that for Lane 1. The reason is because Lane 2 was close to the access point which interrupted the line-of-sight signal more significantly, thereby having more distinctive signal patterns. Another observation was that the lane detection accuracy for the highway was slightly higher compared with the local road due to the environmental factors around the local road, e.g., houses, pedestrians, and trees, etc.

F. Speed Estimation Accuracy

In this section, the vehicle speed estimation accuracy is evaluated. We adopted the Bushnell velocity gun (model 101911) to obtain the ground truth speed data. To calibrate this device, we compared the vehicle speed measured with the velocity gun to the speed data obtained from the vehicle speedometer. The results indicate that the average error was around 1mph. We then trained speed models for passenger vehicles for the highway.
VI. RELATED WORK

The traffic monitoring systems can be largely classified into three categories: in-road-based, and over-road-based, and aerial-sensor-based approaches.

A. In-Road-Based Solutions

The in-road-based solutions embed sensors in the pavement of a roadway. These sensors include inductive loop detectors, magnetometers, weigh-in-motion sensors, and tape switches.

Loop Detectors: Loop detectors have been the most widely used sensors for traffic monitoring due to their mature technology and large experience base. This well understood technology can obtain traffic count, vehicle classification, and vehicle speed [24][25][3]. Although loop detectors usually provide accurate results, they are typically very costly to install.

Magnetometers: To improve the vehicle classification accuracy of loop detector-based systems (e.g., for non-axle-based vehicle classification), magnetometer-based systems were introduced. For instance, Cheung et al. used magnetometers that were glued to the center of a lane [26]. There are other solutions that install magnetometers on the roadside [4][27].

Accelerometers: Accelerometer-based approaches are based on the measurement of vibrations of the pavement when a vehicle’s wheels move across the accelerometer [28][29]. These solutions are dependent on the accuracy of vehicle speed measurement. For example, Ma et al. utilized the magnetometer to measure the vehicle speed [28]. Although this is less costly solution compared with the loop detectors, they are difficult to install and have the energy provision issue.

B. Over-Road-Based Solutions

To address the drawbacks of intrusive approaches, over-road-based solutions deploy sensors (e.g., video image processors, ultrasonic sensors, radar sensors, and acoustic sensors) either above or alongside the roadway.

Video based: With the significant progress in computer vision, the video camera has been a rich source for vehicle detection and surveillance over the last 30 years. The appearance-based methods were developed to detect traffic [5][30][31][32]. Some proposed motion-based approaches to detect moving vehicles [33][34][35]. Major challenges for video-based surveillance systems are weather and lighting conditions, and vehicle occlusion.

Ultrasonic based: Oudat et al. [6] has developed a traffic monitoring system based on the combination of ultrasonic ragefinders and multiple infrared temperature sensors. These sensors are low cost and easy to manage. However, it has low accuracy for multi-lane low-traffic flows primarily due to its limited range [36].

RADAR or LIDAR technology-based: Radar and camera data are typically fusioned to perform vehicle detection in different fusion levels [37]. Radar is used to locate interest areas of an image to expedite the image processing speed. However, these systems are very expensive due to their advanced processing circuitry.

Infrared Detectors: Active and passive infrared detectors capture the energy change measured from the road surface in the absence of a vehicle [2][38]. The advantages of infrared detectors are that they can be operated during both day and night. Disadvantages are that infrared detectors are sensitive to inclement weather conditions and ambient light.

Acoustic Sensor-based: A microphone array is used to collect road-side acoustic signals, and acoustic features are extracted to perform traffic monitoring [39]. However, these approaches are easily affected by noise.

C. Aerial-sensor-based

Recently satellite images and drones are used to capture road images, and extract traffic information via image processing [7]. These approaches, however, suffer from spatio-temporal limitations. The operation time is limited due to the limited coverage and limited battery power. In addition, maneuverability and wireless network communication are two key challenges for UAV-based traffic monitoring systems.

VII. CONCLUSION

We have presented the WiFi-based traffic monitoring system that provides essential functionalities of a traffic monitoring system including vehicle detection, vehicle classification, vehicle lane detection, and vehicle speed estimation. Real-world experimental results demonstrate that the proposed system achieves high vehicle classification and lane detection accuracy in both the local road and the highway settings. The results further show that the proposed speed estimation method is promising and can be improved significantly with more sophisticated vehicle classification models.
WiTraffic is a suitable solution for roads with low traffic volumes such as rural highways for which the number of deployed traffic monitoring systems is limited due to the cost issue. We hope that the extremely low cost of WiTraffic will address this cost issue enabling DOTs to deploy a large number of traffic monitoring systems. Unfortunately, however, WiTraffic will perform poorly on crowded city highways due to a large portion of ‘overlapped vehicles’. Our future work is to extend WiTraffic to make it accurately identifies and classifies overlapped vehicles and to perform lane detection and speed estimation for overlapped vehicles. Another future work is to improve the performance of WiTraffic by developing new features based on the amplitude and phase information of WiFi CSI, and by generating models (i.e., lane/speed models) for more vehicle classes such as minivans or pickup trucks.

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