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SENSING TECHNOLOGIES FOR TRAFFIC FLOW CHARACTERIZATION: FROM HETEROGENEOUS TRAFFIC PERSPECTIVE

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Key words: *traffic flow characterization, heterogeneous traffic, intelligent transportation system, intrusive sensors, non-intrusive sensors, image processing*

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SENSING TECHNOLOGIES FOR TRAFFIC FLOW CHARACTERIZATION: FROM HETEROGENEOUS TRAFFIC PERSPECTIVE

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Importance of detailed traffic flow characterization is immense for achieving an intelligent transportation system. As such, great efforts in existing literature have gone into proposing different solutions for traffic flow characterization. Among these, first generation intrusive sensors such as pneumatic tube, inductive loop, piezoelectric and magnetic sensors were both labor intensive and expensive to install and maintain. These sensors were able to provide only vehicle count and classification under homogeneous traffic conditions. Second generation non-intrusive sensors based solutions, though a marked improvement over intrusive sensors, have the capability to only measure vehicle count, speed and classifications. Furthermore, both intrusive and non-intrusive sensor based solutions have limitations when employed under congested and heterogeneous traffic conditions. To overcome these limitations, a compute vision based solution has been proposed for traffic flow characterization under heterogeneous traffic behaviour. The proposed solution was field tested on a complex road configuration, consisting of a two-way multi-lane road with three U-turns. Unlike both intrusive and non-intrusive sensors, the proposed solution can detect pedestrians, two/three wheelers and animal/human driven carts. Furthermore, detailed flow parameters such as vehicle count, speed, spatial/temporal densities, trajectories and heat maps were measured.

Key words: traffic flow characterization, heterogeneous traffic, intelligent transportation system, intrusive sensors, non-intrusive sensors, image processing

INTRODUCTION

Nation's economic fortunes are tightly linked to efficient transportation systems. However, with rapid urbanization, nations around the world are facing severe mobility issues, causing degradation in overall life quality [1, 2, 3]. These issues range from traffic congestion, time wastage, productivity losses, accidents and excessive greenhouse gas (GHG) emissions such as carbon dioxide, nitric oxides and particulate matter. Associated health issues range from driver stress, cardiovascular, respiratory, pulmonary and cancer [2, 3]. Worldwide, 4.2 million premature deaths were associated with transport related ambient air pollution in 2016 [3]. Demand for effective transport infrastructure and its management is becoming imperative at the peril of it becoming highly inefficient. As an example, according to a Texas Transportation Institute report, US commuters waste 3 billion gallons of fuel per year by spending approximately 42 hours stuck in traffic. The nationwide cost runs in excess of $160 billion, with $960 per commuter [4]. With increasing population and urbanization, these problems will aggravate unless Intelligent Transportation System (ITS) methodologies are employed. ITS is integration of computation hardware, sensors, communication and traffic flow mathematical models for effective planning, designing and management of transportation networks. In this context, traffic flow parameters (such as vehicle count, classification, speed, spatial/temporal densities, trajectories, road capacity) are fundamental building blocks for ITS based solutions. This traffic flow characterization is achieved by integrating sensors in or above roads for data collection and processing. These parameters are then employed for validation and calibration of traffic flow mathematical models and traffic simulation software such as VISSIM, Paramics, Aimsun to name a few [5,6,7,8,9,10]. In this context, enormous effort has gone into proposing different solutions for traffic flow characterization in existing literature. These solutions offered incremental improvement over previous generations of solutions. These can be categorized as (1) manual counting, (2) intrusive sensors, and (3) non-intrusive sensors. However, these solutions have serious limitations such as the number of traffic flow parameters that can be measured and accuracy under congested\heterogamous traffic conditions. These limitations have been discussed in detail in section 3. To overcome these limitations, a compute vision based solution has been proposed for traffic flow characterization. Unlike intrusive and non-intrusive sensor based solutions, the proposed solution has the capability to characterize traffic flow under all (congested, non-congested, homogeneous, heterogeneous) traffic conditions. The proposed solution has the capability to detect pedestrians, human\animal driven carts, two

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three wheelers to name a few. Furthermore, unlike intrusive and non-intrusive sensors, a complex road configuration (two-way, three lanes, three U-turns) has been categorized with a single camera's video. Traffic flow parameters such as vehicle count, speed, spatial/temporal density, time/distance headways, heat maps and trajectories are measured with 87% accuracy. In the rest of this work, section 2 summarizes different sensing technologies employed for traffic flow characterization. Section 3 provides a comparative analysis of different sensing technologies from heterogeneous traffic perspective, while section 4 details compute vision methodologies. Experimental setup and results are discussed in section 5 and section 6 provides conclusion and future work.

SENSING TECHNOLOGIES FOR TRAFFIC FLOW MONITORING

Technological advancement in areas such as computation hardware, sensors, communication, cloud platforms and data analytics have created opportunities for developing efficient ITS solutions. In the near past, manual counting was employed for traffic flow characterization. This method was not only labor intensive but also inaccurate, costly and inefficient. ITS success lies in usage of platforms to access, collect and process accurate data cheaply. From this perspective, varying sensor based solutions have been proposed in existing literature. These solutions can be broadly categorized as either intrusive or non-intrusive sensors. Salient characteristics of these can be observed in Table 1. Intrusive Sensors: as implied by the name are intrusive in nature and are embedded in road surfaces. Though cost efficient, this makes them inherently expensive to install and maintain. Moreover, they are a major source of traffic disturbances during installation and maintenance. Though highly accurate, intrusive sensors can only provide traffic count. Multiple sensors in complex configuration are required to measure additional traffic flow parameters such as vehicle classification and speed. Intrusive sensors have serious limitations when used under congested or heterogeneous traffic conditions as explained in detail in section 3. Pneumatic tube, inductive loop, magnetic and piezoelectric sensors are categorized as intrusive sensors as can be seen in Table 1. Pneumatic Tube: Installed perpendicularly to traffic flow direction, pneumatic tube count vehicle through air pressure created by vehicle's tire passing over it. This air pressure created in turn closes an electric switch and is detected by roadside counters. Pneumatic tubes are used as short-term solutions for counting and classification. Inductive Loop: A loop of long wire is embedded in the road surface. Frequency perturbation occurs when a vehicle passes over it, which is then passed to a road side detecting device. These frequency perturbations are counted toward vehicle counting. These detectors are relatively expensive to install and maintain because they often break down by passing vehicles [12, 13]. Because of their small detection zones, multiple inductive loop detectors have to be employed for multilane roads, vehicle direction, classification and speed calculations [13, 14]. Vehicle classification can be done through frequency signature (variation in frequency shape versus time) [15]. For vehicle speed measurement, two inductive loops are installed in series (on the same road lane). Time difference is calculated between the same vehicle's passings over the two inductive loops [15]. The signatures of vehicles can change to unrecognizable ones if a vehicle stops over the inductive loop during congestion thus making the data unreliable. In [16], a back propagation neural network algorithm was proposed to enhance vehicle classification accuracy. The algorithm took change in frequency rate and frequency waveform into consideration to classify vehicles into five classes. Piezoelectric Sensors: being pressure sensors, are embedded within grooves cut into the road surface. These sensors convert kinetic energy into electrical energy when subjected to vibrations proportional to passing vehicle's weight [11]. This electrical energy is transmitted to a roadside counting device and used to count, classify, estimate speed and weight of vehicles based on axle count and spacing [14]. These sensors can cover the whole road or can be embedded on a single road lane. It has advantages over both pneumatic tube and inductive loop. Unlike them, it can be used for lane utilization, providing more accurate data about vehicle's speed and class based on vehicle's weight. Rajab et al. used single-element piezoelectric sensors and machine learning techniques for vehicle classification and speed estimation [17]. Piezoelectric sensors were installed diagonally on the road, classifying vehicles and motorcycles with 97% accuracy. In further enhancement of the proposed solution, in [18] the authors used 16 multi-element piezoelectric sensors to measure vehicle's width, length and speed. Vehicles were classified in 13 FHWA classes with 86.9% accuracy. The accuracy rate for motorcycles was 100%. Magnetic Sensors: monitor traffic flow through perturbation in earth's magnetic field caused by passing vehicles. These perturbations are then processed to measure vehicle count, occupancy and classification. In comparison to above-mentioned solutions, these sensors are small, sensitive and immune to meteorological conditions such as rain, fog and wind [11, 19]. Performance of magnetic sensors however is sensitive to on-road noise [19]. To overcome this disadvantage, different machine learning techniques have been proposed in literature. In [20], similarity between reference and on-road signal was used for enhancing vehicle detection to 90% while Collaborative Speed Calculation (CSC) mechanism was used for speed calculation with error rate less than 10%. Zu et al. used square deviation and pre-defined threshold comparison for vehicle detection and speed estimation with 99% and 92% accuracy respectively [19]. Anisotropic magnetic sensors based WSNs (Wireless Sensor Network) employing different machine learning techniques were reported in [11]. These solutions can classify and calculate vehicle count and speed. Non-Intrusive Sensors: Non-intrusive

Table 1: Sensors technologies for Traffic flow characterization

Category	Sensing type	Cost	Energy Consumption	Easy to Install	Traffic flow Parameters
Intrusive sensors	Pneumatic Tube	Low	High	No	Count, Classification
	Inductive Loop	Low	High	No	Count, Speed, Classification
	Piezoelectric sensors	Low	High	No	Count, Speed, Classification
	Magnetic sensors	Low	Low	Yes	Count, Speed, Classification
Non-Intrusive sensors	Accelerometers	Medium	Low	Yes	Count, Speed
	Acoustic sensors	High	Low	Yes	Count, Speed, Classification
	Infrared sensors	High	Low	Yes	Count, Classification
	Radar	High	High	Yes	Count, Speed, Classification
	Ultrasonic sensors	High	Medium	Yes	Count, Speed
	Wi-Fi	Low	Low	Yes	Count, Classification
	Bluetooth	High	Low	Yes	Count, Classification

sensors based Wireless Sensor Networks (WSNs) are installed on or above roadways. These are emerging solutions for real time traffic flow characterization with a promise of unmanaged ITS infrastructure. Though expensive, these are easily installable with lower maintenance costs. While adopting WSNs, it is obligatory to satisfy traffic characterization issues at both system level (handling of signals and processing of data without human intervention, network's lifetime, adaptability and reconfiguration) and user level (reliable communication, robustness and powerful graphical user interfaces). Another design consideration is power optimization, where proposed WSNs should operate for a longer period of time without any human intervention. All of the intrusive sensor's functionalities are provided by non-intrusive sensors with fewer difficulties. However, these sensors are handicapped by varying meteorological conditions. Performance limitations of non-intrusive sensors under heterogeneous traffic conditions are detailed in section 3. Commonly used non-intrusive sensors can be seen in Table 1. Accelerometer: characterize traffic flow through measuring passing vehicle's vibrations. In [21] road surface vibrations produced by passing vehicles were used for vehicle detection under moderate but diverse traffic flow. Seismic waves produced by passing vehicle's were measured through three axis accelerometers, establishing feasibility of such a system. In [22], potential of a single accelerometer for vehicle tracking and speed estimation was established. A signal model consisting of wave propagation, excitation, preprocessing and identification was developed. The signal model combined with speed modal and extended Kalman filter was applied to vehicle tracking and speed estimation. Hostettler et al. [23] proposed and discussed adaptive threshold vehicle detection algorithm. Though developed for microphone and magnetometer sensors, the aforementioned algorithm was extended to roadside vibrations generated by vehicles. Proposed algorithm's performance was good in terms of signal and noise separation with high accuracy rates for vehicle detection. In [24], a two-dimensional sensor network using MEMS accelerometer was proposed. An algorithm was developed for vehicle detection and speed estimation on the basis of amplitude and frequency analysis of acquired vibrations. Accuracy of 80% and 90% were reported for vehicle detection and travel direction respectively. It was reported that if bicycles were not considered, vehicle detection rate can increase up to 90%. Acoustic Sensors: characterize traffic flow through passing vehicle's sound. This sound includes engine noise, tire-pavement interaction noise, vibration, horns and vehicle body rattling. Post processing of captured sound is imperative as sound characteristics are dependent on road surface and operating conditions [25]. For example, the same vehicle operating on different roads will emit different sound signatures. Acoustic sensors based solutions can consist of a single microphone for detecting specific occurrences such as passing of an emergency vehicle. However to measure traffic flow parameters (such as vehicle count, classification, occupancy and speed) an array of multiple microphones with post processing algorithms are needed. George et al. used passing vehicle's sound signatures for vehicle detection and classification [27]. Using an Artificial Neural Network (ANN) classifier, vehicles were classified into three categories namely light, medium and heavy vehicles. In [28], acoustic sensors were deployed on roadside to exploit vehicle's tire noise for traffic flow characterization. Using correlation processing on radiated tire noise, feasibility of acoustic sensors for vehicle detection was established through field testing. In [26], a solution based on an array of cross microphones was proposed for vehicle counting, classification and speed estimation. Through measured acoustic signals of vehicular traffic, the vehicle's lane position was estimated using statistical information. Chen et al. proposed a sensing technique using an array of microphones [29]. In this work, detected sound waves were digitized and processed by an on-site computer using a correlation-based algorithm. The proposed algorithm extracted key data that reflected vehicular speed and density on the road. The limitation in this work is its difficulty in differentiating sounds produced by two different cars. Infrared Sensors: sense certain attributes of its surroundings by either transmitting or detecting infrared radiations. This reflected energy is converted into electrical signals for post processing by a roadside processing unit. Two types of infrared sensors are used in traffic flow characterization [4]. In Active Infrared Sensors (AIR), laser diodes emit low power infrared energy to a certain area called detection zone. When a vehicle enters the detection zone, energy is reflected which is captured by the receiving unit. Passive Infrared sensors (PIR) sense the energy emitted by vehicles, road surfaces or any other objects. Infrared Sensors consume less energy and are easily installable. Infrared sensors can calculate vehicle count, lane occupancy and queue detection. In [13], two infrared transceivers installed on elevated structures over the road were employed for vehicle detection and counting. Laser beam deflected by a vehicle is different as compared to road surface deflection, resulting in a change in reflected signal's amplitude. This interruption phenomenon and change of amplitude was used for vehicle counting. In [30], vehicle detection and classification was done using passive infrared sensors. In the proposed work, a combination of ultrasonic and infrared sensors were used for vehicle detection with the help of Gaussian mixture model. Vehicle speed was estimated by calculating delay between detection at two consecutive sensors. The estimated delays were then used by neural networks along with vehicle length for vehicle classification. In [31], a solution was proposed using infrared sensors in conjunction with signal processing and correlation techniques. Traffic flow parameters such as vehicle count, speed and classification based on vehicle length were reported. Microwave Radar Sensors: These sensors, mounted on roadsides transmit low energy microwave radiation across a certain area. When the vehicle passes through that area, a certain portion of energy is reflected. Detection system, consisting of a receiver antenna, calculates traffic flow statistics. Microwave radars for ITS mostly work on either X-band (~10 GHz) or K-band (~24 GHz). These can be classified in three types: (1) Doppler systems using frequency shift; (2) Frequency modulated continuous wave radar, and (3) Unmodulated continuous wave radars [4, 32]. Zwahlen et al. proposed a traffic flow characterization system consisting of two microwave radar units [33]. The proposed system was intended to measure vehicle count, classification, arrival time and average speed. In field testing, the proposed system's accuracy rate for counting was 95%, while average speed was within 3 mph of actual speed. In [34], GSM based passive radars were employed for establishing the feasibility of using such systems for traffic flow characterization. It was concluded that such systems can be employed under different circumstances such as urban settings or on highways. With capability to extract traffic flow parameters such as count, average speed and road capacity. Main drawback of Doppler radar in down-the-road configuration becomes apparent when several vehicles are in the radar beam. Resulting in failure to measure vehicle's speed and identifying the lane vehicle is traveling in [35]. This is overcome by using Doppler radar in across-the-road configuration, where the microwave beam is directed across the road instead of down (or along) the road. This mitigates the problem of more than one vehicle in the microwave beam, but this assumption fails in congested traffic [35]. To overcome this shortcoming, in [35] two interferometric linear frequency modulated continuous wave radar were installed across and down the road. The proposed solution was able to measure speed, range and lane of several vehicles simultaneously. Fang et al. [32] proposed a low cost system based on K-band unmodulated continuous wave radar. Traffic flow parameters such as vehicle classification, speed and flow rate were measured using signal processing. Ultrasonic Sensors: emit sound waves at frequencies between 25-50 KHz (above human audible range). Objects are detected based on elapsed time between transmitted and reflected sound waves off an object. Received ultrasonic energy is converted into electrical energy and processed to collect traffic flow parameters such as vehicle count and speed. In [44], a low power ultrasonic sensors based WSN solution for vehicle detection was proposed. Using low complexity algorithms, feasibility of such a system for vehicle count in single lane was established. Jeon et al. proposed ultrasonic sensors based WSN solution for traffic characterization in multi road lanes scenario [12]. Multiple sensor nodes were mounted on roadsides, measuring traffic flow parameters with an error rate of 3%. Odat et al. proposed integrating Passive Infrared and ultrasonic sensors for vehicles classification and their speed estimation [36]. First, time delay between signals of different sensors was calculated by cross correlation and wavelet transform methods. Then a calibration model based on the Bayesian network was employed for vehicle speed and classification. Field testing demonstrated vehicle detection with 99% accuracy. Mean error of 5 km/h and 0.7 m was noted for vehicle speed and length estimation respectively. Sensing through Communication Networks: In existing literature, efforts have been made to employ wireless communication networks for traffic flow characterization. These efforts were based on inspecting Channel State Information (CSI) [37], received signal strength (RSSI) [39, 40], link quality indicator (LQI) and packet loss rate [38]. In [37], a Wi-Fi based system was proposed for traffic flow characterization. Wi-Fi transmitter and receiver were placed across and opposite to each other on the roadside. Vehicles were counted after removal of noise from CSI data on the receiver side. Furthermore, CSI patterns of passing vehicles were analyzed in order to measure vehicle's speed, classification and lane occupancy. In [38], a radio frequency based system was proposed for traffic congestion detection. Transmitter and receiver were placed across each other on the roadside. In case of no congestion or vehicles moving at high speed, the transmitter and receiver were in line of sight. Freely moving vehicles do not affect packet reception, with receivers collecting a higher strength signal indicating better link quality. In case of stopped or slow moving vehicles, low signal strength and packet ratio were received by the receiver showing poor link quality. Horvat et al. [40] proposed a ZigBee based solution for vehicle detection. A transmitter-receiver pair was placed across each other on the roadside. The transmitter continuously sent radio waves towards the receiver. Passing vehicles intersected the propagation path of radio waves affecting received signal strength. Using correlation between received signal strengths, size and speed of vehicles were measured. In [39] a system based on Mobile devices and Bluetooth Low Energy (BLE) Beacons was proposed for vehicle counting and classification. In the proposed work, multiple BLE beacons and mobile devices (smartphones) were placed facing each other on opposite roadsides. The BLE beacons were installed at different heights to classify vehicles based on height. The beacons transmitted radio frames by using IBeacon protocol, with smartphones collecting these radio frames in order to measure their signal strength. Received signal strength along with device position was transmitted to a server via Wi-Fi for vehicle classification.

COMPARATIVE ANALYSIS FROM HETEROGENEOUS TRAFFIC PERSPECTIVE

For ITS solutions, detailed real-life traffic flow parameters are imperative. These parameters range from vehicle count, speed, classification, road capacity, traffic flow, spatial\temporal densities, horizontal\vertical headway, trajectories and heat maps. These parameters are in turn used to calibrate and validate traffic simulation software and mathematical models for efficient designing and managing of road networks. Intrusive and non-intrusive sensors, though an improvement over manual counting, have serious limitations. These limitations are in the number of traffic flow parameters provided and traffic characterization under congested\heterogeneous traffic conditions. Heterogeneous traffic is where there is no lane discipline with great variation in road plying vehicle types. Vehicle types can range from cars, trucks, buses, three wheelers (both motorized and human driven), bikes, bicycles and animal/human driven carts. Furthermore, random pedestrians crossing at random locations affect traffic flow. Though an improvement over manual counting, intrusive sensors have some major limitations in both scope and capability. These range from expensive installation cost, maintenance and major traffic disturbance during installations. Though highly accurate in counting, multiple intrusive sensors installed in complex configuration are needed to measure vehicle speed and classification with low accuracy. Furthermore, more than one sensor is needed to characterize traffic for multilane roads. Most importantly, intrusive sensors have serious limitations under congested and heterogeneous traffic conditions. All types of intrusive sensor's accuracy suffer under stopped or slow moving traffic. Advantages and limitations of intrusive sensors have been detailed in Table 2. Non-intrusive sensors based WSNs have rapidly evolved to replace intrusive sensors, becoming more reliable and easier to use and deploy. Their advantages over intrusive sensors range from lower costs and reduced traffic disturbances during installation/ maintenance, safety risks, and less detrimental to road pavement. As compared to intrusive sensors, these are more suitable for installation in hard to reach areas such as tunnels and bridges. However, non-intrusive sensors have their own limitations ranging from sensitivity to meteorological parameters, roadway geometrics and traffic behavior [11, 12, 19] as detailed in Table 2. These limitations make non-intrusive sensors not an optimal choice for traffic flow characterization under congested and heterogeneous traffic behavior.

COMPUTER VISION TECHNIQUES ITS

In light of arguments presented in section 3, compute vision based solutions are emerging as the most optimal solution for traffic flow characterization. Especially for heterogeneous traffic conditions, where compute vision based solutions can overcome limitations of both intrusive and non-intrusive sensor based solutions. This is due to the fact that traffic is characterized through definition of properties, shape, illumination and color distribution of images. Therefore, in addition to vehicle count and speed, the great variation of vehicle types under heterogeneous traffic conditions can be classified including pedestrians. Although like non-intrusive sensors, compute vision based solutions are also affected by meteorological conditions such as rain, fog, snow, camera vibration in strong winds, road illumination in sunlight and lighting issues during night [16, 33, 41]. However unlike non-intrusive sensors, these solutions can measure nearly all traffic flow parameters under both congested/ non-congested and homogeneous/heterogeneous traffic conditions. Moreover, these solutions can characterize traffic flow for complex road configurations (such as intersections, multilane roads, U-turns or all in combination) using a single camera sensor as demonstrated

Table 2: Sensors technologies from heterogeneous traffic conditions perspective

Category	Sensing type	Advantages	Limitations
Intrusive Sensors	Pneumatic Tube [11, 12]	It is simple and easy to operate. It is not affected by environmental conditions.	Susceptible to be torn up and prone to vandalism. Inability to detect pedestrians Susceptible to ambient temperature.
	Inductive Loop [11, 19]	Easy and simple to operate.	Affected by traffic stress, poor road surfac and temperature sensitive. Inability to detect non-metallic objects such as pedestrians, animal\human driven carts.
	Piezoelectric sensors [11, 19]	Applicable for homogeneous traffic. These sensors can measure the weight of vehicles.	Sensitive to road surface temperature Error prone due to poor installation procedures. Too complex for heterogeneous traffic. Small detection zones.
	Magnetic Sensors [11]	Developed for homogeneous traffic. Less susceptible to traffic stress as compared to pneumatic tube and inductive loop.	Have small detection zones. Proximity to vehicles for accuracy. Inability to detect non-metallic objects such as pedestrians, animal\human driven carts.
Non-Intrusive Sensors	Accelerometers	Easy installation and low power requirements.Not affected by light and traffic noise.	Sensitive to environmental vibrations. Inability to detect stationary objects. Inability to count pedestrians, bicycles, animal\human driven carts.
	Acoustic Sensors [25, 26]	Low cost and robust against light and meteorological conditions. Not affected by light	Inability to count in noisy congested and heterogeneous traffic conditions. Inability to count quiet objects such as pedestrians, bicycles, animal\human driven carts.
	Infrared Sensors [12]	These sensors can detect bicycles and pedestrians Can transmit multiple beams for accuracy on multilane roads.	Highly sensitive to sunlight and meteorological conditions such as fog, rain, snow, ambient pollutants. Scattering or absorbing infrared signals.
	Microwave radar [4, 12, 32]	Applicable for both homogeneous and heterogeneous traffic Unaffected by wet and cold conditions.	Highly complex, expensive and susceptible to electromagnetic interference.. Inability to detect stationary objects (congestion) without an auxiliary device.
	Ultrasonic Sensors [4, 11, 12, 19]	Applicable for both homogeneous and heterogeneous traffic Simple, cheap and easy to install	Highly sensitive to temperature fluctuations and air turbulence. Inability to detect stopped or slow moving objects.
	Wi-Fi	These sensors are not affected by light, temperature and traffic noi Applicable for both homogeneous and heterogeneous traffic	Performance is hindered in congested or illegal parked vehicles. Inability to detect variation in vehicle types.
	Bluetooth Beacons	Easy to install, small and inexpensive	These sensors have security limitations. Perform poorly in congested conditions.

in the result section of this work. In existing literature, compute vision based solutions for traffic flow characterization are implemented using either edge computing or video streaming methodologies. Edge Computing: Edge computing is a distributed and open architecture in which data is processed at the network's edge, instead of data transmission to a centralized data processing server. This helps in eliminating internet bandwidth costs (video streaming cost) by processing data near the edge. This also adds an additional layer of security by non-transmission of videos over the internet to public clouds. Nearly all edge computing solutions proposed in existing literature have employed Raspberry Pi (because of its low cost and ease of use) with OpenCV for traffic flow characterization. However, these proposed solutions are constrained under the compute resources of compute board. In existing literature, at most only two traffic flow parameters have been measured such as counting\classification [41, 42] or counting\speed [43, 44]. Distributed Computing: To overcome edge computing limitations in terms of computation resource constraints, distributed computing methodology has been employed in this work. In existing literature, very few real-time video streaming solutions have been proposed. Furthermore, these proposed solutions provide limited traffic flow parameters. Considering limitations of proposed solutions in existing literature (intrusive, non-intrusive sensors and edge computing solutions), commercial traffic monitoring software (TMS) have emerged as the most viable solution. Even more so for traffic characterization under congested and heterogeneous traffic behavior. These TMS can provide nearly all traffic flow parameters in addition to pedestrian's jaywalking and illegally parked vehicles on overall traffic flow. Most commonly used TMS are characterized in Table 3.

Table 3: Commercial Traffic Monitoring Software Characteristics

Traffic Monitoring Software	Traffic Flow Parameters
TrafficVision [45]	Count, Classification, Speed, Pedestrian crossings, Vehicles in wrong direction, road occupancy exceeding a threshold, vehicle stopped at a location beyond specified time.
Smart Traffic Analyzer [46]	Count, Speed, Classification (light, heavy) Vehicle moving in wrong/reverse direction, illegal overtaking, incident detection
Autostrade Tech [47]	Count, Speed, Stopped vehicles, Vehicles moving in wrong direction, traffic flow statistics
Camlytics [48]	Count, Speed, pedestrian crossing, trajectories, heat maps

In this work, we have employed Camlytics for heterogeneous traffic flow characterization. Camlytics [48] is multi-camera management software for traffic flow surveillance and characterization. Camlytics has the capability to analyze both real-time video streams and pre-recorded videos. It has the ability to allow users to detect and record a large number of traffic flow events. These events range from counting, speed, vehicle motion in specific direction, trajectories, heat maps and traffic flow statistical analysis. Furthermore it can be used for pedestrian counting/crossings and their effect on traffic flow. Camlytics can perform traffic analysis on video streams from four different cameras simultaneously, when running on a Windows based PC with a 4GB RAM and 200 GB free hard disk space.

RESULTS

In order to characterize heterogeneous traffic flow, a two-way multi-lane road located near Phase-3 Chowk, Peshawar was chosen. This road section includes a two-directional multi-lane road with three U-turns as can be seen in Fig. 1. For traffic flow analysis, Camlytics has been employed for characterize traffic flow parameters such as vehicle count, speed, temporal densities, time headway, density maps and vehicle trajectories [48]. Camlytics was running on a Dell Desktop with i5 quad-core processor and 4 GB RAM with Window 10 operating system. A video of 640x480 resolutions at 20 frames per second was recorded from 16:02:29 to 16:37:29 (2100 s) on Tuesday 26 November 2019.

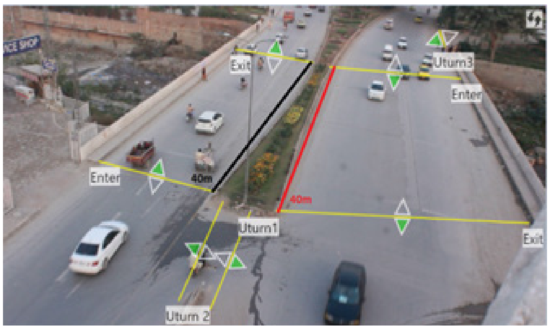
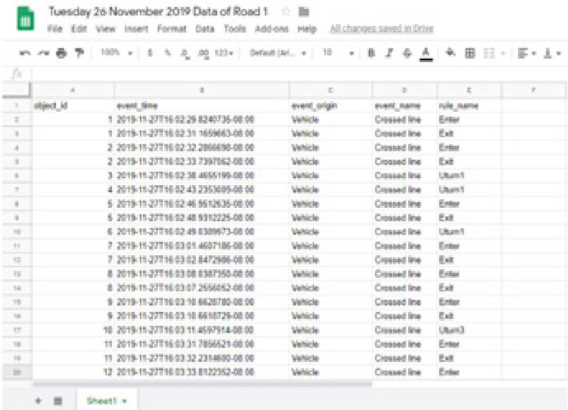


Figure 1: Experimental setup for traffic flow characterization in Camlytics GUI

Camlytics comes with a simple Graphical User Interface (GUI), which can be used to create event generation lines and zones as can be seen in Fig. 1. Events are generated when a vehicle crosses a line, type of line (Enter or Exit) and where vehicle crosses it. At each generated event, different associated parameters (such as event ID, vehicle ID, type of line crossed (Enter or Exit) and event time) are logged in a .CSV file as can be seen in Fig. 2. These lines (Enter and Exit) can count vehicles in specific directions and are drawn 40 m apart on both road 1 and 2 as can be seen in Fig. 1. Uturn1 line records the number of vehicles that enter from road 2 to road 1, whereas the Uturn2 line records the number of vehicles that enter from road 1 to road 2. The line marked Uturn3, records the number of vehicles merging onto road 1. The logged events can be seen in Fig. 2, which are used for traffic data analytics. Vehicle Count & Temporal Density: Using .CSV logged files as shown in Fig. 2, vehicles were counted on road 1, road 2 and three U-turns from a video of 2100 s time duration. In 2100 s time period, 482 and 469 vehicles were counted on road 1 and road 2 respectively. Of the 482 vehicles counted on road 1,



Tuesday 26 November 2019 Data of Road 1

	A	B	C	D	E
1	object_id	event_time	event_origin	event_name	rule_name
2	1	2019-11-27T16:02:29.8240735-08:00	Vehicle	Crossed line	Enter
3	1	2019-11-27T16:02:31.1659663-08:00	Vehicle	Crossed line	Exit
4	2	2019-11-27T16:02:32.2866698-08:00	Vehicle	Crossed line	Enter
5	2	2019-11-27T16:02:33.7397062-08:00	Vehicle	Crossed line	Exit
6	3	2019-11-27T16:02:38.4655199-08:00	Vehicle	Crossed line	Uturn1
7	4	2019-11-27T16:02:43.2353009-08:00	Vehicle	Crossed line	Uturn1
8	5	2019-11-27T16:02:46.9512635-08:00	Vehicle	Crossed line	Enter
9	5	2019-11-27T16:02:48.9312225-08:00	Vehicle	Crossed line	Exit
10	6	2019-11-27T16:02:49.0389673-08:00	Vehicle	Crossed line	Uturn1
11	7	2019-11-27T16:03:01.4607186-08:00	Vehicle	Crossed line	Enter
12	7	2019-11-27T16:03:02.8472986-08:00	Vehicle	Crossed line	Exit
13	8	2019-11-27T16:03:06.0387350-08:00	Vehicle	Crossed line	Enter
14	8	2019-11-27T16:03:07.2556052-08:00	Vehicle	Crossed line	Exit
15	9	2019-11-27T16:03:10.6620780-08:00	Vehicle	Crossed line	Enter
16	9	2019-11-27T16:03:10.6618729-08:00	Vehicle	Crossed line	Exit
17	10	2019-11-27T16:03:11.4597914-08:00	Vehicle	Crossed line	Uturn3
18	11	2019-11-27T16:03:31.7856621-08:00	Vehicle	Crossed line	Enter
19	11	2019-11-27T16:03:32.2314600-08:00	Vehicle	Crossed line	Exit
20	12	2019-11-27T16:03:33.8122352-08:00	Vehicle	Crossed line	Enter

Figure 2: Logged .CSV file of events generated on Road 1

85 vehicles merged onto road 1 through Uturn1 and 34 vehicles through Uturn3. Of the 469 vehicles counted on road 2, 67 vehicles merged onto road 2 through Uturn2. Temporal densities of vehicles on road 1 and 2 for 50 s timeslots can be observed in Fig. 3. The highest vehicle density on road 1 was observed during 1300-1350 s timeslot. During this time slot, 20 vehicles were present on road 1. While on road 2, the highest vehicle density was observed at 21 vehicles between 1750-1800 s timeslot as can be observed in Fig. 3.

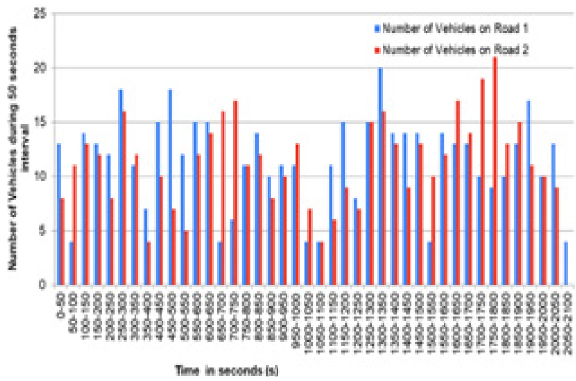


Figure 3: Road 1 and 2's temporal densities for 2100 s duration on Tuesday 26 November 2019

Vehicle Speed and Time Headway: In Camlytics, enter and exit times of a vehicle (each with unique vehicle Id) are logged through event generation lines as can be seen in Fig. 2. The time a vehicle takes to cover the distance between enter and exit lines is calculated as

$$Time\ Taken = T_{exit} - T_{enter} \quad (1)$$

The distance between the Enter and Exit lines is 40 m on road 1 and 2 as can be seen in Fig. 1. Hence, average speed of each vehicle is calculated as

$$Speed = \frac{Distance}{Time\ Taken} \quad (2)$$

The relationship between speed and time taken by vehicles between enter and exit lines are determined through the trendline analysis tool in Excel. In trendline, best fit lines can be generated by employing built in correlation functions based on data points. Using the logged data of time taken from (1) and speed of vehicles obtained from (2) on road 1 and road 2, an XY scatter graph is plotted. The x-axis represents time taken by vehicles, and y-axis represents speed of vehicles. Then exponential fits as shown in Figs. 4 and 5 are generated for both roads 1 and road 2 by using the exponential correlation function. The accuracy of regression is given by an R-squared value such that a larger R-squared value has a larger accuracy of data fit. It can be seen from Figs. 4 and 5 that the R-squared value is approximately 0.93 for both road 1 and 2 such that the exponential line fits 93% to data. The exponential behavior on road 1 between speed and time taken is y = 72.23e-0.175x as shown in Fig. 4. The exponential behavior on road 2 between speed and time taken is y = 56.44e-0.137x as shown in Fig. 5. On road 1, speed of vehicle decreases exponentially at the rate of 0.175 while on road 2, speed of vehicle decreases exponentially at the rate of 0.137.

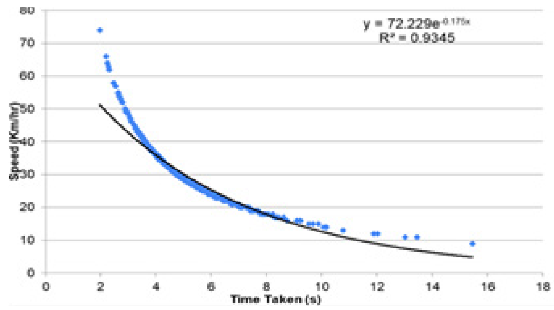


Figure 4: Relationship between Time Taken and Speed on Road 1

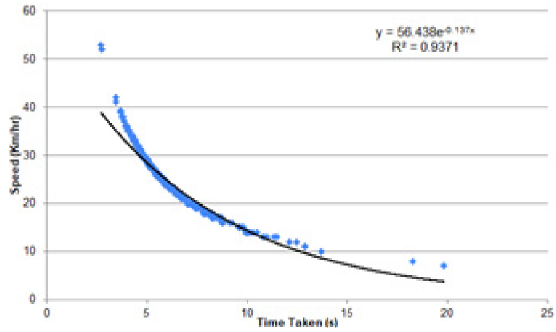


Figure 5: Relationship between Time Taken and Speed on Road 2

Average speed of each vehicle passing through road 1 & 2 is calculated using equation (2). Average speed on road 1 & 2 are shown in Fig. 6 & 7 respectively. As can be seen from Figs. 6 & 7, vehicle's average speeds vary between 20 km/h to 40 km/h. The fastest vehicle's speeds measured on road 1 & 2 were 74 km/h and 54 km/h at 16:31:40 and 16:13:35, respectively.

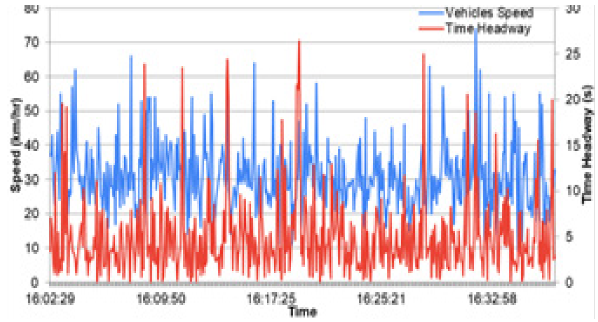


Figure 6: Speed and time headway of heterogeneous traffic on road 1

Time headway is the difference of arrival time between two vehicles at the same point. Using logged data, time headway is calculated for both road 1 & 2 as can be observed in s 6 & 7. The maximum time headway recorded on road 1 was 26.40 s at 16:20:11, while the corresponding traffic speed was 47 km/h. The minimum time headway value recorded was 0.049 s at 16:09:25, while the corresponding traffic speed was 24 km/h. The average time headway and the average speed recorded on road 1 are 4.87 s and 30 km/hr. Maximum time headway recorded on road 2 was 28.40 s at 16:18:23, while the corresponding traffic speed was 37 km/h. Minimum time headway recorded was 0.001 s at 16:11:30 while corresponding traffic speed was 11 km/h. The average time headway and average speed measured on road 2 were 4.85 s and 25 km/h, respectively. So it can be deduced from the above discussion that as the time headway increases the speed of vehicles increases and as time headway decreases the speed of vehicles decreases.

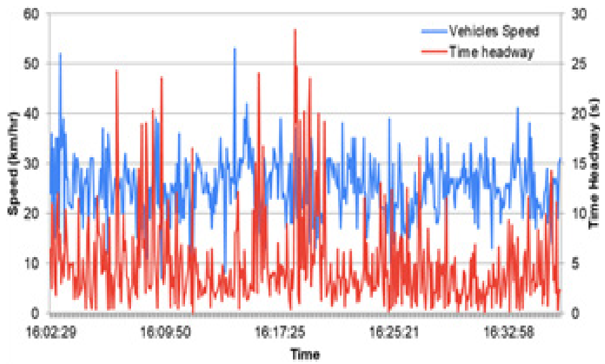


Figure 7: Speed and time headway of heterogeneous traffic on road 2

Vehicles Trajectories: Camlytics provides the capability to examine vehicles directional flows by analyzing their trajectories between enter and exit lines drawn. Vehicle trajectories on road 1 & 2 can be observed in Fig. 8 and 9 respectively. As can be seen in the two figs., trajectories on road 1 are irregular as compared to road 2's trajectories. The reason for these irregularities is heterogeneous traffic behavior. Vehicles taking Uturn1 from road 2 to road 1 travel in both directions on road 1. Most of the vehicles join the traffic flow, while some vehicles travel in opposite direction of traffic flow toward Uturn3. The black triangle in Fig. 8 represents the trajectories of vehicles moving in opposite direction on road 1 toward Uturn3. While the green square in Fig. 8 represents movement of vehicles that join the traffic flow on road 1.

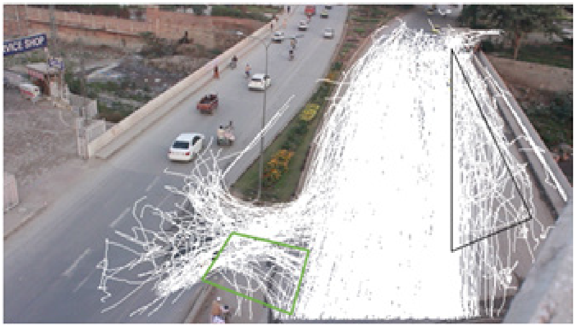


Figure 8: Vehicles Trajectories on Road 1 recorded from 2100 s Video scene

Trajectories on road 2 are smooth because vehicles taking Uturn2 from road 1 travel in traffic flow direction. Orange box in Fig. 9 represents these trajectories. Furthermore, trajectories on pedestrian way of road 1 & 2, show the movement of pedestrians as can be seen in Fig. 8 & 9.

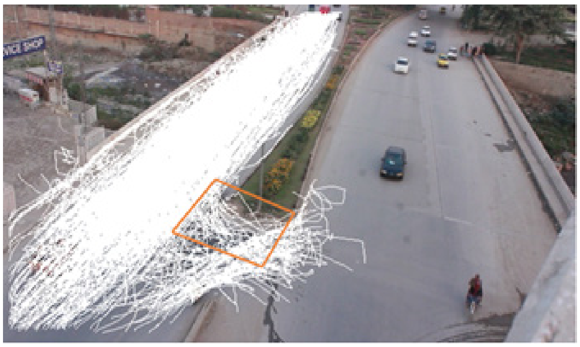


Figure 9: Vehicles Trajectories on Road 2 recorded from 2100 s Video scene

Spatial Density Maps: Camlytics provides the capability to represent spatial densities on different road sections through heat maps. Number of vehicles passed through different road sections are represented with the help of hot colors as can be seen in Fig. 10 & 11. As can be seen in Fig. 10, 325 vehicles were concentrated on road 1 represented by red color. Fig. 11 shows that 459 vehicles were concentrated on road 2 at road locations represented by red color. As can be seen in Fig. 10 & 11, spatial density of vehicles are not distributed evenly but concentrated at the center of roads. This is typical of heterogeneous traffic behavior.

Figure 10: Spatial density map of Road 1 for 2100 s duration

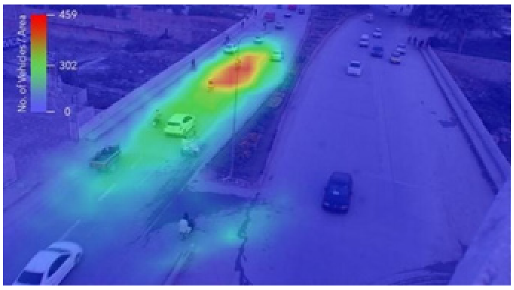


Figure 11: Spatial density map of Road 2 for 2100 s duration

CONCLUSION

In this work, we have proposed a compute vision based traffic flow characterization solution. The proposed solution, in addition to all functionalities provided by intrusive and non-intrusive sensors, also has the capability to characterize traffic under both congested and heterogeneous traffic conditions. Additional advantages of the proposed solution are its easy installation, nonexistent traffic disturbances and ability to characterize traffic for complex road configurations. Detailed traffic statistics measured will be instrumental in validation and calibration of traffic mathematical flow models and traffic simulation software such as VISSIM, Corsim and Aimsun. Thus helping traffic engineers in planning, designing and efficient management of the road network. For field evaluation, a complex road configuration consisting of two-way multi-lane roads with three U-turns was chosen. Traffic flow was characterized for 2100 s (35 minutes) measuring parameters such as vehicle count, speed, temporal and spatial densities, time headway, trajectories and heat maps. The proposed solution was able to overcome both intrusive and non-intrusive sensor based solutions limitations such as; (1) characterizing pedestrian behavior, (2) all types of vehicles including two-wheelers, three-wheelers and animal/human driven carts. In future, we plan to devise a sensor node with video streaming capabilities over the internet. Such devices will make it possible to remotely characterize traffic. Furthermore, traffic flow on more complex road configuration will be characterized by streaming synchronized video streams from multiple cameras.

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