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Vehicle Classification in Intelligent Transport Systems: An Overview, Methods and Software Perspective

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ABSTRACT Vehicle Classification (VC) is a key element of Intelligent Transportation Systems (ITS). Diverse ranges of ITS applications like security systems, surveillance frameworks, fleet monitoring, traffic safety, and automated parking are using VC. Basically, in the current VC methods, vehicles are classified locally as a vehicle passes through a monitoring area, by fixed sensors or using a compound method. This paper presents a pervasive study on the state of the art of VC methods. We introduce a detailed VC taxonomy and explore the different kinds of traffic information that can be extracted via each method. Subsequently, traditional and cutting edge VC systems are investigated from different aspects. Specifically, strengths and shortcomings of the existing VC methods are discussed and real-time alternatives like Vehicular Ad-hoc Networks (VANETs) are investigated to convey physical as well as kinematic characteristics of the vehicles. Finally, we review a broad range of soft computing solutions involved in VC in the context of machine learning, neural networks, miscellaneous features, models and other methods.

INDEX TERMS Intelligent transportation system (ITS), vehicle classification (VC), vehicular ad-hoc networks (VANETs), soft computing.

I. INTRODUCTION

THE term of VC is the collection of methods used to extract the vehicle's parameters and classify the vehicle into different classes. There exist distinct definitions for VC in the publications. Reference [1] defines VC as a tool for an accurate counting of the axles number and spacing of the distinct vehicles traveling in a lane. Reference [2] considers VC as a pattern recognition (PR) issue where vehicles are grouped into various classes, namely off-road, sedan, two wheeler, bus, and pick up truck. Reference [3] deems VC as a vital part of ITS that collects precious information for different applications such as system planning and surveillance. References [4] and [5] describe VC in such a way that vehicles are detected and categorized with respect to their types and certain sub-classes respectively. Reference [6] specifies VC by assigning the vehicles into various groups. In [7], [8], VC is defined as a process of splitting up the vehicles based on different predetermined classes. Reference [9] denotes VC as one of the vehicle identification methods. Reference [10] defines the VC as a means to provide information about the types of the vehicles that traverse a monitoring zone by categorizing them into classes. Reference [11] performs the VC by evaluating the shape or size of a crossing vehicle.

Vehicle classification is one of the main components of traffic monitoring systems. It plays a crucial role in transportation planning and traffic engineering. For example, safety organizations are very interested in identifying capacity and geometric design of the freeways and pavement maintenance according to the vehicle types, numbers and so forth. In ITS, different applications like automated parking systems [12], [13], structural health monitoring [14], [15], [16], [17], [18], security enforcement [19] and monitoring of traffic flow [20], [21] widely avail of VC. For vehicles detection, various methods such as transiting monitoring areas [22], [23], crossing in front of fixed

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sensors [10], [24], global coverage [25], [26] or hybrid methods [24], [27] are used. Data gathered by sensors and detectors encompasses a broad range of information including speed [28], [29], acceleration/deceleration [30], number plate [31], [32], make and model [33], [34], [35], axle weight and spacing [36], [37], and vehicle count and shape, i.e., height, width and length [23], [38].

Recently, several VC systems have been introduced due to the tremendous advancements in soft computing, wireless communication and sensing technologies. These methods have different requirements and specifications in terms of hardware and configuration settings, deployment environment, cost, sensor types etc. This makes it challenging for industry and scientists to apt for a justifiable solution for their VC applications.

The simplest method of VC is the manual count, nonetheless it is prone to errors, laborious and also time consuming. Vision-based methods as the most commonly used and studied approach for VC detect and track the vehicles by withdrawing visual features like textural patterns, colors and lines of the video [39]. Vision-based methods undertake some phases including image segmentation, PR, feature extraction, and training.

In 1920, pneumatic tube detectors were introduced for VC and today they collect the vehicular data for a short period of time [40]. However, this method is not feasible for highly congested and high-speed roadways, but it can recognize axle spacing and axles number in a moving vehicle.

Magnetic loop detector is a technology that detects the vehicle length and has been used in the recent decades for VC [41], [42]. Dual loop detectors can measure the speed of a target vehicle [43], [44]. Similar to the pneumatic tube detectors, they do not perform well in high volume roads although they are fairly cheap and perform automatic classification [30].

Axle configuration and weight of the vehicle are detectable by piezoelectric sensors [28], [45]. This kind of sensors is sensitive to the pavement temperature and speed of the vehicle and can be used individually or along with weigh-in-motion (WIM) systems.

Radar sensors are customary tools that are capable of classifying vehicles according to their dimensions like length, size, height etc., [46], [47]. Despite their deficiency for the dense traffic and compared to the other VC methods, they are more resistant to the environmental variations [30].

Infrared sensors use the reflection light of a vehicle in order to seek the equivalent match in the database [48], [49], [50]. Environment changes have a negative impact on the infrared sensors.

Acoustic sensors utilize acoustic signatures that are speed independent to determine the vehicle classes [51].

A VC system based on the Global Positioning System (GPS) is shown to be the most dependable way to extract the global movement parameters of the vehicle whereas it lacks the information about the vehicle's physical properties. Furthermore, portable GPS and GPS mobile devices, or smartphones that can provide kinematic characteristics of the vehicles are not a reliable information source to classify the vehicles a in real-time state.

A fusion of the methods based on the fixed location sensors with other methods seem to be able to provide detailed information [52], [53]. For example, information regarding the make and brand of a vehicle obtained via vision-based methods can help to gain other data such as weight and axle specifications [54], [55]. Moreover, the camera can also retrieve mobility parameters like speed, acceleration/deceleration, direction within the coverage range [52], [56].

Except for GPS-based methods, current VC approaches have generally local essence as mentioned earlier. As two principal requirements for a reliable classification of vehicles, the real-time collection of traffic information together with having global access to the sensor data are necessary. In the VC methods, mobility and physical parameters are to be taken into account. This paper investigates the state of the art including real-time methods like VANETs that can classify the vehicles in a global mode. VANETs comprise vehicles that are interconnected wirelessly and exchange real time traffic information.

This paper is organized as follows. In Section II, VC taxonomy spanned over five fundamental methods is presented whereby each method can acquire a wide spectrum of information. Methods are broken down into subsections based on the operational environment, sensor types, VC mechanisms and sensors methodologies. Section III offers a comprehensive overview on the state of the art, smart technologies and novel breeds of VC methods like VANETs, Wireless-Fidelity (Wi-Fi), Long Term Evolution (LTE), wireless sensor networks (WSNs) and radio frequency (RF) including analysis, challenges, issues, comparison, description and relevant algorithms. Here, VANETs are discussed as a superior and plausible approach that can dependably classify the vehicles by meeting the corresponding VC requisites. Finally, the last section summarizes the findings of this work.

II. VEHICLE CLASSIFICATION TAXONOMY

This section describes the vehicle classification taxonomy. VC methods are organized into five main categories depending on the required physical changes on the roadways as well as the deployment conditions of the equipment as follows: intrusive, non-intrusive, off-road, manual or a combination of aforementioned items called hybrid methods. Each method is unique in terms of the extracted traffic information. They vary from local to global, physical to kinematic and manual to automatic.

Intrusive sensors are located under the road surface in holes or attached to the road surface [57]. They are in contact with the vehicles and contain diverse kinds of sensors such as loop detectors [42], magnetometers [58], [59], piezoelectric sensors [60] and vibration sensors [61]. Hence, they operate

TABLE 1. Taxonomy of vehicle classification methods and related extracted traffic information.

			Mobility Info.				Physical Info.				
Deployment	Category	Method	Global Position	Acceleration	Direction	Speed	Axle Configuration	Type and Model	Weight	Count	Automatic
Non-intrusive	Vision-based	Video Images	✗	✓	✓	✓	✗	✓	✗	✓	✓
Non-intrusive	Sound-based	Acoustic	✗	✓	✓	✓	✗	✗	✗	✓	✓
Non-intrusive	Sound-based	Ultrasonic	✗	✗	✗	✗	✗	✗	✗	✓	✓
Non-intrusive	Remote Sensing	Infrared	✗	✓	✓	✓	✗	✗	✗	✓	✓
Non-intrusive	Remote Sensing	Laser Scanner	✗	✓	✓	✓	✗	✗	✗	✓	✓
Non-intrusive	Remote Sensing	LiDAR	✗	✓	✓	✓	✗	✗	✗	✓	✓
Non-intrusive	Remote Sensing	Radar	✗	✓	✓	✓	✗	✗	✗	✓	✓
Non-intrusive	Remote Sensing	RF Transceivers	✗	✓	✓	✓	✗	✗	✗	✓	✓
Non-intrusive	Remote Sensing	Wi-Fi-LTE Transceivers	✗	✓	✓	✓	✗	✗	✗	✓	✓
Intrusive	Contact	Inductive Loops	✗	✓	✓	✓	✗	✗	✗	✓	✓
Intrusive	Contact	Magnetic Sensors	✗	✓	✓	✓	✗	✗	✗	✓	✓
Intrusive	Contact	Fiber Optic	✗	✓	✓	✓	✓	✗	✗	✓	✓
Intrusive	Contact	Piezoelectric	✗	✓	✓	✓	✓	✗	✗	✓	✓
Intrusive	Contact	Pneumatic	✗	✓	✓	✓	✓	✗	✓	✓	✓
Intrusive	Contact	Strain Gauge	✗	✓	✓	✓	✓	✗	✗	✓	✓
Intrusive	Contact	Seismic and Vibration	✗	✗	✗	✗	✗	✗	✗	✓	✓
Off-road	Aerial	UAVs	✗	✗	✗	✗	✗	✓	✗	✓	✗
Off-road	Aerial	Satellite	✗	✗	✗	✗	✗	✓	✗	✓	✗
Off-road	GPS-based	In-vehicle GPS Device	✓	✓	✓	✓	✗	✗	✗	✗	✗
Off-road	GPS-based	Mobile Apparatus	✓	✓	✓	✓	✗	✗	✗	✗	✗
Hybrid	Multi-Methodical	WIM	✗	✓	✓	✓	✓	✗	✓	✓	✓
Hybrid	Multi-Methodical	WSN	✗	✓	✓	✓	✓	✗	✓	✓	✓
Hybrid	Multi-Methodical	VANETs	✓	✓	✓	✓	✓	✓	✓	✓	✓
Manual	Manual	Manual Observation	✗	✗	✓	✓	✓	✗	✗	✓	✗

accurately in retrieving miscellaneous data like the vehicle's physical information along with the motion signature.

Non-intrusive sensors are located above or next to the road and their monitoring data are less influenced by pavement quality compared to the intrusive sensors and have simpler installation and maintenance [62]. These roadside sensor-based systems span a broad range of varieties including laser light detection and ranging (LiDAR) [13], [63], accelerometers [64], infrared sensors [2], acoustic sensors [65], magnetometers [66], [67] and Wi-Fi transceivers [68]. On the downside, theses sensors highly require appropriate placement and direction adjustment [2]. Moreover, classification of overlapping vehicles is very troublesome for this sort of systems. Additionally, data calibration algorithms are needed to reduce the noise impact on classification. Besides, both intrusive and non-intrusive sensor-based VC systems can be characterized by costly implementation and maintenance and they are highly sensitive to the ambient status [69].

Mobile sensors embedded and deployed by satellite, airplane, or in vehicle GPS-enabled receivers are called off-road sensors [70]. Sensors in satellites and unmanned aerial vehicles (UAVs) are aerial systems that cover multiple lanes from above roadways or even a road segment [71], [72]. Vision sensors are the dominant technology [73], [74] in this category. Despite their little construction and maintenance cost, these systems are not accurate and are sensitive to lighting and severe weather conditions.

Hybrid methods such as WIM, VANETs and also WSNs consolidate multiple approaches for VC. The next section extensively describes the VC methods. Taxonomy of VC along with the information extracted via each method are summarized in Table 1.

III. VEHICLE CLASSIFICATION METHODS

There exist a few surveys about VC systems whilst most surveys focus on the vision-based VC systems ignoring other VC approaches [75], [76], [77], [78], [79], [80]. Others only address particular types of VC systems. For instance, [81] reviewed only road sensors such as inductive loop detectors, piezoelectric, magnetic sensors, and also pneumatic tubes while [82], [83] reviewed unmanned aerial vehicles UAVs. Bouckerche *et al.* [35] presented a survey that just focused on vision-based methods and categorized the vehicle classification based on the vehicle type recognition (VTR), vehicle make recognition (VMR), and also vehicle make and model recognition (VMMR). In their work, they investigated the relevant models, methods and techniques. Most of the papers concentrated on conventional VC methods. However, some papers explored vehicle related methods for VC via exploiting mobile devices like smartphones or GPS receivers in an obscure manner and from confined perspectives. They nearly overlooked the impact of groundbreaking vehicular communications technologies and sensing techniques in their studies. Jain *et al.* [80] mainly reviewed the traditional VC methods in addition to the vision-based ones. They analyzed different techniques for traffic monitoring and examined the drawbacks and security weaknesses of the information. But, they did not address a large spectrum of VC methods including hybrid, remote sensing and also GPS-based methods in their paper. In another research work, Won [21] presented an overview on current VC systems from various aspects excluding notable methods such as LTE transceivers, GPS-based methods and also vehicle-to-everything (V2X) communication. Furthermore, in a recent review article [84], although researchers introduced VANETs capabilities for VC, their research lacked some paramount VC methods encompassing aerial, WSN as well as RF, Wi-Fi and LTE transceivers.

The findings demonstrate that available VC methods cannot offer mobility and physical information of vehicles globally and in a real-time fashion. We definitively believe that vehicular networks are an effective solution to provide the VC globally and in a real-time manner. This paper investigates the traditional, state of the art and also global methods like VANETs that classify the vehicles in a real-time mode. In contrast to the all existing surveys and review papers that are cited in this paper, our review has effectively complemented the weaknesses of the mentioned papers by gathering all the related VC methods ranging from conventional to emerging in the miscellaneous journals. It is worth mentioning that in the presented paper, the length of the description varies significantly from one VC method to another. This is due to the fact that some methods like vision-based are widely favored by scientists while others such as pneumatic tubes, piezoelectric sensors, fiber optic sensors, strain gauge, GPS-based, LiDAR, Wi-Fi/LTE transceivers and infrared/ultrasonic are rarely attractive for VC. Moreover, compared to other surveys and reviews, we have thrived to more deeply study VANETs and propose them as an alternative tool for VC. To this end, we have conducted a comprehensive inspection to find the current state of the art VC articles. We originally began with around 500 publications that consequently resulted in 284 final references for our work.

A. VISION-BASED METHODS

Most researchers have conducted their VC studies based on the vision-based methods, which are applied in the most popular VC systems [73], [74]. This is due to the fact that cameras can properly feature the visual and geometrical characteristics of a vehicle [161]. Image/video detection from a fixed location mostly comprises most of the vision-based VC literature. They are ambient-sensitive and have relatively low maintenance and operational costs. Besides, video/image detection methods possess high capital cost, expensive computational burden and also privacy concerns. In contrast to the in-road-based classification systems, a single camera can cover several lanes. The relative VC process includes images capture, feature extraction, and finally the classification of the vehicle. Data collection use various types of cameras such as aerial images [162], [163], surveillance video systems, closed-circuit television (CCTV) [105], [115], normal cameras [114], [124] or omni-directional cameras [121]. Image processing techniques are the underlying elements of the detection, tracking and classification of the vehicles in these methods.

Sotheany and Nuthong [10] used back propagation neural network (BPNN) and radial basis function neural network (RBFNN) for VC. Mei and Ling [50] investigated robust vision-based VC and tracking using sparse approximation theory. Wang and Cai [144] conducted an extensive review on the vision-based methods. Many researchers like [23], [73], [93], [94], [110], [122], [123], [125], [151], and [152] proposed image segmentation from video footage as one of the most significant techniques of image processing to classify the vehicles. Tripathi *et al.* [4] and Tamam *et al.* [19] employed background subtraction (BGS) as an image segmentation method for VC. Gaussian mixture model (GMM) [164] is recognized as one of the principle segmentation techniques in image processing. As regards to other vision-based VC methods, some papers like [126], [128], [129], [143], [146] focused on shadow removal techniques [165] to improve the image and video quality in image processing. On the other hand, Moutakki *et al.* [127] and Velazquez-Pupo *et al.* [23] used occlusion handling for tracking and classification of the vehicles in an obstructed situation. Image detection encompasses the feature extraction step, in which appropriate features for VC are selected.

Most popular features for VC include speeded-up robust features (SURF) [130], [133], scale invariant feature transform (SIFT) and Texture and shape features [113], [131], [132], VMMR [34], [139], oriented fast and rotated brief (ORB) [136] and pose estimation with convex hull (PE-CH) [138]. Yan *et al.* [27] proposed principle components analysis (PCA) and BPNN for VC. Tripathi *et al.* [4] made use of Blob detection technique as a feature extraction technique for VC. Manzoor and Morgan [33] devised a VMMR-based VC system based on the random forest (RAF) and used SIFT and histogram of oriented gradient (HOG) for image processing. Similarly, Siddiqui *et al.* [156] proposed VMMR-based VC using SVM, SURF features and RAF.

Some literature like [24], [32], [91], [92], [95], [96], [105], [134], [137], [140], [141], [142], [149], [153], [155], and [11] addressed VC via the application of feature extraction techniques. Javadi *et al.* [99] designed a vision-based system that classifies analogous vehicles based on fuzzy c-means clustering (FCM) [166] and using dimensions and speed attributes. Zhao *et al.* [100] emphasized the relevant key parts of the vehicle image to improve the accuracy. Mishra *et al.* [160] used a non-linear kernel classifier, while Theagarajan *et al.* [98] and Kim and Lim [97] benefited from different approaches to address VC using the largest ever image dataset. Liu *et al.* [104] also investigated the issue of imbalanced dataset. Zhang and Pan [157] adopted kernel principal component regression (KPCR) for VC. Liang *et al.* [106] investigated the classification of the

TABLE 2. Summary of literature reviews on vision and sound-based methods.

Literature	Sound	Vision
Piyush et al. [85], Daniel et al. [86]	✓	✓
Kerekes et al. [87], George et al. [65], Borkar et al. [88], Ntalampiras [89], Bischof et al. [90]	✓	✗
Huttunen et al. [91], Dong et al. [92], Mei et al. [50], Bautista et al. [74], Mithun et al. [93], Unzueta et al. [94], Chen et al. [73]	✗	✓
Adu-Gyamfi et al. [95], Karaimer et al. [96], Kim et al. [97], Theagarajan et al. [98], Javadi et al. [99], Zhao et al. [100]	✗	✓
Gupte et al. [39], S. Matos et al. [38], Chang et al. [101], Moussa et al. [102], Hasnat et al. [103], Liu et al. [104]	✗	✓
Chen and Pears et al. [105], Liang et al. [106], Chandran et al. [107], Ahmed et al. [108], Atiq et al. [109], Buch et al. [56]	✗	✓
Abinaya et al. [110], Sotheany et al. [10], Daigavane et al. [111], Abdulrahim et al. [112], Narhe et al. [113], Yousaf et al. [78]	✗	✓
Lee et al. [114], Chen and Ellis et al. [115], Hadi et al. [116], Misman et al. [117], Shukla et al. [118], Mokha et al. [119]	✗	✓
Yan et al. [27], Nam et al. [120], Can et al. [121], Singh et al. [122], Chen and Qin et al. [123], Li and Ikeuchi et al. [124]	✗	✓
Kul et al. [79], Zhang et al. [125], Lim et al. [11], Yu et al. [126], Moutakki et al. [127], Meher et al. [128], Yang et al. [129]	✗	✓
Velazquez-Pupo et al. [23], Meng et al. [3], Prasad et al. [130], Sun and Zhang et al. [131], Wang et al. [132], Shih et al. [133]	✗	✓
Cretu et al. [134], Hsieh et al. [135], Yang et al. [136], Jayadurga et al. [137], Liu and Wang et al. [138], Manzoor et al. [139]	✗	✓
Biglari et al. [32], Ghassemi et al. [34], Ambardekar et al. [140], Liu and Zhang et al. [104], Song et al. [141], Khanaa et al. [142]	✗	✓
Asaidi et al. [143], Siddiqui et al. [24], Yao et al. [5], Yousaf et al. [78], Wang et al. [144], Almehmadi Tarig Saeed et al. [145]	✗	✓
Jehad et al. [146], Hannan et al. [147], Tamam et al. [19], Kafai et al. [148], Muthu Vaanathi et al. [149], Yu et al. [150]	✗	✓
Manzoor et al. [33], Chen and Ruan et al. [151], Zhang and Chen et al. [152], Jo et al. [12], Bai et al. [153], Silva et al. [154]	✗	✓
Hussain et al. [155], Siddiqui et al. [156], Zhang et al. [157], Peng et al. [158], Mussa et al. [159], Mishra et al. [160]	✗	✓

highway vehicles via regression analysis and image warping. Chang *et al.* [101] discussed the matter of vehicle occlusion. Other researchers such as Ahmed *et al.* [108], Moussa [102], and Chandran and Raman [107] concentrated on the vision-based methods. Hsieh *et al.* [135] classified the vehicles based on the color. Peng *et al.* [158] robustly classified vehicles based on PCA. Hannan *et al.* [147] and Yu *et al.* [150] adopted fast neural network (FNN) and deep learning for VC respectively. Nam and Nam [120] proposed creative methods using thermal cameras and visible light images for vehicle detection and classification. Mussa *et al.* [159] outperformed VC by using probabilistic neural network (PNN) to correctly assign the vehicle's classes. Silva *et al.* [154] adopted multiple classifier algorithms to detect and classify motorcyclists. Saeed and Htike [145] benefited from the Viola-Jones method as well as invariant moments features and multi-layer feed forward perception (MLP) artificial neural network as PR techniques in VC. On the other hand, Jo *et al.* [12] used the LeNet model from convolutional neural networks (CNN) along with Haar-like features for image recognition of VC. Hasnat *et al.* [103] combined optical sensors with a camera to classify vehicles with hybrid algorithms like gradient boosting (GB) [167] and CNN. Gupte *et al.* [39], Ha *et al.* [168], and Matos and Souza [38] also deployed vision-based methods where the last two papers considered the edge detection and features for VC.

B. SOUND-BASED METHODS

Acoustic sensors are low cost and simple, but they require complex data extraction mechanism and they are not appropriate for stop-and-go traffic. Ultrasonic sensors are contamination proof, weather-sensitive and relatively less costly than acoustic sensors. Moreover, they can be easily installed. Acoustic sensors capture the audio signals generated by a passing vehicle via microphones. Ambient noise largely impacts the performance of these sensors thereby making the feature extraction a challenging problem. Therefore, either acoustics sensors are generally deployed in group to decrease the negative influence of environmental noise [89] or they are integrated with other type of sensors like cameras to boost the effectivity of those solutions [90].

Borkar and Malik [88] benefited from smart cameras, robotic sensors, smartphones and also drones to evaluate the vehicle density, speed, and classification through practice of acoustic signals. George *et al.* [65] employed acoustic signals while Ntalampiras [89] established an innovative wireless acoustic sensor network (WASN) to overcome the ambient noise problem. The system was composed of several wireless microphones. Bischof *et al.* [90] benefited from an acoustic sensor to better support the operation and activate the autonomous training of the vision-based VC system. Different kinds of algorithms like artificial neural network (ANN), support vector machine (SVM) and k-nearest neighbor (KNN) were used for classification. Piyush *et al.* [85] and Daniel and Mary [86] devised a scheme based on the combination of video and audio methods. In the proposed approach, they used the MLF algorithm, and the vehicle image was extracted from the relevant video frames through BGS once the vehicle was detected by the acoustic signal. Table 2 summarizes literature reviews on vision and sound-based methods.

C. REMOTE SENSING METHODS

The provision of global information by remote sensing methods introduce them as one of the quickest trends for VC. A wide range of methods can be named in this group including infrared sensor, laser scanner, LiDAR, radar, RF, Wi-Fi, and LTE transceivers. Table 3 summarizes the literature reviews on remote sensing methods.

1) INFRARED/ULTRASONIC

Infrared sensors are expensive, sensitive to ambient conditions and advisable for night vision and rainy weather. They have low image quality and are typically used for battlefield VC. Odat *et al.* [2] proposed a collaborative system including ultrasonic and infrared sensors for VC. Otto [6] utilized two mobile infrared sensors and denoised the data mainly using

TABLE 3. Summary of literature reviews on remote sensing methods.

Literature	Infrared/Ultrasonic	Laser scanner	LiDAR	RADAR	RF Transceivers	Wi-Fi-LTE Transceivers
Mei et al. [50], Otto et al. [6], Odat et al. [2]	✓	✗	✗	✗	✗	✗
Xiao et al. [169], Chidlovskii et al. [170], Xiang et al. [171], Sandhawalia et al. [172]	✗	✓	✗	✗	✗	✗
Asborno et al. [173], Lee and Coifman et al. [63], [174]	✗	✗	✓	✗	✗	✗
Bernas et al. [175], Kerekes et al. [87], Sliwa et al. [20], [176], Haferkamp et al. [177]	✗	✗	✗	✗	✓	✗
Hyun et al. [55], Chen and Lin et al. [178], Saville et al. [179], Abdullah et al. [46]	✗	✗	✗	✓	✗	✗
Aziz et al. [180], Lee et al. [181], Urazghildiiev et al. [47], Meng et al. [3], Raja et al. [182]	✗	✗	✗	✓	✗	✗
Sardar et al. [183], Won et al. [68], Won, Sahu, and Park et al. [184]	✗	✗	✗	✗	✗	✓

wavelet for VC. Mei and Ling [50] used infrared sensors for classification and robust tracking of the vehicles.

2) LASER SCANNER

Laser scanner is another technology for VC that is sensitive to weather conditions. Besides, it has more installation expenses than cameras. Sandhawalia *et al.* [172], Chidlovskii *et al.* [170], and Xiang *et al.* [171] performed different VC approaches via laser scanners. Chidlovskii used dynamic time wrapping (DTW) [185] and global alignment kernel (GA) [186] as classifiers. Xiao *et al.* [169] designed a street park monitoring system where vehicles were classified using mobile laser scanners.

3) LIDAR

In LiDAR-based systems, light detection and ranging sensors record the reflections of the laser beams to recognize the shape and size of the passing vehicle for VC. LiDAR has easier usage but worse performance than Radar in snow and rain. Additionally, they are less expensive than Radar in terms of production. LiDAR VC systems have high accuracy in vehicle detection though they mainly suffer from the vehicle occlusion issue. This technology appeared after RADAR in the industry and uses laser light pulses instead of radio waves. Shorter wavelength of LiDAR than RADAR allows the detection of small objects. Besides, every second the LiDAR system receives information from a large number of laser pulses due to its high speed. This implies that data is updated with higher frequency, thereby more accurate information is received by the device. A LiDAR system can create a precise 3D image of a vehicle or other objects by storing each reflection point of a laser beam. Moreover, as one of the applicable features in the automotive industry, the LiDAR receiver is capable of measuring the distance to the detected object where the reflection time and laser speed are used. As a result, autonomous vehicles with onboard LiDAR sensors can scan the environment and avoid collisions.

Researchers in [63] and [174] adopted LiDAR beams for VC while Asborno *et al.* [173] concentrated on the truck body classification by establishing two LiDAR units on the roadside. Extracted features are fed to the several classifiers such as SVM, decision tree (DT), naive bayes (NB) and ANN. Lee and Coifman [63], [174] launched LiDAR systems in which the driver side of a car which is parked on the roadside is equipped with two LiDAR sensors to vertically scan the body of the passing car and extract the required features for a highly precise VC.

4) RADAR

Radar systems use radio waves and perform the classification depending on the reflected radio signals from the body of the vehicles. They are relatively cheap and unlike LiDAR sensors, radar sensors are more resistant to the inclement light and weather conditions. On the downside, they are not generally designed for stop-and-go traffic and represent a less accurate vehicle body than LiDAR. Raja *et al.* [182] exploited the KNN as classifier and analyzed the VC using forward scattering radar (FSR). Hyun and Jin [55] proposed a scheme for classification of mobile humans and moving vehicles based on the Doppler spectrum feature. Urazghildiiev *et al.* [47] proposed a VC solution based on the vehicle physical profiles in terms of height and length using a microwave radar sensor. In a similar approach, Meng *et al.* [3] benefited from the Bayesian network and GMM to classify the vehicles using video and microwave radar sensors for height measurement. Aziz and Thani [180], Lee *et al.* [181], Abdullah *et al.* [46] combined Z-score feature extraction method with NN for VC using forward scattering radar. Chen and Lin *et al.* [178] and Saville *et al.* [179] also employed radar as a commonly used method in VC and traffic monitoring.

5) RF TRANSCEIVERS

When a vehicle crosses the line of sight between an RF receiver and transmitter installed on opposite road sides, the propagation of the RF signals is disturbed leading to attenuation and reflection. As a result, the receiver captures the RF signals that carry distinctive patterns according to the size and shape of the passing vehicle. Consequently,

TABLE 4. Summary of literature reviews on contact-based methods.

Literature	Loop Detectors	Magnetic Field	Seismic-Vibration	Pneumatic tubes	Piezoelectric	Fiber Optic	Strain Gauge
Al-Tarawneh et al. [204]	✗	✗	✗	✗	✗	✓	✓
Yang and Lei et al. [67], Liang et al. [205], Yang et al. [206], Cheung et al. [207],Taghvaeeyan et al. [208]	✗	✓	✗	✗	✗	✗	✗
Kaewkamnerd et al. [209], Haj Mosa et al. [210], Xu et al. [211], Markevicius et al.[212], Wang et al. [66]	✗	✓	✗	✗	✗	✗	✗
Balid et al. [70], Kerekes et al. [87], Dong et al. [213], Lan et al.[214], Sarcevic et al. [215], Bottero et al. [58]	✗	✓	✗	✗	✗	✗	✗
Xu et al. [59], He et al. [216], Li and Dong et al. [217], Li and Dong and Shi et al. [218], Li and Lv et al. [219]	✗	✓	✗	✗	✗	✗	✗
Gajda et al. [44], Lao at al. [200], Cheevarunothai et al. [201], Jeng and Chu et al. [193], Meta et al. [42]	✓	✗	✗	✗	✗	✗	✗
Coifman et al. [196], Lamas-Seco et al. [29], [192], Mocholí-Salcedo et al. [41], Jeng and Chu et al. [199]	✓	✗	✗	✗	✗	✗	✗
Liu and Sun et al. [195], Sun et al. [7], [8], Tok et al. [197], Li et al. [203], Wei et al. [202], Wu et al. [53], [43]	✓	✗	✗	✗	✗	✗	✗
Rajab and Mayeli et al. [60], Santoso et al. [220], Rajab and Al-Kalaa et al. [28]	✗	✗	✗	✗	✓	✗	✗
Ma et al. [64], Bajwa et al. [221]	✗	✓	✓	✗	✗	✗	✗
Ye et al. [222], Stocker et al. [61], Jin et al. [223] Zhou et al. [224], Du et al. [225], Zhao and Wu et al. [226]	✗	✗	✓	✗	✗	✗	✗
Nordback et al. [227]	✗	✗	✗	✓	✗	✗	✗
Peters et al. [228]	✗	✗	✗	✗	✗	✗	✓

the vehicle classification is performed based on these patterns. Haferkamp *et al.* [177] utilized the received signal strength indicator (RSSI) of the attenuated signal as the key input for the classifier algorithms like SVM and KNN for a very accurate VC. Silwa *et al.* [176] used the low-rate wireless personal area networks (LR-WPANs) with the Institute of Electrical and Electronics Engineers (IEEE) 802.15.4 standard to classify the passing vehicles in response to their particular radio fingerprints. It is comparable to the previous work in terms of RSSI application, but more accurate in a sense that it adopts three transceivers on the roadsides. CNN [187], RAF [188] and SVM [189] were the applied classifiers. In their following research [20], they exploited a novel approach where signal attenuation patterns were considered as radio fingerprints for VC. They applied four machine learning algorithms such as RAF, proximity forest (PF), SVM and deep Boltzmann tree (DBT) in their work. Bernas *et al.* [175] developed a roadside-based system, in which RSSI analysis from Bluetooth Low Energy (BLE) beacons was performed using ML algorithms to detect and determine the vehicles classes.

6) WI-FI-LTE TRANSCEIVERS

Traffic monitoring systems recently aim to utilize Wi-Fi transceivers to cover a large area as they are scalable and low cost. VC is performed by using unique patterns of channel state information (CSI) including spatio-temporal correlations of amplitude and phase induced by the target vehicle [190]. In a similar work, Sardar *et al.* [183] availed of PCA and NB algorithms to classify the vehicles using LTE and CSI analysis. Won *et al.* developed a Wi-Fi-based system [68] and an advanced version of it [184] with sound classification accuracy.

D. CONTACT-BASED METHODS

Contact-based methods span a wide spectrum of sensors including loop detectors, magnetic, seismic and vibration, pneumatic tube, piezoelectric, fiber optic and strain gauge. Table 4 summarizes the literature reviews on contact-based VC methods.

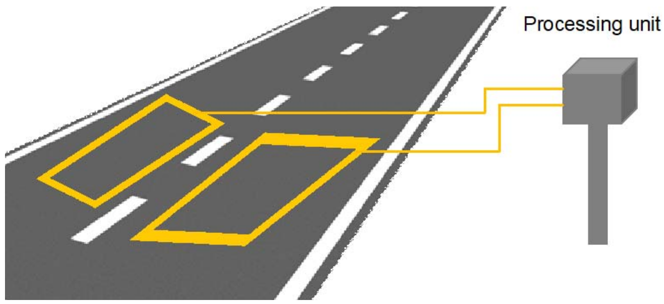

FIGURE 1. Inductive loops.

1) MAGNETIC FIELD: LOOP DETECTORS

Inductive magnetic loop detectors as shown in Fig. 1 are considered as one of the most prevalent and popular traffic monitoring systems for VC [191], [192]. They have a long installation process. Researchers have conducted numerous works that discuss about the loop detectors for VC which is a wire coil under the road pavement. When a vehicle passes over it, a peculiar signal called magnetic profile [193] is produced depending on the type of the vehicle to perform classification. Inductive loops make use of a magnetic signature as a feature to detect and classify the vehicles [41], [192], [194]. Mocholí-Salcedo *et al.* [41] studied the inductive loops in the form of asymmetrically shaped, e.g., rectangular loops for the VC. Loop detectors are divided into single and dual loop detectors. Sun *et al.* [7], [8] also took advantage of inductive loop detectors and heuristic algorithms in his study on VC.

1) *Single loop detectors:* Single loop detectors are low-cost. Liu and Sun [195], Lamas-Seco *et al.* [29], [192], Coifman and Kim [196], Gajda *et al.* [44], and Meta *et al.* [42] researched the use of single loop detectors as the VC method.

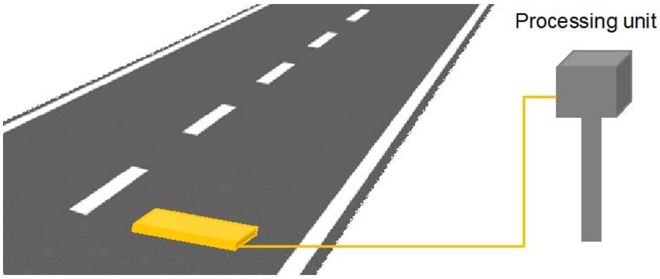

FIGURE 2. Magnetic sensor.

Tok and Ritchie [197] combined the passing vehicle's magnetic signature with the axle configuration method to classify vehicles with the similar axle structure using multi-layer feed forward (MLF) artificial neural network [198]. Jeng *et al.* [199] availed of akin VC system based on the evaluation of vehicle's body signature. Lao *et al.* [200] developed an approach to classify vehicles using GMM.

2) *Dual loop detectors:* Dual loop detectors as opposed to the single loop detectors have higher cost. Additionally, they can measure information like length, average speed, flow and occupancy yielding to better classification. Cheevarunothai *et al.* [201] adopted the vehicle length for the VC which is known as the main feature for VC. Wu and Coifman [43], [53], Wei *et al.* [202], and Li [203] employed dual loop detectors for the VC.

2) MAGNETIC FIELD: MAGNETIC SENSORS

Magnetic sensors as shown in Fig. 2 are less sensitive to noise, Doppler effects and weather conditions, but they require calibration.

1) *In-road magnetic sensors:* A vehicle that passes the magnetic sensors induces distortion to the Earth's magnetic field [207], [212]. Different vehicles cause distinctive alteration in the magnetic field that are captured by magnetic sensors. Contrary to the loop detectors, energy efficiency, cost, size and weight are some of the strengths of the magnetic sensors.

Balid *et al.* [70] used the vehicle length metric for VC. Bottero *et al.* [58] and Li and Lv [219] devised a WSN of two magnetic sensors and then performed the VC-based on the vehicle length and additionally magnetic waveform respectively [58]. Li *et al.* [217] used a single magnetic sensor and applied a minimum number of split-sample (MNS) and classification and regression tree (CART) models [229] for VC. Ma *et al.* [64] proposed a hybrid system consisting of accelerometers and a wireless magnetic sensor network to enhance the VC functionality. Xu *et al.* [59] addressed the imbalanced data-sets effect of the magnetic sensors for VC. They used various machine learning (ML) algorithms such as KNN [230], SVM [231], CNN [232], and BPNN [233] to classify vehicles. Dong *et al.* [213] demonstrated that only one magnetic sensor is capable of a robust VC. Their work was based on XGBoost classifier [234]. Yang and Nin [206] and Xu *et al.* [211] proposed a vehicle classification and detection based on magnetoresistive sensors using the BPNN algorithm. Tong and Li [205] studied the use of micro ferromagnetic induction coil sensor via RBFNN. Kerekes *et al.* [87] evaluated a VC using an ensemble of methods including magnetic, acoustic, and RF sensors. They made use of KPCR and radio fingerprints for a better classification.

2) Roadside magnetic sensors: Magnetic sensors are frequently used in VC systems in the road or on the roadside. Both solutions share the same mechanism based on the vehicle's magnetic profile. However, the latter classification system is designed to mitigate the high installation and maintenance cost of the in-road-based systems.

Lan *et al.* [214] used roadside magnetic sensors for VC. Taghvaeeyan and Rajamani [208] focused on a challenging theme and developed a magnetic-sensor-based system to classify vehicles with identical body sizes. Another challenging issue in VC based on this method arouses especially when traffic is congested and vehicles are driving slowly and closely to each other. The vehicle proximity distorts the magnetic signals enormously. Yang and Lei [67] and Kaewkamnerd *et al.* [209] investigated this problem from different aspects. Magnetic sensors can also be combined with other VC methods. Reference [66] proposed a heterogeneous energy efficient system in which a camera is turned on in case of a vehicle detection by a magnetic sensor. Several researchers like Mosa *et al.* [210], He *et al.* [216], Sarcevic [215], Li *et al.* [218], Yang and Lei [67], and Taghvaeeyan and Rajamani [208] have conducted their research on magnetic sensors instead of magnetic loops because they are cheaper and less complex.

3) FIBER OPTIC SENSORS

Many traffic applications recently tend to use fiber optic sensors since they are light, small and fairly immune to electromagnetic interference [235]. Furthermore, they have a large bandwidth. The weakness is the limited angles range that Fiber Optic system can sense. Al-Tarawneh *et al.* [204] employed fiber bragg grating (FBG) sensors for VC. These sensors capture the strain signals induced by a passing vehicle from the road surface.

4) PIEZOELECTRIC SENSORS

Piezoelectric sensors are embedded under the road surface across the lanes and are capable of collecting information regarding traffic counting, speed and axle of the vehicles. Following the mechanical impacts or vibrations, piezoelectric sensors convert pressure to the electrical charges. They can also operate inside a WIM system. Moreover, they are sensitive to temperature variations and also to surface conditions due to voltage changes. Piezoelectric sensors are speed and time independent. Furthermore, they are sensitive to temperature drifts. Rajab *et al.* [28], Rajab *et al.* [60], and Santoso and Nurriyah [220] used piezoelectric sensors to classify vehicles.

TABLE 5. Summary of literature reviews on off-road-based methods.

Literature	Aerial Platforms	GPS-based
Liu and Mattyus et al. [237], Audebert et al. [162] Li et al. [163], Kanistras et al. [83], Puri et al. [82]	✓	✗
Cao et al. [72], Tan et al. [238], Tang and Zhou et al. [71]	✓	✗
Basyoni et al. [239], Simoncini et al. [26], Sun and Ban et al. [30]	✗	✓

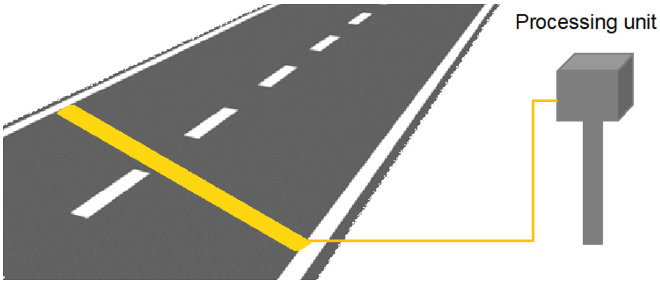

FIGURE 3. Pneumatic tube.

5) PNEUMATIC TUBES

Pneumatic tubes are portable and installed on the road surface across the lanes as shown in Fig. 3. They are primarily used for temporary traffic counting and can be extended to collect data concerning speed and axle of the vehicle. Pneumatic tubes suffer from low profile and easy deformation. Moreover, they are moderately suited for VC. Currently, bike classification and counting avail these tubes in the market. Nordback *et al.* [227] worked on pneumatic tubes to categorize vehicles.

6) STRAIN GAUGE

Strain gauge sensors measure the various strain response of the pavement for the vehicles via PR for VC. They face challenges concerning sensors adhesion and also compensation for temperature variations. Al-Tarawneh *et al.* [204] explored these sensors as the VC method.

7) SEISMIC AND VIBRATION

Vibration sensors catch the unique seismic wave-forms caused by a passing vehicle. Vibration-based sensor systems perform VC using two underlying features; axle count and spacing characteristics [221] and seismic signals induced by a passing vehicle that includes unique characteristics [61], [223]. These sensors have good detection range but they require careful calibration.

Bajwa *et al.* [221] utilized magnetic sensors for vehicle detection purpose incorporated with vibration sensors used for axle count and spacing as the key feature for VC method. Zhao *et al.* [226] proposed the same technique for VC as [221], but with further properties to achieve more efficient classification. Stocker *et al.* [61] using MLP [236] and Jin *et al.* [223] analyzed the specific seismic wave forms of the passing vehicles for VC. Du *et al.* [225] and Zhou *et al.* [224] applied seismic sensors for the localization and identification of the vehicle classes. Ye *et al.* [222] deployed vibration sensors in the pavement and classified the vehicles using ANN and K-means clustering (KMC).

E. OFF-ROAD-BASED METHODS

Off-road methods cope with the classification techniques that occur off the roads such as using different aerial platforms or via GPS receivers. Literature discussing off-road-based methods are cited in Table 5.

1) AERIAL PLATFORMS

Although aerial images from UAVs and satellites cover large road segments and have simpler data acquisition, they can hardly detect a vehicle due to a wide range of objects. Furthermore, they can not provide high resolution images for VC. Cao *et al.* [72] worked on vehicle detection and classification of low altitude airborne videos. Audebert *et al.* [162] employed aerial images for VC using different CNN models such as LeNet [240], AlexNet [232] and VGG-16 [241] and image segmentation techniques. Li *et al.* [163] also investigated the application of aerial images for VC. Liu and Mattyus [237] employed HOG features [242] and investigated an aerial platform to classify a few types of the vehicles that are simply distinguishable. In addition, Tan *et al.* [238] exploited an aircraft to collect images for VC using the inception model [243]. Kanistras *et al.* [83], Puri [82] and Tang *et al.* [71] used airborne imagery for classification. Moreover, Ma *et al.* [244] introduced a vehicle detection mechanism for aerial images based on rotation-invariant descriptors and cascade forest. They could reach accurate, robust results for VC. Aerial images are prevalent information source due to their extensive coverage. Vision-based methods are the dominant technology for aerial platforms.

2) GPS-BASED METHODS

GPS on board of the vehicle has challenging technical, privacy, security and institutional issues while Smartphones equipped with different sensors are not reliable sources as the provided direction in relation to the vehicle's direction is variable all the time. Basyoni and Talaat [239] focused on VC based on data from cellular phones using genetic fuzzy (GF) algorithms. Simoncini *et al.* [26] adopted GPS to recognize and categorize vehicles on the road by applying a recurrent neural network (RNN). Sun and Ban [30] proposed a low cost procedure to extract GPS data from mobile sensors in an urban traffic for the VC.

F. HYBRID METHODS

Hybrid methods include WIM, WSN and VANETs that benefit from various technologies for VC. Table 6 summarizes the literature addressed hybrid VC Methods.

TABLE 6. Summary of literature reviews on hybrid methods.

Literature	VANETs	WIM	WSN
Sengkey et al. [251], [252], Mitra and Mondal et al. [253], Alhammad et al. [254], Jalooli et al. [255]	✓	✗	✗
Peters et al. [228], Roh et al. [245], Romanoschi et al. [246], Hernandez et al. [247]	✗	✓	✗
Bottero et al. [58], Ma et al. [64], Li and Lv et al. [219]	✗	✗	✓
Bajwa et al. [221], Kaewkamnerd et al. [209], Ntalampiras et al. [89]	✗	✗	✓

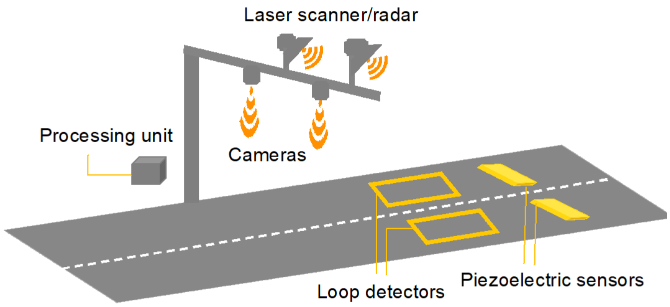

FIGURE 4. Weight-in-Motion (WIM) system.

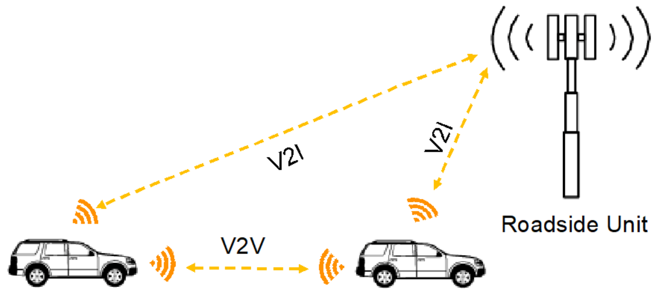

FIGURE 5. Communication in VANETs.

1) WIM

Weight-In-Motion (WIM) systems play an important role in traffic engineering in terms of data aggregation and VC. Modeling and estimation are the components of the WIM architecture. A WIM system consists of multiple sensors, computers and digital cameras that are planted on a bridge structure and measures the dynamic axle load of the vehicle to compute its weight data [228] as shown in Fig. 4. WIM employs several techniques to classify vehicles accurately [245], [246]. They are safe and efficiently collect data. WIM limitation is that the measurement is based on the fixed location sensors. Besides, it has low weight accuracy estimation and also it is expensive which is not suitable for local roads. Hernandez *et al.* [247] consolidated loop detectors with weight-in-motion sensors using various neural network (NN) algorithms such as NB, SVM, DT, MLF [248], and also PNN [249] and multiple classifier systems (MCS) [250] for VC. Won [21] and Shokravi *et al.* [84] included WIM in their survey. Peters [228], Roh *et al.* [245] and Romanoschi *et al.* [246] also developed their systems based on this method.

2) WSN

VC methods based on wireless sensor networks (WSN) are basically integrated with other methods and to a great extent with magnetic and vibration sensors like magnetometer and accelerometer as cited in [58], [64], [89], [209], [219], [221]. Sometimes, they are incorporated with sound sensors as referred in [89]. Won *et al.* [21] implicitly addressed WSN in their review for VC.

3) VANETS-BASED METHODS

Vehicular ad-hoc networks (VANETs) promise to be one the most revolutionary technologies in the last decade, so that a large number of use cases in transportation and traffic domain can profit from them [256]. A VANET-based system consists of roadside units (RSUs) and vehicles with mounted onboard units (OBUs), antennas, GPS and other sensors [257]. An OBU is a telematics computing device installed in a vehicle and it is a combination of various communication interface modules [258]. Vehicular connectivity is provided by the infrastructure along the roads called RSUs [259]. Vehicles can use dedicated short-range communication (DSRC) to periodically exchange traffic information [260]. VANETs have two variants as depicted in Fig. 5: vehicle-to-vehicle (V2V) that concerns communication between vehicles, and vehicle-to-infrastructure (V2I) that deals with communication between the vehicles and an RSU.

In the recent years, VANETs have drawn intensive attention. They can collect a wide range of information in terms of mobility and physical features such as speed, traveling lane, acceleration, deceleration, position, direction as well as height, type, length, and width respectively. Within the scope of VANETs, most of the papers concern using mobility and physical information of the vehicles for a particular application. Among them, few papers have focused on VC area. For example, Shokravi *et al.* [84] included VANETs in their survey as an emerging VC method. Researchers have addressed VANET-based VC methods from the kinematic and physical information perspective as follows.

1) *Mobility parameters of vehicles–general use cases:* VANETs benefit from the GPS receivers to localize and gain mobility parameters of vehicles containing traveling lane and position [261] as well as deceleration, acceleration and speed [30], [262], [263]. Shao *et al.* [264] exploited a cooperative vehicular system in highway scenarios, in which various mobility information such as acceleration, deceleration in addition to other parameters were used in order to achieve an accurate localization in a cluster. Padron *et al.* [265] deployed a cooperative system based on VANETs to broadcast the mobility information including direction, position and speed.

It integrated a wireless communication interface, GPS receiver and a real time clock. Nayak *et al.* [266] introduced a VANET algorithm that observed vehicle lane changes using directional indicators plus speed limit in each traveling lane so that speed violations were detected rapidly. In this position-based system, vehicular communication was performed in a secure manner. Kerekes *et al.* [87] and Siddiqui *et al.* [156] employed mobility information like speed, direction and position for density estimation through beacon broadcasting.

2) *Physical parameters of vehicles–VC use cases:* In the literature, many VC methods based on diverse kinds of sensors deal with the detection of the physical parameters of the vehicles. However, these sensors encounter some constraints including short coverage area with limited information accuracy or devoted for proprietary routes [253]. Vision-based VC methods are also prone to occlusions caused by trees, vehicles, inclement weather conditions like precipitation, snow or light changes. Therefore, the VC might be not so reliable due to the poor image quality [120].

A vehicle identification number (VIN) is a particular identifier that determines some vehicle's features such as the type, brand and model [267]. It serves as the vehicle's fingerprint and comprises 17 characters distributed in three sections namely vehicle identifier section (VIS), vehicle descriptor section (VDS), and world manufacturer identifier (WMI). Based on this method, in [253], Mitra and Mondal used VANETs to track, identify and classify vehicles via vehicle identification number. Alhammad *et al.* [254] proposed an intelligent street parking lot system where drivers sent their reservation requests comprising various vehicle's physical data such as type, size, registration number as well as drivers information using VANETs. On the other hand, Jalooli *et al.* [255] benefited from VANETs to devise a highway speed limit advisory system based on some road safety measures such as weather and traffic conditions as well as vehicle's size and type. Finally, Sengkey *et al.* [251], Sengkey [252] utilized VANETs-based vehicle classification to assess traffic density. In their proposed model, packets disseminated vehicle types and ids to the neighboring vehicles. Therefore, each vehicle received packets from different classes of vehicles in the vicinity and could estimate the density on the road. Besides, they could figure out the traffic congestion based on the density and also the road capacity threshold.

3) *Advantages:* VC using VANETs has some fascinating advantages over existing methods as mentioned below.

Firstly, as discussed before, VANETs can provide all the real-time and global kinematic and physical vehicular information in a dependable way. Secondly, VANETs can take advantage of heterogeneous classes of vehicles incurring an added value and better classification in contrast to most of the traditional VC methods that adopt only a limited number of vehicle classes. Furthermore, the classification in VANETs is performed without the need for generic time and resource demanding soft computing techniques including ML, NN or other available features and models. Every vehicle broadcasts its mobility and physical information (especially its vehicle class) to the surrounding vehicles and infrastructure for further processing. This ability results in a very accurate VC through VANETs with less computational overhead compared to the conventional methods that suffer from different range of classification errors. Classification of vehicles via VANETs bears also other benefits. For example, some authors have proposed to use VC so that it can serve other purposes. For instance, they can calculate vehicular density based on different classes of vehicles which is very useful for traffic management. In addition, vehicles on the road have distinctive behaviors such as speed, braking distance, stopping distance, etc. which needs to be taken into account when identifying a hazardous situation. Hence, a sustainable VC with respect to the different vehicles characteristics is very beneficial for traffic safety. Last but not least, as opposed to the traditional methods, VC is more resilient to some negative influences like vehicle occlusion, obstacles, weather conditions, and the number of lanes that can significantly impact the VC accuracy.

4) *Challenges:* Recently, the emerging V2X technology appears to be able to easily classify vehicles by sending traffic information including the vehicle's class via broadcast safety messages to the classification system. This dramatically increases the classification accuracy. However, to reach a concrete result, we confront some issues as mentioned below.

GPS receivers of vehicles in a VANET do not perform well for the localization purpose due to their limited accuracy which is around 20 to 30 meters and also low functionality in high speed and urban areas with congestion and no direct links to satellites. For the sake of a more accurate localization, there is the demand to couple other techniques like image/video localization [268], dead reckoning [269], [270] and cellular localization [271], [272] with GPS information. Data fusion methods can help merge all these information [273], [274], [275], [276]. Wisitpongphan *et al.* [277] proposed an algorithm to improve the precision of the vehicle's localization in a VANET, while Boeira *et al.* [278] used 5G technology for positioning of the nodes. Time synchronization among all V2X nodes is also required for safety for the road users [222]. Basically, this is carried out by GPS receivers. Nonetheless, other alternatives should undertake this responsibility in case of unavailable or poor GPS signal [222].

Reliable data transmission requires a reliable communication protocol. Communication efficiency is another challenge which is greatly affected by high speed and congestion. High speed can lead to fast obsolescence of the position information while traffic congestion results in a broadcast storm [279] and in losing seamless connectivity. In broadcast storms, a redundant number of broadcast beacons causes collisions in the data link layer. The broadcast storm problem in VANETs was analyzed by Wisitpongphan *et al.* [277]

considering packet loss and delay. He suggested a mechanism to achieve a trade-off between delay and packet loss. Alwan *et al.* [280] evaluated the beaconing frequency variation based on real-time vehicles positioning and proposed a scheme to increase the performance of the position-based routing in VANETs. In addition, authors in [281] evaluated the communication performance of cooperative awareness messages (CAM) standardized by European telecommunication standard institute (ETSI) using traffic jams and platooning mobility scenarios. The results showed a decline in CAM functionality that required to be improved. In a similar approach, in [282] researchers examined the ETSI CAM at curvy roads and realized that dissemination performance decreased. Other challenges are range adaption and interference, that must be taken into consideration.

Both communication between vehicles and infrastructure (V2I) and directly between vehicles (V2V) have pitfalls and advantages. In the centralized approach, a road side unit (RSU) is the single point of failure that can jeopardize the reliability. Moreover, it is less scalable than the distributed approach [222]. On the other hand, the deployment of RSUs can centralize the information for the classification system, reduce excessive computation overhead, and guarantee seamless connectivity even in non-line-of-sight (NLOS) situations. Furthermore, although V2V communication incurs trivial cost, V2I communication requires maintenance and installation cost for deploying RSUs. The integration of vehicle to infrastructure (V2I) and vehicle to vehicle (V2V) communications bear some exceptional advantages as follows: [283]

- Sound information dissemination and fast packet delivery for VANETs using powerful antennas,
- Plausible deployment cost,
- Short and long range communications coverage,
- Topology partitioning prevention due to high mobility,
- Resolving broadcast storms problems in dense areas [284].

Furthermore, it provides interoperability with heterogeneous solutions like Wi-Fi, cellular networks, WiMAX, and visible light communication (VLC). The notion of ubiquitous approaches have some strengths such as reducing packet loss due to line of sight (LOS) and broadcast storms and also provision of reliability, higher data rate and illumination.

IV. SOFT COMPUTING TECHNIQUES

Soft computing plays a significant role in VC. Wide range of algorithms in terms of ML and NN contribute to VC systems. Besides, VC benefits from numerous features, models and other classifiers that significantly increase the classification accuracy. We have classified all the software-based VC techniques in a systematic way in three tables based on NN, ML and other solutions. Each technique serves various purposes based on the application area for VC. They comprise classification, training, segmentation, image/PR and feature extraction. Furthermore, corresponding literature using these soft computing methods have been distributed in the tables accordingly. Bayesian networks (BNs) [3], [148], [150], [203] as a widespread method for the data fusion are used when multiple sensors are involved for the detection and classification of the vehicles. The three tables list the most frequently used soft computing techniques in VC.

In addition to the typical and also aforementioned NN algorithms, VC take advantage of many other NN-based classifiers, such as random neural networks (RANN), soft radial basis cellular neural network (SRBCNN), deep convolutional neural network (DCNN), and deep neural network (DNN). Table 7 shows the divers range of NN techniques used in VC along with the related literature and application areas. The application areas of NN techniques are divided into two groups namely *Feature Extraction* and *Classification, PR and Training*. Totally, 16 types of NN algorithms were used for VC such that only three of them dealt with feature extraction application. In total, 47 publications employed different NN algorithms to classify vehicles such that 17 publications availed feature extraction. The table shows that CNN was the leader of NN algorithm from the usage perspective in VC systems. 15 articles utilized CNN for feature extraction. Moreover, the sum of MLP, MLF and ANN algorithms proved to become the second most popular NN algorithms by 9 related publications for classification, PR or training. Additionally, 7 papers exploited BPNN for the same application areas as the three mentioned techniques.

Features, models and other methods including bag-of-visual words (BOVWs), discrete Fourier transform (DFT), recursive segmentation and convex hull (RSCH), etc. also hugely contribute to VC. Table 8 demonstrates the literature that used various types of features, models and other techniques in VC in different application domains. The results describe that segmentation, image/PR, feature extraction and classification contributed to the application types of VC. 61 articles were mentioned in this category that benefited from 33 distinctive features, models and other methods. Among 23 publications that addressed segmentation as their VC application, GMM and PCA methods each with 5 and BGS with 4 publications were the most interesting techniques. With respect to the segmentation part, 10 types of features and models were involved. With regard to image and PR, the HOG model with 5 and VMMR with 3 out of 14 publications showed to be more prevalent for this sort of VC application. Besides, 9 kinds of features and models were discussed in this application area. In terms of feature extraction application, 12 types of models and features participated in this section. SIFT was the most commonly used feature extraction method holding 5 out of 22 corresponding publications. Further, SURF with 3 related articles possessed the second favorite soft computing technique. Lastly, classification had the smallest share of the applications by only two articles that worked on two different features/models.

Akin to ML algorithms, specifically, apart from prevalent ML algorithms, VC benefits from many other ML-based classifiers such as histogram intersection-based kernel

TABLE 7. Neural network algorithms for vehicle classification.

Literature	NN Algorithms	Application
[59], [206], [42], [137], [211], [27], [10]	BPNN	Classification, PR, Training
[26]	RNN	Classification, PR, Training
[210]	SRBCNN	Classification, PR, Training
[155]	RANN	Classification, PR, Training
[147]	FNN	Classification, PR, Training
[154], [205], [10]	RBFNN	Classification, PR, Training
[154], [145], [197], [247], [61], [222], [85], [86], [65]	MLP, MLF, ANN	Classification, PR, Training
[159], [247]	PNN	Classification, PR, Training
[162], [238]	AlexNet	Classification, PR, Training
[162], [12]	LeNet	Classification, PR, Training
[162]	VGG-16	Classification, PR, Training
[59], [150], [223], [95], [92], [68], [97], [104], [101], [103], [100], [162], [238], [12], [5]	CNN	Feature Extraction
[95]	DCNN	Feature Extraction
[91]	DNN	Feature Extraction

TABLE 8. Features, models and other methods for vehicle classification.

Literature	Features, models and other methods	Application
[247]	MCS	Classification
[106]	Regression Model	Classification
[151], [73], [152], [105], [200]	GMM	Segmentation
[151]	Sparse Coding	Segmentation
[4], [19], [85], [86]	BGS	Segmentation
[150], [148]	BN	Segmentation
[42], [158], [182], [27], [183]	PCA	Segmentation
[42], [192]	DFT	Segmentation
[73]	Shadow Removal	Segmentation
[106]	Image Warping	Segmentation
[101], [138]	RSCH, PE-CH	Segmentation
[238]	Inception	Image and PR
[99]	FCM	Image and PR
[237], [72], [96], [83], [33]	HOG	Image and PR
[145]	Viola-Jones	Image and PR
[145]	Invariant moments	Image and PR
[12]	Haar-like	Image and PR
[34], [35], [139]	VMMR	Image and PR
[35]	VTR and VMR	Image and PR
[96], [93]	Shape-based	Feature Extraction
[125], [83]	Gabor Filter	Feature Extraction
[153]	Part-based	Feature Extraction
[124], [93]	Spatio-Temporal	Feature Extraction
[155]	BOVWs	Feature Extraction
[152], [132], [131], [113], [33]	SIFT	Feature Extraction
[133], [130], [156]	SURF	Feature Extraction
[239]	GF	Feature Extraction
[4]	Blob Detection	Feature Extraction
[46]	Z-Score	Feature Extraction
[38], [168]	Edge Detection	Feature Extraction
[136]	ORB	Feature Extraction

(HIBK) or genetic algorithm-extreme learning machine (GA-ELM). Table 9 lists the literature that availed ML techniques for VC in different application fields. Comparably, this division with 70 papers held the highest number of papers in soft computing techniques. Additionally, 17 different ML algorithms were introduced here. ML application domains were congruent with NN ones. The table shows that nearly all the ML algorithms targeted classification, PR or training applications by 58 articles where algorithms for feature extraction formed a smaller part of the literature with presenting two types of algorithms that were discussed in 12 papers. In addition, it indicates that the majority of researchers, 27 papers were inclined to use SVM for VC while KNN with 11 publication appeared to be the second most favorite ML algorithm. VC took advantage of SVM for classification, PR or training whereas KNN was applied to feature extraction.

Overall, it is concluded that researchers tend to prefer ML algorithms over other techniques. SVM for classification, PR and training followed by CNN and KNN for feature extraction were recognized to be the most used techniques in the investigated literature.

V. DISCUSSION

VC has been improved significantly in the recent years in terms of accuracy and cost due to advancements in sensing, soft computing techniques and various types of communication technologies. However, some issues are still open for

TABLE 9. Machine learning algorithms for vehicle classification.

Literature	ML Algorithm	Application
[51]	GA-ELM	Feature Extraction
[154], [179], [149], [199], [59], [93], [96], [182], [177], [65], [83]	KNN	Feature Extraction
[247], [70], [173], [135]	DT	Classification, PR, Training
[59], [83], [70], [73], [96], [176], [177], [247], [90], [173], [125], [120], [105], [95], [24], [218], [134], [214], [151], [153], [123], [127], [32], [20], [156], [72], [154]	SVM	Classification, PR, Training
[154], [247], [70], [2], [173], [183]	NB	Classification, PR, Training
[217]	CART	Classification, PR, Training
[217]	MNS	Classification, PR, Training
[213]	XGBoost	Classification, PR, Training
[154], [176], [33], [20], [156]	RAF	Classification, PR, Training
[170]	DTW	Classification, PR, Training
[124], [5], [170]	GA	Classification, PR, Training
[103], [94], [96]	GB	Classification, PR, Training
[160]	HIBK	Classification, PR, Training
[20]	PF	Classification, PR, Training
[20]	DBT	Classification, PR, Training
[222]	KMC	Classification, PR, Training
[157], [87]	KPCR	Classification, PR, Training

discussion and more research that we aim to address in this section.

Firstly, in order to evaluate the performance of VC systems in a fair and more effective manner, it is imperative to have a common, universal and standard data set containing the certain vehicle types. As a result, this enables the transport sector, users or developers to opt for the most suitable VC system. Nowadays, VC systems are benefiting from distinct vehicle types that makes it extremely difficult to have an unbiased comparison between them. besides, it has been investigated that the more vehicle types there are, the lower VC accuracy is derived.

Performance metrics is another significant challenge that VC systems need to comply to. The majority of VC systems concentrate only on the evaluation of accuracy and overlook other important metrics including resistance to inclement weather conditions, overlapping vehicular positions, noise vulnerability, installation or maintenance costs, and operational sustainability. For instance, many intrusive VC systems provide high accuracy since they are in contact with the vehicles though they are so expensive with respect to installation as well as maintenance. Likewise, vision-based systems undergo privacy concerns despite having high classification precision.

Additionally, to analyze the performance and compare VC systems rightfully, it is required to take into consideration the empirical conditions as a significant factor in VC. Weather conditions, lane numbers or obstacles are some examples of the environmental issues that can affect the classification results. Weather conditions highly influence specific sensors such as Wi-Fi, LiDAR, camera, RF. Moreover, infrared sensors and acoustic sensors are affected by the number of lanes causing overlapping vehicles and environmental noise respectively. Therefore, there is a necessity to develop a global standard for the experimental setup in order to address such a problem.

A large number of VC systems rely on ML methods. A tremendous amount of information is required to be gathered for training and building an efficient classification model which results in high accuracy VC. Besides, this is a very time-consuming process which demands huge efforts to achieve reliable data. In the future, it is suggested to develop self-learning VC systems so that classification models can be trained and enhanced automatically and constantly.

Vehicle occlusion is known to be one of the serious challenges for VC specifically for non-intrusive roadside sensors such as LiDAR, Wi-Fi, magnetic sensors, Radar, and RF by causing disruption in their operation and incurring inaccuracies in classifying the overlapping vehicles. A feasible solution is to employ non-intrusive sensors which are located above the road leading to a more effective VC system. Sensors like LiDAR can be installed in various heights above each lane of the road to resolve the interruptions due to the occlusion dilemma.

It is proved that we can obtain a high accuracy in classification. But gaining the perfect VC with 100 percent accuracy is yet a challenge to the researchers particularly when we are dealing with numerous types of vehicles. One of the underlying reasons for such a failure is that most of the approaches depend on a specific kind of sensor for VC. On the other hand, there exist scant multi-methodical methods that exploit hybrid and collaborative solutions with even various deployment strategies to consolidate the strength of various kinds of sensors, rectify their drawbacks and increase the VC accuracy. The combination of heterogeneous roadside and in-road sensors, WIM, VANETs and WSN lie in this category. For example, for the sake of energy efficiency, a surveillance camera can be activated once the vehicle is detected by a low-energy sensor. Similarly, a camera can start monitoring when the light is adequate while infrared sensors can function at night. Hence, integration of different VC systems seems to be very useful for an optimal classification.

The emergence of VANETs has revolutionized VC systems. In the near future, all road users including vehicles will be equipped with this technology enabling them to forward the vehicle class data using vehicular communication to the VC system. This property makes agencies to

TABLE 10. Vehicle classification technology roadmap.

Technology	Maturity	Deployed Since
Magnetic Sensor	Commercialized	1830s
UAV	Commercialized	1840s
Seismic and Vibration Sensors	Commercialized	1850s
Infrared / RF Transceiver / Pneumatic Tube	Commercialized	1920s
Ultrasonic / Inductive Loop / Radar / Strain Gauge	Commercialized	1930s
Video-Images	Commercialized	1940s
Piezoelectric Sensor / Satellite / WIM	Commercialized	1950s
WSN	Under Development	1950s
Laser Scanner / LiDAR / Fiber Optic Sensor	Commercialized	1960s
GPS Sensor	Commercialized	1970s
Wi-Fi Transceiver	Commercialized	1980s
VANET / LTE Transceiver	Under Development	2000s

perform VC easier with higher accuracy. More importantly, users can utilize VANETs-based VC as they are capable of providing all physical and mobility information of the vehicles globally and in a real-time manner as opposed to other VC methods. Our current literature review depicts that more efforts are desired to leverage the application of VANETs in the market. VANETs can produce near 100 percent VC accuracy compared to the traditional methods. Nonetheless, as previously mentioned, an important challenge is to guarantee solid communication between vehicles and also with the infrastructure so that messages can be transmitted in a secure and dependable way. Other factors that matter for seamless connectivity are interference decline, range adaptation, and usage of heterogeneous technologies like cellular, Wi-Fi, etc.

Our review covers a broad range of mature technologies for VC such as seismic or magnetic sensors that are already commercialized. On the other hand, some methods including WSN, VANETs or LTE transceivers are still developing and require more studies to reach a full readiness level. Table 10 summarizes the technology roadmap of different kinds of VC technologies. Pros and cons of all methods were priorly mentioned in the related parts.

VI. CONCLUSION

Over the past decade, we have beheld the development of VC systems due to the tremendous advancements in soft computing methods, wireless communications and sensing technologies. In this paper, we presented a pervasive taxonomy of VC technologies in five major categories of intrusive, non-intrusive, off-road, hybrid and manual approaches. It was realized that conventional methods such as remote sensing, vision, sound and contact-based form the biggest part of VC systems. Comparatively, other approaches like aerial, GPS-based and multi-methodological have drawn less attention. Among all VC methods, video images are the most favorite and widespread solution for researchers.

We investigated the diverse mobility and physical parameters that can be retrieved using each method. As opposed to the other methods, it was indicated that VANETs are the most ubiquitous approach by providing all the physical and mobility vehicular information. Furthermore, VANETs demonstrated that they can provide reliable VC due to their real-time data compilation and also global traffic information access. However, in some VANETs circumstances, we might encounter some issues such as communication deficiency that can degrade VC performance and should be taken into account. Subsequent to VANETs, WSN and WIM as hybrid methods and pneumatic tubes in the class of contact-based methods manifested to be able to extract the most kinematic and physical information for VC.

This paper tried to review the most commonly used VC systems in a systematic way. Strengths, pitfalls and methodologies of the VC methods were discussed. Finally, we conducted a comprehensive study on various soft computing techniques in the literature for VC. These methods containing ML and NN algorithms as well as features and models can enormously alleviate the performance of VC. We distinguished them into distinct groups based on the specific application domain to better comprehend the correct usage of the technique in classifying vehicles. ML and NN algorithms incorporated the highest number of articles in VC respectively. SVM exhibited to be by far the most customary algorithm among all soft computing technique for VC.

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