Classification of Moving Vehicles in Traffic Videos

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Abstract. In this paper, we propose a model for classification of moving vehicles in traffic videos. We present a corner-based tracking method to track and detect moving vehicles. The detected vehicles are classified into 4 different types of vehicle classes using optimal classifiers. The proposed classification method is based on overlapping the boundary curves of each vehicle while tracking it in sequence of frames to reconstruct a complete boundary shape of it. The reconstructed boundary shape is normalized and a set of efficient shape features are extracted. Vehicles are classified by k-NN rule and the proposed weighted k-NN classifier. Experiments are conducted on 23.02 minutes of moderate traffic videos of roadway scenes taken in an uncontrolled environment during day time. The proposed method has 94.32% classification accuracy which demonstrates the effectiveness of our method. The proposed method has 87.45% of precision with 79% recall rate for classification of moving vehicles.

Keywords: Corner-based tracking, shape reconstruction, shape normalization, shape feature extraction, vehicle classification, k-nearest neighbor, weighted k-nearest neighbor.

1 Introduction

Vision-based traffic video monitoring systems have reduced the cost of traffic monitoring with increased quality. In addition to vehicle counts, a set of traffic parameters such as vehicle labels, lane changes, illegal U-turns, posture, speed and moving direction can be measured. Vision-based traffic video monitoring systems help us in gathering statistical data on traffic activity through monitoring the density of vehicles and also assist us in taking intelligent decisions in any abnormal conditions by analyzing the traffic information. Vehicle classification is one of the key tasks in any vision-based traffic monitoring system. Important data about vehicle classes that use a particular street or highway can be obtained which on the other hand can provide the accurate design of roadways and highways.

Detection and tracking of vehicles are the preliminary steps in the task of vehicle classification. Vehicles are extracted from the scene using motion cues [2], or by background subtraction [3]. The extracted vehicles are tracked in a sequence of

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frames using region-based [5], active contour-based [6], model-based [7] and feature-based [3, 8-9] tracking methods. Tracked vehicles have to be classified. However, classification of vehicles in traffic videos imposes challenge due to their high intra class variations. Many types of vehicles belonging to the same class have various size and shape features. Transformation of vehicles, occlusion, shadow, illumination, scale, pose and position of a camera in a scene make the shape of vehicles to be changed while moving. In addition, stereo cameras are rarely used for traffic monitoring [14]. Hence, it would become more complex to recover vehicle parameters such as length, width and height from a single view camera. However, the inherent complexity of stereo algorithms makes them impractical in real-time applications.

The approach proposed in this paper is an integrated approach that combines vehicle extraction, tracking and classification. Moving vehicles are tracked and detected within a video sequence. A complete boundary shape of every vehicle is reconstructed. The boundary shapes of vehicles are normalized and a set of efficient shape features are extracted. Moving vehicles are classified into 4 different categories using optimal classifiers.

The rest of the paper starts by describing an overview of the related works in section 2. A description of our approach for classification of vehicles is presented in section 3. Section 4 details the experimentation carried out on traffic videos along with the results. Finally, conclusions are given in section 5.

2 Related Works

In literature we can find a number of works on classification of vehicles in traffic videos. Sullivan et al. [11] proposed a 3D model matching scheme to classify vehicles into various types like wagon, sedan, hatchback, etc. They developed a simplified version of a model-based tracking approach using orthographic approximations to attain real-time performance. Although, 3D features obtained from stereo cameras might be useful for categorizing different classes of vehicles, the computational time of 3D model approaches are very high and classification of vehicles relies on detailed geometric of various types of traffic vehicles which might not be available all the time. In [12], the virtual loop assignment and direction-based estimation methods are used to identify different types of vehicles. Each type of a vehicle is represented by a 1-D signature chart. A parameterized model was proposed to describe vehicles by Wu et al. [13]. They proposed to consider the vertices and topological structure of vehicles as the key features. However, extracting the topological structures of vehicles requires high quality of frames that is not always achievable in a real traffic monitoring system. Gupte et al. [14] proposed a region-based tracking approach to track vehicles. They classified vehicles based on the establishment of correspondences between regions and vehicles. In their work only two categories, categories of cars and non-cars are considered and occluded vehicles are also misclassified as non-cars. Hsieh et al. [15] proposed a classification method which has a good capability to categorize cars into more specific classes with a new "linearity" feature extraction method. A maximum likelihood estimation based classifier is designed to classify vehicles even in the existence of shadow, occlusion and other noise. To increase the classification accuracy, they integrate the vehicles of the same trajectory from different appearances. In [16], they proposed a method in which vehicles are classified into two groups of vehicles and false vehicles and "Adaboost" is used for such a purpose. Rad and Jamzed [10] proposed speed parameter in addition to the width of the bounding box surrounding the vehicles for classification. They used the fact that usually heavy vehicles run more slowly than the cars. However, this is not always the fact in real-time traffic videos. Vehicle classification based on Eigenvehicle and PCA-SVM was proposed by Zhang et al. [17]. They proposed to normalize the extracted vehicles along the same direction and measured at the same scale. For each vehicle segment, only the most significant eigenvector is chosen to represent the vehicle. They apply One-Class Support Vector Machine to classify vehicles. Chen and Zhang [18] designed an algorithm for vehicle classification at a finer granularity. They proposed an ICA based vehicle classification platform. One-Class Support Vector Machine is then used for classification of vehicles.

From the literature survey, it is clear that vehicle classification based on shape features in traffic videos suffers from high computational time if the extracted features are based on 3D modeling of vehicles or dimensionality reduction of the extracted vehicle features. Besides, the classification methods that are based on template matching of vehicles involve the detailed geometric of various types of traffic vehicles which is impractical to use in real-time traffic videos. In addition, the classification accuracy of detected vehicles depends on the extracted features of vehicles used for classification and the type of a classifier used. Classification accuracy can be obtained with an appropriate combination of the extracted features with a particular classifier. Thus, we still need to further explore methods that can reveal the real, invariant characteristics and shape features of the type of vehicles having no requirement of template matching for classification in real-time traffic videos. The classification system should be robust, efficient and accurate.

In this direction, we propose a shape-based method for classification of moving vehicles in this paper. Moving vehicles are tracked and detected by the method proposed in [3]. We propose to reconstruct a complete boundary shape of every detected vehicle by overlapping all of its boundary curves while it is tracking in a sequence of frames. The reconstructed boundary shape is normalized and for that a set of shape features are extracted. The proposed method has good capability and robustness to categorize vehicles into more specific classes. Vehicles are classified into 4 different categories such as 1- motorcycles and bicycles, 2- cars, 3- heavy vehicles (minibus, bus and truck) and 4- any other (complement class).

3 Proposed Model

This paper presents a vision-based traffic surveillance system to classify detected moving vehicles in a video captured by a stationary camera. Moving vehicles are tracked and detected using the corner-based tracking approach proposed in [3]. The complete boundary shape of every detected vehicle is reconstructed by translating all the boundaries of a vehicle during its tracking to the center of a temporary framework. The reconstructed boundary shape is normalized and the shape features are extracted. k-NN and the proposed weighted k-NN classifiers are then applied to classify vehicles.

3.1 Corner-Based Tracking

We use the approach proposed in [3] to segment, track and detect moving vehicles in traffic videos. To track the extracted moving vehicles, a bounding box is used to initially enclose the corner points of each vehicle of a current frame. The corner points are then labelled based on the label of the candidate corner points located in a mapped bounding box of that of the previous frame. Fig. 1 illustrates the corner-based tracking approach proposed in [3] to track moving vehicles in a traffic video.

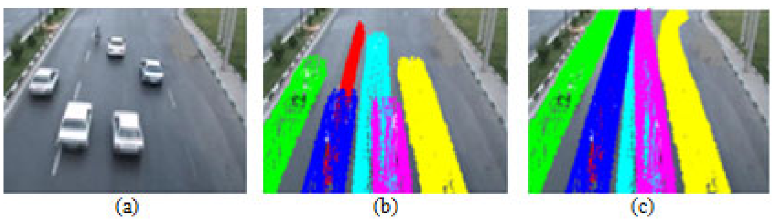


Fig. 1. (a) Main frame. (b) Tracked vehicles in a shot. (c) Vehicles are tracked from the time of appearance to the time of disappearance in the scene.

3.2 Feature Extraction

In this subsection, we outline the proposed approach to extract the shape features of a detected moving vehicle in order to classify it. To extract the shape features of a vehicle, first, we propose to reconstruct a complete boundary shape of a vehicle during the period of its tracking as detailed in section 3.2.1. The reconstructed boundary shape is normalized by sampling the data points. The shape features of the normalized boundary shape are extracted as given in section 3.2.2.

3.2.1 Shape Reconstruction

It is known that a vehicle has many different appearances as it moves along a lane. The factors such as vehicle movement, illumination and shadow might affect the extracted shape of a vehicle while it is moving. Hence, there exists high variation among the extracted boundary curves of vehicles. To extract the robust shape features for a vehicle, we propose to reconstruct the complete boundary shape of a vehicle during the period of its tracking. We propose to overlap all the boundaries of a vehicle while it is tracking in sequence of frames from the time of its appearance to the time of its disappearance in the scene. Thus, for all the frames where a vehicle is tracked, its closed boundary curves are located in the center of a temporary framework such that the centroid of the boundaries, represented in terms of the vector $\vec{V}=(V_{\bar{x}}, V_{\bar{y}})$, coincides with the center of the coordinates of a temporary framework, termed as $\vec{C}=(C_{\bar{x}}, C_{\bar{y}})$. Fig. 2 shows an example of two different traffic vehicles that the closed boundary curves of each vehicle are located to the center of a framework while tracking. Before extracting the shape features, the outline of the reconstructed boundary shape is sampled to a fixed number of points. The sampling process normalizes the sizes of the boundary shapes, smoothes the shapes as well as eliminates the small details along the boundary shapes [4]. In this paper, the boundary shape of a vehicle is normalized using the equal arc-length sampling method [4] as it achieves the best equal space effect. Fig. 3 shows the normalized boundary shapes of the vehicles as reconstructed in Fig. 2.

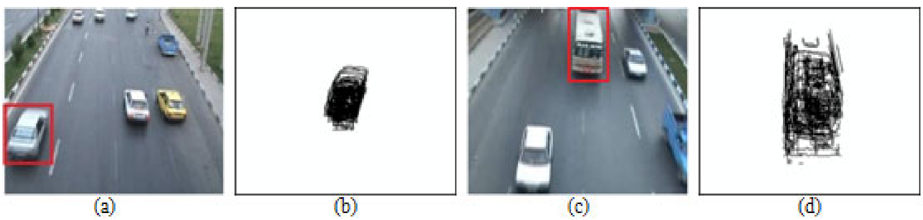


Fig. 2. (a) A sample car enclosed in a bounding box. (b) The shifted boundary curves of the car to the center of a framework during its tracking. (c) A sample bus circumscribed by a bounding box. (d) The located boundary curves of the bus to the center of a framework while it is tracking.

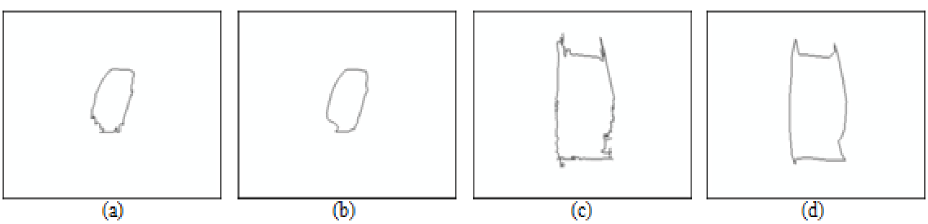


Fig. 3. (a)&(c) The reconstructed boundary shapes of two different vehicles. (b)&(d) Boundary shapes normalization.

3.2.2 Shape Feature Extraction

It is well-known that there exist a number of techniques such as Fourier descriptors, Zernik moments and Boundary moments that can extracts the shape features of vehicles based on boundary. On the other hand, it is also well clear that there are high variations among the boundary shapes of different traffic vehicles belonging to the same class. So, the shape features extracted from such mentioned techniques are not applicable for our application. In this direction, we propose to extract a set of shape features which is robust, efficient and applicable for classification of traffic vehicles. Thus, in this paper the following shape features are extracted.

A number of basic features of a minimum bounding box (MBB) circumscribing the normalized boundary shapes are obtained as follows.

- ***Normalized Length*:** It is a length of the MBB. The length is as well normalized via NL=L/LF (where, 'LF' is the length of a framework).
- ***Normalized Width*:** It is a width of the MBB. The obtained width is also normalized with NW=W/WF (where, 'WF' is the width of a framework).
- ***Length by Width Ratio*:** This ratio is calculated by NL/NW.
- ***Width by Length Ratio*:** It is the computed ratio of NW/NL.
- ***Area*:** The area of the MBB i.e., A=NL×NW.
- ***Perimeter*:** The perimeter of the MBB viz., P=(NL+NW)×2.

Further, the region properties of a vehicle are computed in terms of *Eccentricity*, *Solidity*, *Centroid Size*, *Minimum Distance to Centroid* and *Maximum Distance to Centroid*.

- ***Eccentricity*:** The eccentricity is the ratio of the distance between the foci of the ellipse of a vehicle and its major axis length.
- ***Solidity*:** It is a scalar specifying the proportion of the pixels in the convex hull that are also in the region.
- ***Centroid Size*:** An alternative characterization of the size of a vehicle is defined as the square root of the sum of the squared Euclidean distances between each landmark point and the centroid of a boundary [1].
- ***Maximum and Minimum Distance to Centroid*:** Maximum distance from the centroid to the boundary points as well as Minimum distance from the centroid to the coordinates of the border [1].

3.3 Vehicle Classification

We use k-Nearest Neighbor approach (k-NN) to classify detected moving vehicles into 4 different categories. To improve the classification accuracy, in this paper we propose weighted k-NN for classification. We propose to estimate the dissimilarity value based on the weighted features. If the features extracted from training and testing sample vehicles are similar, then the dissimilarity values computed among the features can be reduced by weighting. This in turn increases the corresponding classification accuracy. On the other hand, the features with high correlation will have the lesser variation amongst the features. Hence, we propose to assign weights to the extracted shape features in terms of '*global weights*' and '*local weights*'. In this direction, the standard deviation of the entire training sample vehicles belonging to each feature is calculated as '*global weights*'. Moreover, '*local weights*' are obtained by computing the standard deviation of all training sample vehicles belonging to each feature of the same class. Let $[W_1, W_2, W_3, \ldots, W_Q]$ be a set of 'Q' global weights, $[Fv_1, Fv_2, Fv_3, \ldots, Fv_Q]$ be a set of 'Q' features of a test vehicle and $[Ft_1^j, Ft_2^j, Ft_3^j, \ldots, Ft_Q^j]$ be a set of 'Q' features of the j^{th} training sample, then the dissimilarity measure of a testing sample with respect to j^{th} in terms of '*global weights*' is computed as follow.

$$\mathrm{Dis}(j)=\sqrt{\sum_{i=1}^{Q} W_i \times \left(Fv_i - Ft_i^j\right)^2}. \quad (1)$$

The value of the dissimilarity measure in terms of '*local weights*' is calculated by Equation 2. For computing the dissimilarity measure, let $[W_1^m, W_2^m, W_3^m, \ldots, W_Q^m]$ be a set of 'Q' local weights of the m^{th} class of the vehicles, $[Fv_1, Fv_2, Fv_3, \ldots, Fv_Q]$ be a set of 'Q' features of a test vehicle and $[Ft_1^r, Ft_2^r, Ft_3^r, \ldots, Ft_Q^r]$ be a set of 'Q' features of the r^{th} training sample in the m^{th} class, then:

$$\mathrm{Dis}(r)=\sqrt{\sum_{i=1}^{Q} W_i^m \times \left(Fv_i - Ft_i^r\right)^2}. \quad (2)$$

4 Experimental Results

The traffic videos used in this experiment were captured with a fixed digital camera in RGB color space mounted on a pole or other tall structure, looking down on traffic scenes. The frame rate of the videos is 25 frames per second with resolution of 320 × 240 pixels. In our system, the experiments are conducted on 23 real traffic videos (34,529 traffic video frames totaling about 23.02 minutes of inner city video) having different complex background, illumination, motion, position of a camera and moving direction.

Extracted vehicles are tracked using the proposed corner-based tracking approach proposed in [3] and vehicles are detected as moving vehicles if the distance of movement from the time of their appearance to the time of their disappearance in the scene is significant. However, some extracted false vehicles are also detected as moving vehicles in our experiment. In this paper, vehicles are classified into 4 categories: 1- motorcycles and bicycles, 2- cars, 3- heavy vehicles (minibus, bus and truck) and 4- any other (compliment class).

From our experimentation, 70,934 vehicles have been tracked in all the frames of the traffic video samples which also include tracking the false detected vehicles. Out of these tracked vehicles in all the frames, 858 vehicles are reconstructed. The reconstructed boundary shape of vehicles are normalized by selecting K=30 as the total number of the candidate points to be sampled along the boundary shapes presented in [4]. The system is trained and evaluated in three sets. In the first set, we consider the reconstructed vehicles belonging to the 40% of the traffic video samples used in this experiment. Similarly, we consider the reconstructed vehicles belonging to the 50% and 60% of the traffic video samples as the second and third sets respectively. The k-NN and weighted k-NN are used under varying parameter for k=1,3,5,7, and 9. From the experimental results, it is observed that the system performs well with k>=9. Furthermore, it is clear that local weights preserve the correlation exist among the values of each feature belonging to the same class and so, local weighted k-NN achieves the highest accuracy in classification. The performance evaluation of the proposed approach for classification of detected vehicles is tabulated in Table 1and shown in Fig. 4 as well. The highest classification accuracy achieved is

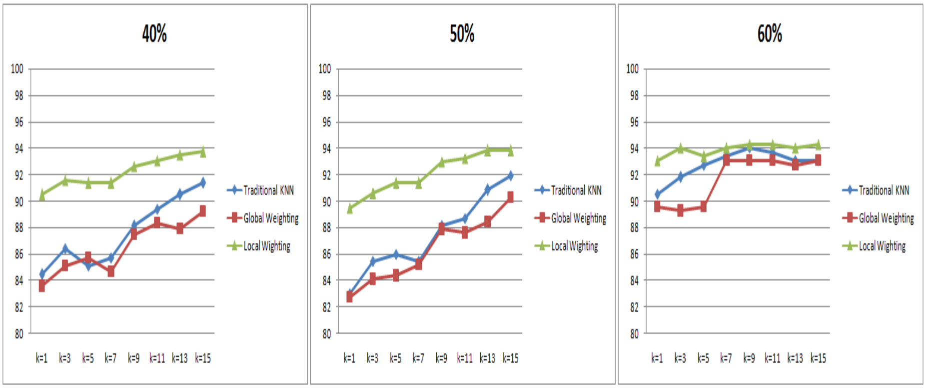
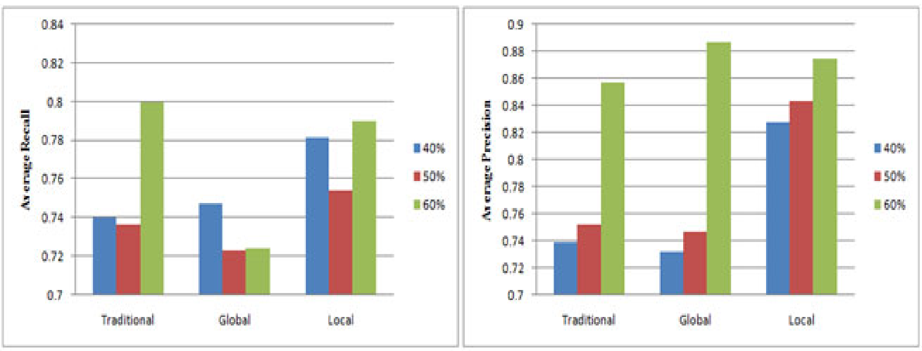
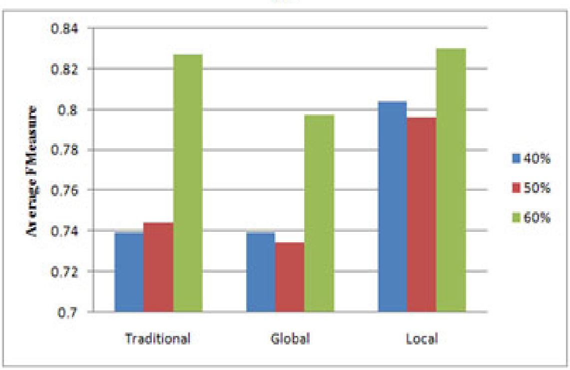


Fig. 4. Classification accuracy under varying parameters and different weighting schemes



(a)



(b)

Fig. 5. (a) Average Recall and Precision for k=9 under different weighting schemes. (b) Average FMeasure for k=9 under different weighting schemes.

Table 1. Tabulated values of k-NN classifier under varying parameters and different weighting schemes

	40% of the Traffic Video Samples **Total no. of Tested vehicles=463**			50% of the Traffic Video Samples **Total no. of Tested vehicles=371**			60% of the Traffic Video Samples **Total no. of Tested vehicles=317**		
	Traditional	Global Weighting	Local Weighting	Traditional	Global Weighting	Local Weighting	Traditional	Global Weighting	Local Weighting
k=1	84.45	83.59	90.50	83.02	82.75	89.49	90.54	89.59	93.06
k=3	86.39	85.10	91.58	85.44	84.10	90.57	91.80	89.27	94.01
k=5	85.10	85.75	91.36	85.98	84.37	91.37	92.74	89.59	93.38
k=7	85.75	84.67	91.36	85.44	85.18	91.37	93.38	93.06	94.01
k=9	**88.12**	**87.47**	**92.66**	88.14	**87.87**	**93.00**	**94.01**	**93.06**	**94.32**
K=11	89.42	88.34	93.09	88.68	87.60	93.26	93.69	93.06	94.32
K=13	90.50	87.91	93.52	90.84	88.41	93.80	93.06	92.74	94.01
K=15	91.36	89.20	93.74	91.91	90.30	93.80	93.06	93.06	94.32

94.32% using local weighted k-NN with k=9 heuristically. The precision, recall and FMeasure are also computed by considering k=9. The average calculated precision, recall and FMeasure are shown in Fig. 5 respectively. From Fig. 4 and Fig. 5, it can be observed that the traditional k-NN has achieved high performance when the system has been trained by the vehicles belonging to the 60% of the traffic video samples. However, our proposed local weighted k-NN has performed well in case of training the system by using the vehicles belonging to the 40% and 50% of the traffic video samples.

To corroborate the efficacy of the proposed vehicle classification, we have compared the proposed method with the other state of the art techniques on well accepted classifier such as ICA-SVM, PCA-SVM and Eigenvehicle which is given in Table 2. In [18], the pixel values inside the bounding box of each vehicle form a basic feature vector. Independent Component Analysis (ICA) and also a Principle Component Analysis (PCA) are performed on training images to reduce the dimension of the feature space. One-class SVM is used to categorize vehicles into certain classes. The reported performance is on average of 71.12% FMeasure using ICA-SVM. It also gives an average 60.05% FMeasure using PCA-SVM. Zhang et al. [17] proposed two classification algorithms - Eigenvehicle and PCA-SVM to classify vehicles. These two methods exploit the distinguishing power of PCA at different granularities with different learning mechanisms. The performance presents an average 61.70% FMeasure using Eigenvehicle. It provides an average 64.80% FMeasure by PCA-SVM. By using the proposed approach, we accomplish on an average of 82.74% FMeasure using 9-NN after training the system by the reconstructed vehicles belonging to the 60% of the traffic video samples. The performance is also achieved on an average of 83.00% FMeasure using our proposed local weighted 9-NN.

Table 2. Comparative analysis of the proposed method with other state of the art techniques

Title	Method	Number of Frames	Frame Rate (fps)	Number of Training & Testing Vehicles	Average FMeasure in %	Comments
Vehicle Classification from Traffic Surveillance Videos at a Finer Granularity [18]	ICA & SVM PCA & SVM	67,635	NA	150 Training Vehicles + 450 Testing Vehicles	71.12% 60.05%	3 Categories: 1- Passenger Cars (PC) 2- Pickup Tracks (PK) 3- Vans and SUVs
A Pca-Based Vehicle Classification Framework [17]	Eigenvehicle PCA & SVM	2,943	5	90 Training Vehicles + 300 Testing Vehicles	61.70% 64.80%	3 Categories: 1- Passenger Cars (PC) 2- Pickup Tracks (PK) 3- Vans and SUVs
Proposed Method	Shape Features & k-NN Shape Features & Local Weighted k-NN	34,529	25	(60% of the Traffic Video Samples) 541 Training Vehicles + 317 Testing Vehicles	82.74% 83%	4 categories: 1-Motorcycles and Bicycles 2- Cars 3- Heavy Vehicles (Minibus, Bus and Truck) 4- Any Other (Complement Class)

5 Conclusion

In this paper, we propose to overlap the boundary shapes of moving vehicles while tracking to obtain the complete boundary shapes of vehicles. A set of efficient shape features of vehicles are extracted. To increase the classification accuracy, we propose to estimate the dissimilarity measure used in k-NN classifier based on the weight features. Our proposed method is able to detect and classify moving vehicles in an uncontrolled environment having variations in illumination, motion, clutter, position of a camera and moving direction. Our proposed approach is able to deal with different types of deformations on the shape of vehicles even in cases of change in size, direction and viewpoint. Results show the robustness and efficiency of our classification model. In future, we plan to exploit other classification techniques and study the classification accuracy. We will further explore different techniques of fusion of the various classifiers to study the performance.

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