Computer Vision based Vehicle Recognition on Indian Roads

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Abstract

Feature extraction and classification are two most important modules for any vision-based object recognition system. In the case of vehicles, most of the methods in these modules found to be less accurate in recognition even though they work well for other objects. We are interested in recognition of vehicles on Indian roads. There are number of challenges in implementing vehicle recognition in Indian scenario like bad road conditions, traffic rules violation and variance among vehicles, etc. In order to overcome these difficulties, we implemented feature extraction module using bag of features (combination of Harris-corner detector and SIFT features), and classification is performed using Support vector machines (SVM). To validate our proposed method, we have introduced Indian Vehicle Database. The images in this database are extracted from daylight Indian urban traffic scenes. Our proposed method achieves 40-45 percent improvement over the baseline methods.

Keywords: feature extraction, bag of words, recognition, support vector machine

1. Introduction and related work

In recent years, Computer Vision based vehicle recognition (recognizing the vehicle in a digital image or video sequence) has become an active research area in Intelligent Transportation Systems (ITS)[1]. This is mainly due to impact in numerous applications like electronic toll collection management (collect tolls on highways electronically to eliminate delay), to identify unauthorized vehicles on roads as a part of vehicle surveillance and traffic data analysis (useful in decision making in terms of safety evaluation, pavement design, funding, forecasting, and modeling). The other applications of vehicle recognition are, license plate localization, computer assisted driving and methods for reducing road accidents.

Although vehicle recognition has been an area of recent interest to the Computer Vision community, no prior research study has been used to build an on-road vehicle recognition. The main reason is vehicle recognition is quite different from other object recognition scenarios. This is mainly due to the following two difficulty's. First, since

Figure 1: The two important challenges in vehicle recognition to apply for Indian scenario *Row1:* Complex road conditions (non lane system, heavy loaded vehicles, unstructured vehicle parking system and obstacles on roads respectively) *Row2:* Intraclass variation among vehicles, here Truck is shown as an example.

vehicle recognition task deals with only images in outdoor or natural lighting it is known to cause noise related problems. The other is typical geometry of vehicles. Vehicles chassis are constructed in a significantly greater variety of geometries as compared to other objects. There are number of dissimilarities in vehicles [2] like height, number of wheels, body shape and color.

The problem of recognition of Vehicles was previously

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attempted by researchers using different techniques [3]. Three important categories in this area are Wavelet based, methods based on contour or edge and feature extraction with classification. Papageorgiou and Poggio [4] applied wavelet analysis and learn a Support Vector Machine (SVM) or neural network (NN) to recognize cars on highways. This approach seems to be tolerant to scale and illumination variance [4]. Similar to this type of work but wavelet replaced by curvelet is done by Farhad mohamad and Saeed samadi [5] [6]. An extensive comparative study of fourier, wavelet and curvelet Transforms is done by [7]. All the above said methods works better but little bit sensitive to noise. The other methods like contour feature algorithm and sobel edge based algorithm [8], [9] are computationally expensive.

ND Matthews *et al* [10] proposed vehicle recognition using PCA as feature extraction and SVM for classification. Goerick *et al* [11] proposed local orientation coding as feature extraction and NN as classifier. In the same direction another method was implemented by sun *et al* [12] using Gabor like features and SVM. The another improved algorithm using adaboost is done by Xeezhiwen [13]. All the above methods acquired good results in some aspects, but still have some limitations like high computational time and ineffectiveness in recognition.

Visual object class classification was first started by PASCAL in 2005 [14]. The goal is to recognize objects from a number of classes in realistic scenes. PASCAL and Caltech are two popular datasets in this area. For Caltech dataset, state-of-the-art results were obtained using the combination of Bag of features (BOF) as feature extraction and Support vector machine (SVM) as classifier. This dataset consists of several objects like human faces, vehicles, chairs, and tables, etc. Our proposed method use BOF and SVM to recognize Indian vehicles.

The rest of the paper is organized as follows: Information Regarding Indian vehicle database is described in Section II. The process of Vehicle recognition is summarized in Section III. Experimental results on Indian vehicle database are discussed in Section IV. Finally conclusion with future work is described in Section V.

2. Indian Vehicle Database

The main goal of this paper is to implement an efficient method for recognizing vehicles in Indian conditions. There are some challenges in these conditions that makes vehicle recognition much harder. Figure-1 describes this scheme.

- In western countrys like USA, lane marking system is implemented. Vehicles are allowed to move in specific rows according to speed limit and vehicle type, etc. But in India in most of the cases traffic system is non lane based.

- Road conditions are more varied and traffic is unstructured, there is lack of discipline and overloaded vehicle movement is quite natural.

- In India, vehicles are parked frequently by the sides of the roads. There is no separate system for vehicle parking management.

- Roads are not only occupied with vehicles, so many obstacles on roads create disturbance to the traffic. Pedestrians do not have separate ways for their movement in most of the cases.

- Shapes of the vehicles have a key role in recognition, there is high intra-class variance among Indian vehicles(row2 in figure-1). It creates the chances for miss recognition.

- With in same vehicle class there are large variety's and models. These looks different in size and appearance. It is generally observed in Indian vehicles like cars and Truck's.

Figure 2: Sample Images from *Indian Vehicle database* includes four classes (Truck, Auto, Bus and Car respectively). Images were captured with variance in pose, view and lightning constraints.

In order to apply vehicle recognition in Indian scenario, we have introduced Indian vehicle database in this paper. It is build by capturing vehicle images on several Indian highways and traffic roads. Vehicle types considered are Auto, Car, Bus and Truck. Sample images from the entire database are shown in figure-2. The complete description is presented in Table-I.

This database can be provided to computer vision researchers for nonprofit use only. A request e-mail need to sent in order to obtain this database.

3. Vehicle recognition process

Vehicle recognition process in Indian scenario has several challenges that are discussed in section-II. To address these challenges features of a individual vehicle from different directions are to be considered. For this reason ,

Table 1: Description of Indian Vehicle database

Properties	Description
Name	Indian Vehicle database
Sources	Static vehicle pictures captured using camera on Indian roads, Pictures collected from Internet resources like Goggle images etc. and Pictures cropped from a traffic videos
Constraints	Pose, lightning and view
Number of classes	4
vehicle types	Truck, Auto, Bus and Car
Number of images per class	450
Total Images	1800

Figure 3: Vehicle recognition process in series of five steps using Histogram of features and Support vector machine

the present paper use Bag of features (BOF) and Support vector machines for vehicle recognition.

BOF works on the principle that every object can be represented by its parts. For example, a Truck contains parts like big-tyres, number plate, cabin etc. Also car contains wheels, number plate and windows, but the basic difference between an Truck and car is observed to be in size and tyres. So, in order to recognize an object it is necessary to first recognize the parts of it and based on the parts identify the object correctly.

Basing on above principle vehicle recognition process in Figure-3 is initiated to recognize parts (step-1 and step-2) of the vehicle images by extracting image patches. This can be done by the combination of Harris corner [15] and Sift [16] points because these contain rich local information of the image.

For each patch, descriptors were calculated in the form of vectors. To address the cardinal and ordering problems, clusters are generated by apply K-means algorithm on these descriptors. Each cluster is refereed as word for an image. Thus image is represented as a bag of words or bag of visual words (step-3). These words are represented as a histogram (step-4) and referring as histogram of features. Features obtained in the above process are classified by train and test process using SVM (step-5).

The reason for the select of SVM as a classifier is that, it has some superiority over other approaches. The impor-
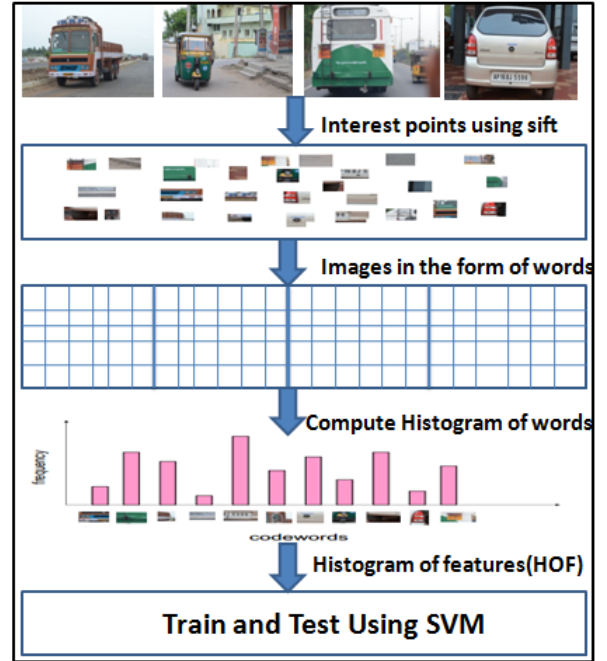
tant points are global minimum solution, learning and generalization in huge dimensional input spaces, use of kernel function and classification is done by the separating hyper plane at a maximum distance to the closest points in the training set.

4. Evaluation and Analysis

Experimental results of vehicle recognition are presented in this section. Accuracy is evaluated for all the cases of recognition methods. Analysis is performed by varying the feature extraction and classification methods. The main idea is implemented from Caltech [17]. Other procedures like SIFT descriptors and SVM are implemented using Vlfeat [18] and Libsvm [19].

The two modules in recognition pipeline are feature extraction and classification. At first traditional methods like PCA, SIFT, LDA and LBP are applied as feature extraction and classified using KNN(K-nearest neighbor) and SRC(space representation classifier). Table II presents average performance of this base line result scheme.

The approximate accuracy is noticed between 50-74 percent only. But these methods have good accuracy in other object recognition methods [20] like face etc. The main reason for less accuracy is due to use of local features. This is clearly addressed in the rest part of the experimental process and compensated by the virtue of visual features.

Experiments performed on 1800 vehicle image sequences. These image sequences are divided into 200 validation, 200 training and 50 testing samples randomly per each class.

Table 2: Accuracy (%) of vehicle recognition process using (PCA, SIFT, LDA and LBP over KNN and SRC) as a baseline results

Feature extraction	Classifier	Accuracy
PCA	SRC	50.00
SIFT	SRC	67.80
LDA	KNN	61.75
LBP	KNN	74.00

From validation samples shape parameters can be achieved through Harris corner and SIFT features.

These are used for training the SVM [21]. Testing is performed with total of 4*50=200 samples. Multi-class classification is done with a support vector machine (SVM) trained using the one-vs-rest rule.

Figure 4: Vehicle recognition result that shows the images which are *correctly* recognized

Figure 5: Vehicle recognition result that shows the images which are *wrongly* recognized

There is an increase in accuracy percent by the apply of BOF as feature extraction and SVM as a classifier. Accuracy percent for the present case is between 78-90. This has shown in Table-III. It also illustrates that the best results are yielded in the case of RBF kernel [22] among the three types of kernels like linear, quadratic and RBF along with bag of features.

It is observed that the proposed method is performed correctly in recognition even for some complex conditions like overloaded vehicles and shape variations. The method

Table 3: The proposed method for vehicle recognition process deals with three types of kernels like linear, quadratic and RBF in SVM. Accuracy (%) along with Bag of features are tabulated here

Classifier	Kernel type	Accuracy
SVM	Linear	78.54
SVM	Quadratic	81.00
SVM	RBF	90.00

also recognized different vehicle poses and views properly.

The result of vehicle recognition is further analyzed using confusion matrix. It is a two dimensional array shows relationships between true and predicted classes. It is shown in table-IV. Here we can observe a clear diagonal correlation between four types of vehicles.

Since Truck has some similar structure with other vehicles like bus, it is getting confused and viceversa. Generally car has similar features like shape and size with auto and viceversa. The 9% of confusion is noticed here. But these vehicles are not confused much in present case. This improvement is only due to implementation features from interest points. Confusion% in this case is 3.

we can assume two sets of vehicles from entire database. Heavy : bus & Truck, light : car & auto. These two sets of vehicles have dissimilar structure and features. Due to this reason a negligible confusion of 0.25% is noticed in this case.

4.1. Failure Case Analysis and Challenges

Figure-4 represents vehicle recognition results for the proposed method by correctly representing in to labels. As discussed in introduction, there are some challenges in vehicle recognition, due to this some failure cases are noticed. These are given in figure-5. Here Truck is recognized as bus, auto recognized as car, bus recognized as Truck and car recognized as auto.

The following four main reasons illustrates why failures are arises in our method. Figure-6 represents spectrum of images which are failed in recognition due to specified reasons.

- Objects in small size
  If the objects of interest is very small in region it will be difficult to extract meaning full information and recognition accuracy decreases. Related example images as shown in Figure 6(a). This problem can be overcome by performing localization as a preprocessing step for recognition.

- Novel model
  The database consists of images of some particular known number of classes in large variety's and shapes. It will be very difficult to build a model

which captures all the intra-class variances. As a result some test images which has model variance from training images were recognized wrongly. This type of variances among car, Truck and auto are shown in figure 6(b) respectively.

- Clutter
  As shown in Figure 6(c), some times unwanted information like hoardings and other obstacles on roads were also captured along with vehicle images. This introduces noise in features and makes confusion in recognition. Due to this reason testing becomes more complex.

- Poor quality images
  Quality of the image has a key role in recognition. Important reason is it has a direct influence on performance of edge based features like sift which is implemented in this method. Figure 6(d) shows some images with poor quality. Recognition percent is observed to be very low in this case.

Table 4: Performance evaluation of vehicle recognition using confusion matrix. Here 50 testing images from each of four classes are used. Images are considered from Indian vehicle database

	Truck	Auto	Bus	Car
Truck	46	0	4	0
Auto	1	48	0	1
Bus	3	0	47	0
Car	0	2	0	48

5. Conclusion and future work

This paper describes a robust method for recognizing the vehicles. A prototype system for vehicle recognition has been presented. This proposed method can be useful in several applications specifically suitable for Indian conditions. Objects of interest are recognized from images by the sift and Harris corner features, these are converted further in the form of Histogram of words so called as bag of features. Classification is performed by using Support vector machine. With respect to the Indian conditions the recognition rates so far promised its usability within the context of a state-of-the-art. Experimental results show that, proposed vehicle recognition method is accurate up

Figure 6: In the process of recognizing Indian vehicles the system has attained *some failures*. The important reasons noticed are due to (a)very small objects, (b)novel models (in car, truck and auto as an example), (c)clutter and (d)images with poor quality

to moderate level as compared to base line result. Analysis for the failure cases in the system and their solutions also presented. Future work will concentrate on the optimization of the run time of the system and improvement of recognition robustness for the case of intraclass variation. This work can also be extended by improving database size and number of vehicle classes.

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