Real Time Vehicle Make and Model Recognition Based on Hierarchical Classification

Hajar Emami, Mahmood Fathi, and Kaamran Raahemifar

***Abstract*—In recent years Intelligent Transportation Systems (ITS) have become an important research area. Vehicle make and model recognition is one of the topics in the domain of ITS for secure access and traffic monitoring applications. This paper presents an effective approach for fast recognition of vehicle make and model form back views. We use efficient hierarchical classifier that determine the class of vehicle at first and then recognize vehicle make and model in a smaller group which dramatically increases the speed and performance of the method by focusing attention on the most discriminative regions. In this method, different classes are defined based on the location of license plate and taillights of vehicle. By considering the vehicle initial class, we can select different regions and features for different classes in recognition step that improve the results. Results confirm our prediction that hierarchical classification is more powerful in vehicle model recognition. The final system is capable of recognition rates of 96% on a dataset of over 280 back view images of vehicles. The proposed algorithm is robust to illumination and weather conditions.**

***Index Terms*—Vehicle make and model recognition, vehicle classification, hierarchical classification, intelligent transportation systems.**

I. INTRODUCTION

Intelligent Transportation Systems (ITS) have become an important research area in recent years, this is because of their application importance in real world problems. ITS is the application that incorporates electronic, computer and communication technologies into vehicles and roadways for monitoring traffic conditions, reducing congestion, enhancing mobility and so on. Vehicle Make and Model Recognition (MMR) is one of the important subjects of study in ITS. Identifying vehicles just by their license plate number may be insufficient for various situations. Automatic Number Plate Recognition (ANPR) is complemented by the MMR, for further confirmation of the vehicle. If vehicle type recognition solved accurately, is beneficial for authentications checking, police camera control systems on crossings to match the number-plate against the car make and tracking the special car. In this paper we focus on car make and model recognition. The proposed method will provide valuable situational information for law enforcement units in a variety of civil infrastructures. By unification of ANPR and MMR systems useful information can be obtained.

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Various researches have been done on just vehicle detection [1] or vehicle classification to generic classes: cars, trucks, buses etc. [2], [3]. On the other hand, not many existing solutions to recognize vehicle manufacturers and models are available in the literature. Some of the existing methods use a combination of some features for vehicle model recognition [4]-[6].

Petrovic and Cootes [7] looked for structures in car frontal images to use as a basis for MMR. A number of different features are then extracted over a region of interest. The best feature is found to be square mapped gradients, which are gradients formed from vertical and horizontal sobel edge responses. The recognition rate of over 93% was achieved.

In [8] redness measure and dominant edge orientation features are extracted for building a car recognizer based on small training set. It detects back views of Honda Accords 2004. They apply machine learning methods in an attempt to solve the problem of detecting rears of a particular car type.

Pearce and Pears [9] use Harris corner strengths and two different classification approaches for make and model recognition from frontal images of cars. Zhang *et al.* [10] take Gabor wavelet coefficients to cope with the view variations and ULLELDA algorithm for feature extraction to recognize the make and model of a vehicle. Jang and Turk, [11] combined SURF features and bag-of-words model with structural verification techniques and validated their approach on realistic-looking toy car datasets.

This paper presents a new method for car make and model recognition that uses vehicle images as input, obtained at different daytime and weather conditions. Special efforts have been directed toward handling reliably images of poor quality. The experiments with common car models in Iran have shown that the system is robust to illumination, slope and scale. The situation we are interested in is the rear view of cars. This situation is typically used in monitoring traffic since license plates are universally found at the rears of vehicles. The proposed algorithm consists of two main steps. The first step of this approach is vehicle class recognition by investigating some features related to the location of license plate and taillights. In the second step, vehicle make and model is recognized within the class form previous step. This hierarchical classification can improve both accuracy and speed of the system. The proposed approach for vehicle make and model recognition is illustrated in Fig. 1.

The paper is organized as follows: Section II describes vehicle class recognition, At the Section III vehicle make and model recognition method is presented. We discuss Experimental results in Section IV and Conclusions are outlined in Section V.

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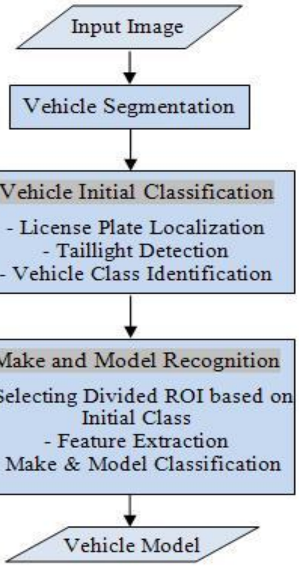

Fig. 1. Overview of the proposed MMR system.

II. Vehicle Class Recognition

The recognition system proposed in this paper use Hierarchical approach that certainly improves classification rate and speed. For this purpose, firstly car class is determined based on the location of taillights and license plate then we recognize car make and model within that class form previous step just based on the features that exhibit the greatest variation over samples in selected class. By this method, we can use different features for recognition within different classes. Car class recognition step can simplify the MMR by reducing the number of car model candidates and also can be helpful for the region of interest (ROI) selection step.

A. License Plate Localization

The process initialed by locating the license plate in the input image. We apply one reliable approach based on our earlier work [12] for fast license plate localization that use a sequence of classifiers which dramatically increases the speed of the detector by focusing attention on promising regions of the image. If any classifier rejects the sub-window, no further processing is performed. This approach attempts to reject as many negative license plate candidates as possible at the earliest stage. The vehicle image undergoes a series of processing steps such as edge counting, detection of the plate's position, searching for the "signature" of the license plate at candidates from previous step and then verification step using several context-dependent geometric constraints such as width, height, aspect ratio and gray-level distribution properties, color checking, etc.

The result from License plate localization step allows us to normalize the scale and skew of car image based on the license plate. We also mask the license plate region in the image for next steps so features from the license plate couldn't be considered for classification process because they are not related to the model and can cause misclassification that reduce the performance of the method.

B. Taillight Detection

Scale normalized vehicle images from previous step are passed to this step for taillight detection. Two taillights at rear view of vehicle can easily be located by searching red areas in the picture which have the admissible area size and distance to each other. HSV color space is used to assist in the detection of red areas. In this color space components represent hue, saturation and value respectively. All images in our dataset are RGB color images which means that each of their pixels is represented by quantity of red, green and blue in a pixel, respectively. Images are processed by color space converting (RGB to HSV color space) and considering special combination for H,S and V components in new color space. Then one threshold method is used to find out whether the detected red color region is car's taillight based on its area size. If area of red color region is in the specific range, this region is considered as taillight. An example of taillight detection is shown in the Fig. 2.

C. Vehicle Class Recognition

In order to improve recognition performance and speed, initial classification of input images is proposed. The aim is to identify the class of vehicle based on the location of license plate and taillights before make and model recognition step.

Vehicle images in dataset can be classify in 3 groups based on the location of license plate and taillights. First class is related to vehicles that license plate is located between two taillights both horizontally and vertically ($h1$ is within a range of $h2$ and $w1$=$w2$).The second class includes vehicles with $h1$ below $h2$ and $w1$=$w2$. Finally, if two distances between license plate and taillights aren't equal, vehicle belongs to the third class ($w1 \neq w2$). As it can be seen on a Fig. 3 $h1$ is the license plate height, $h2$ is taillight height, $w1$ and $w2$ are distances between license plate and 2 taillights.

This initial classification will reduce the number of model classes that the input image may be belonged in the model recognition step hence reduce misclassification rate and time of process. The results of this step pass to MMR for make and model recognition. Examples of 3 classes are shown in Fig. 4.

Fig. 2. an example of detected taillights on a test image.

Fig. 3. Class of vehicle defined relative to location of license plate and taillights.

III. Make and Model Recognition

The proposed method for MMR contains ROI selection, feature extraction and then classification. In order to find an optimal ROI for each vehicle image, information about vehicle class derived from previous step is used. Different feature extraction techniques are investigated and *k* nearest neighbor (*k*-NN) classifier is used for classification.

Fig. 4. Examples of 3 vehicle classes, Red Regions defined ROI relative to just license plate and white regions extracted optimal ROI by considering vehicle class.

A. ROI Selection

Most MMR systems select license plate based ROI for feature extraction [7]-[13]. In order to find an optimal region for extracting features, the important structures for discriminating between various car models such as full width of the car back, taillights, badge and bumper should be included within the ROI. Selecting license plate based ROI without considering the vehicle class derived from previous step may result a poor region of interest especially for vehicles from class 2 and 3, as shown in Fig. 4. Since they have the license plate located in a different location to most other car manufacturers, selected ROI just based on the location of license plate may include some parts of background. This causes irrelevant parts in ROI instead of discriminative structure. In this paper we define different ROI for 3 classes to solve the problem. White regions in Fig. 4 show extracted optimal ROI by considering the vehicle class for class 2 and 3. We also classify four divided ROI separately instead of using the whole ROI for classification. This method can improve the result especially in cases that one part of vehicle like left taillight may cause misclassification because it's dirty, dusty, containing small mechanical damages or because of its appearance changes. Hence, dividing ROI and classifying four parts separately yields better result. To emphasize areas that exhibit the greatest variation over the registration set (between different models), different parts of ROI are considered with different weights for classification that improve the recognition rate.

B. Feature Extraction and Classification

Taillight features like a width/height coefficient and some related to imfeature like EquivDiameter, Solidity, Extent, Orientation, etc are used in proposed system. These features can be used to classify images obtained at different daytime even at night. Since taillights are on at night, they can be detected by the same method. This paper reports Sobel edges as another extracted feature only for daylight images. Both types of feature are then combined in order to obtain a robust MMR system for daylight images.

We used the Euclidean metric in a *k*-nearest neighbour (*k*-NN) scheme. We investigate different *k* for classification. Best classification rate are obtained for 1-NN and 5-NN scheme. Experimental results for various combination of feature extraction method and classification approach are described in next Section.

IV. Experimental Results

Extensive testing has been conducted with more than 280 images from back view of various vehicle models in RGB color map. JPEG image compression was used. Our data set contains pictures of common vehicle models in Iran. We are interested in rear view of vehicles for collecting dataset. License plates are useful for ROI selection and also initial class recognition process and they are universally positioned at rear side of vehicles. The existence of strong features like taillights, badge, etc. at rear view of vehicles is another reason for selecting this view. Pictures were taken from different distances and the camera pan angle varies few degrees. Images have size 640×480 points. Different daylight conditions were examined, from bright sunlight illumination to foggy half-darkness. We also have night pictures in our data set.

We tested different classification systems, by varying the combination of feature extraction and classification method. Different features include 1) tailight features 2) sobel edges 3) using vehicle badge and make logo. Classification with all available features yields excellent results, using hierarchical classification and divided ROI also exhibit the best performance with fast process. Fig. 5 shows the comparative performance of each MMR systems. We also tested proposed classifier with night images that produced poor results with classification rate 53.1%.

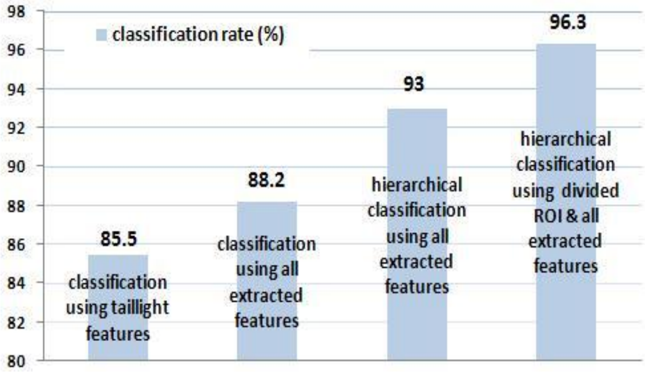

Fig. 5. Classification rates for various MMR systems.

Fig. 6. Vehicles misclassified in proposed systems.

Most miss-classifications were on images containing poor lighting conditions and vehicles with dirty or damaged parts. Also less populated classes with few samples in the training set may be difficult to classify correctly. A number of incorrectly classified vehicles are shown in Fig. 6.

The MMR algorithm runs on Intel(R) Core(TM) 2 CPU T7200 @ 2.00GHz with 2 GB of RAM. Running results show that the average recognizing time for one vehicle image is approximately 30s. The computation cost is small and it is satisfied with requirement of real world system.

V. Conclusion

The method proposed in this paper seems to be universal in case of make and model recognition of different vehicles under various environmental and lighting conditions. It has ability to correctly recognize model of vehicles in the picture in a short time. The preliminary results obtained on real data are quite satisfactory. In this method MMR results are affected by License plate localization and taillight detection steps. Our taillight detection technique also can be used in turn light recognition algorithm for intelligent vehicles in autonomous navigation.

We use hierarchical classification for vehicle class recognition and then make and model recognition that efficiently decrease the time of process. Using divided ROI and considering different weights for features provide further recognition confidence by emphasizing differences between various vehicle classes. The conclusion is that in case of reasonably good images the above-described MMR approach yields excellent results with fast process.

Our future work will be to test the approach on a larger dataset with more classes of vehicle. It should be mentioned finally that these results could be obviously extended to other applications in the input-output transport systems, where automatic make and model recognition of vehicles is useful. For instance, by integration MMR with vehicle classification (generic classes like buses, tracks, cars, etc), license plate recognition and car color identification, valuable information can be derived for surveillance systems, intelligent transport systems and traffic management systems.

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