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# Automated Vehicle Classification with Image Processing and Computational Intelligence

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## Abstract

Classification of vehicles is an important part of an Intelligent Transportation System. In this study, image processing and machine learning techniques are used to classify vehicles in dedicated lanes. Images containing side view profile of vehicles are constructed using a commercially available light curtain. This capability makes the results robust to the variations in operational and environmental conditions. Time warping is applied to compensate for speed variations in traffic. Features such as windows and hollow areas are extracted to discriminate motorcycles against automobiles. The circularity and skeleton complexity values are used as features for the classifier. K-nearest neighbor and decision tree are chosen as the classifier models. The proposed method is evaluated on a public highway and promising classification results are achieved.

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## 1. Introduction

Automated vehicle classification is such an important problem that many Intelligent Transportation Systems (ITS) are facing with it. Classification is required for identifying specific vehicles such as motorcycles. Unquestionably, if vehicles are classified accurately in real-time, overall system efficiency can be improved significantly.

For vehicle classification, traditional hardware based methods that employ road sensors are widely used. Axle detectors and height sensors are being used for this purpose. However, these sensors may not provide accurate results in case of congested lanes. Additionally, these sensors performance tend to degrade over time. On the other hand, software based classification rely on image and video processing techniques and they are more robust than the

hardware based ones. Because of ease of installation and maintenance, software based classification is advantageous. Despite its advantages, software based methods have some drawbacks. Processing time is a major constraint of video processing, in addition ambient lighting affects overall performance. Additively occlusion is a major issue in case of congestion. Bad weather conditions such as rain, snow or fog will decrease imaging performance drastically.

In the past few decades, studies are made to find a solution to automated vehicle classification problem. Ryan et al. (2004) presented a video based vehicle classification which uses length information. Zhang et al. (2007) investigated a similar approach in classification. Videos are taken from cameras mounted on top of the road. In order to overcome slow processing times of video processing, image based methods are developed. Goyal et al. (2007) adopted neural network to classify vehicles. Features are extracted from vehicle images and used for training.

In summary, many solutions to unresolved problems exist in automated vehicle classification. In free flowing traffic, vehicle recognition is performed before classification; on the other for dedicated lanes, it is easier to detect vehicles. Additionally, dedicated lanes have slower cruising speeds compared to free flow, which improves sampling performance.

In this paper, a novel automated vehicle classification method is presented. Light curtain information is used to generate side view profile of ongoing vehicles through dedicated lanes. Moreover, this side view profile information is used to reconstruct a representative binary image of the vehicle. By combining image processing with machine learning techniques, motorcycles are differentiated from cars.

The rest of the paper is organized as follows. Section 2 describes our Automated Vehicle Classification method. Section 3 provides experimental results and discussion of highlight features. Finally, conclusions and future work are given in Section 4.

## 2. Automated vehicle classification scheme

Automated vehicle classification consists of three phases: data collection, feature extraction and training. In this section each of the phases are given in detail. Overall system diagram is given in Fig.1.

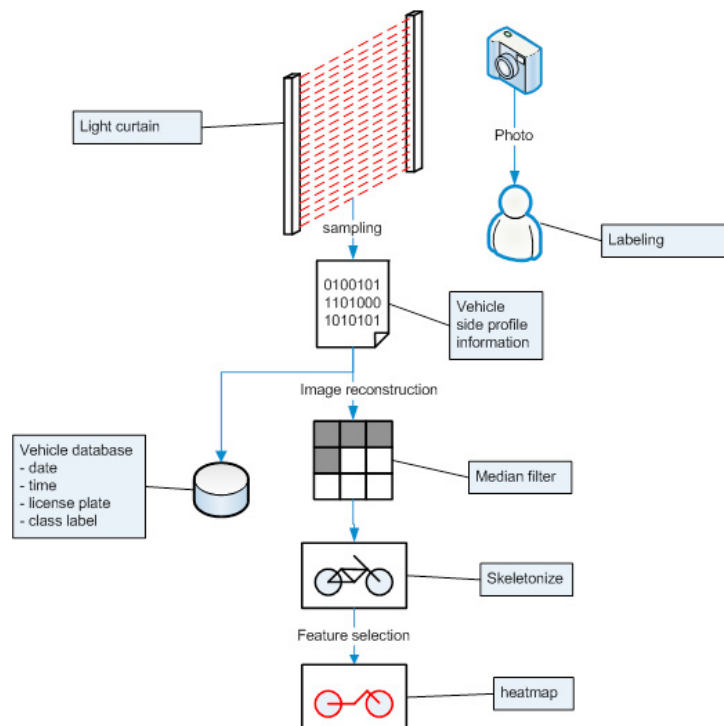


Fig.1. Vehicle classification states

## 2.1. Data collection

Data is collected from two different locations on a public motorway. Upcoming traffic is divided into four dedicated lanes; each lane is equipped with its own light curtain and enforcement camera, installation overview is given in Fig.2. For every vehicle, side view profile is constructed by continuous sampling from light curtain. 100Hz is selected as sampling rate, e.g. every ~10ms a reading is performed. Light curtain uses infrared beams such that it is not affected by weather and ambient lightning conditions. Another advantage is no need for background subtraction, shadow removal, edge detection and complex filtering operations. Reconstructed images of a motorcycle and a sedan car are given in Fig.3.

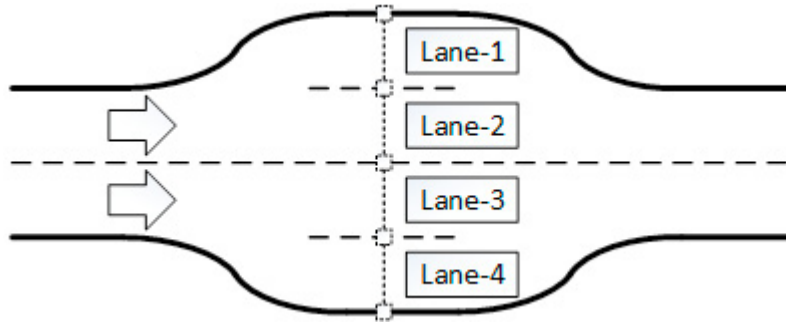


Fig.2. Roadside overview

Vehicles entering to and exiting from light curtain are photographed using enforcement cameras. Class labeling is performed according to the photograph taken. All this information along with date, time and license plate is used to generate a vehicle database for training and test purposes. In the next subsection, features extraction process from this database is given in detail.

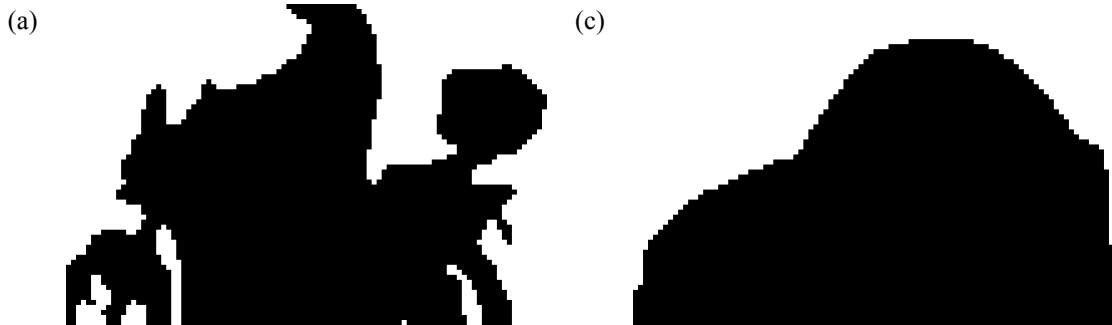


Fig.3.(a) Reconstructed side-view of a motorcycle, (b) Reconstructed side-view of a sedan car

## 2.2. Feature extraction

Feature extraction is performed in two phases. In the first step, filtering and image morphing operations are applied to the reconstructed image. Median filtering with a 3x3 window is applied to fill relatively small regions. Larger contours are also detected and fixed if necessary. Following these operations, skeletonization is performed. Skeleton of a binary image reduces foreground regions and remaining connected pixels gives the best representation of the figure. Certain important locations such as joints and end points are selected as features. Results of skeletonization and feature extraction are given in Fig.4 and Fig.5.

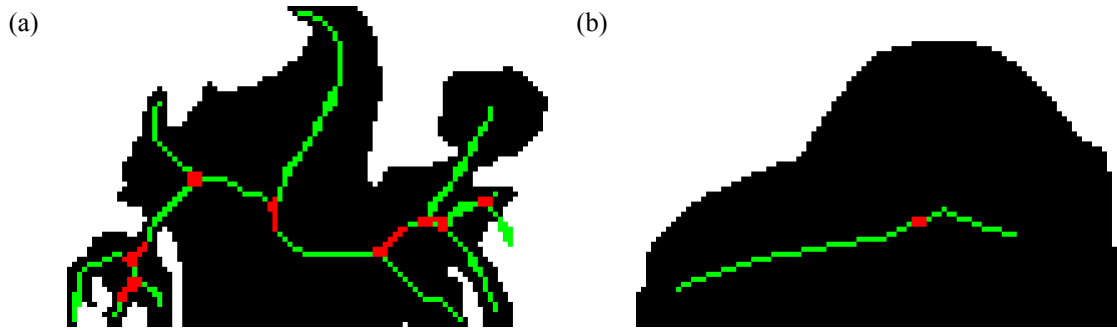


Fig.4.(a)Extracted features from motorcycle, (b) Extracted features from sedan car; green lines showing image skeleton

Extracted features from a human passing by are shown in Fig.5. Legs and the arm can be recognized easily.

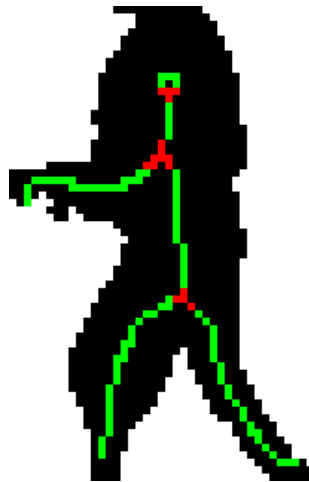


Fig.5. Extracted features from a human

### 2.3. Training

Different types of motorcycles and cars are selected for training. Training set consists of 580 cars and 500 motorcycles. Training set entries are randomly selected from vehicle database. By combining and normalizing images in the train set, heat maps ( $HM$ ) are generated. Generated heat maps for motorcycles and sedan cars are given in Fig.6. Similar to eigenfaces approach in face detection and recognition, these heat maps forms a basis.  $HM_C$  is defined as follows, where  $c$  is the vehicle class label,  $n$  is the number of elements in the training set and  $x$  is the corresponding training set item.

$$HM_C = \frac{1}{n} \sum_i^n x_{C,i} \quad (1)$$

Classification is achieved by measuring similarity between test image and corresponding heat map. In order to increase computational efficiency and decrease processing time rather than comparing whole image, a smaller subset of original image is processed. For this purpose, important features are trained and stored only. As can be seen in Fig.7, motorcycles have a lot of feature locations details. On the other hand, cars have a much smoother shape and less detail.

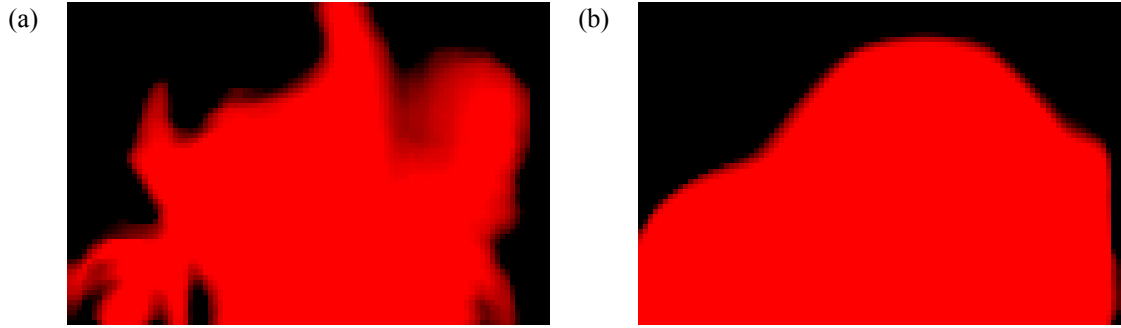


Fig.6.(a)Heat map of motorcycle train set, (b) Heat map of sedan car train set

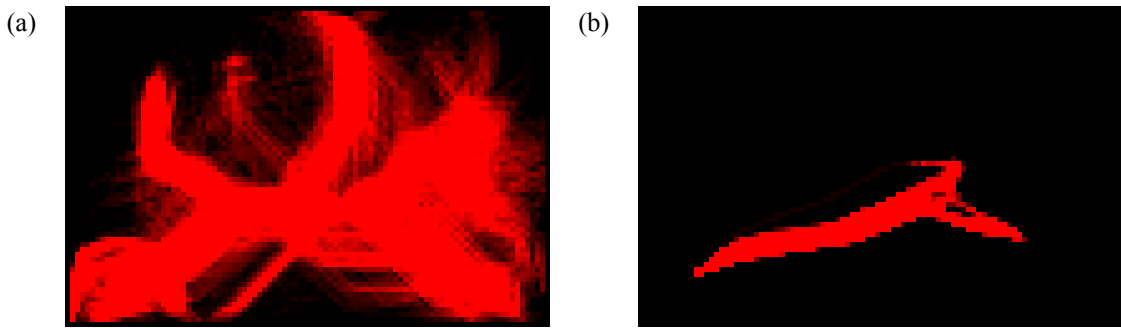


Fig.7.(a)Combined features from motorcycle train set, (b) Combined features from sedan car train set

### 3. Experimental results

To evaluate the performance of the classification scheme proposed, vehicle classification software is implemented. The experimental platform is built on OpenCV, Weka and Java. Each vehicle in the test set is compared against generated heat maps to find similarities. Two machine learning methods are used to obtain results. These are k-nearest neighbor and decision tree learning. Experiments are performed on a computer with 1.73GHz CPU and 8GB RAM.

Similarity score  $sim_C$  between test set entry  $x$  and corresponding heat map  $HM_C$  calculated as:

$$sim_C = \frac{1}{C_{MAX}} \sum_i^W \sum_j^H (x_{ij} \neq HM_{C,ij}) \quad (2)$$

where  $W$  is image width and  $H$  is image height in pixels.  $C_{MAX}$  is the area of the vehicle. Fig.8 and Fig.9 illustrates relation between similarity scores of motorcycle and sedan classification.  $x$  axis represents similarity to motorcycles; on the other hand  $y$  axis shows sedan similarity scores.

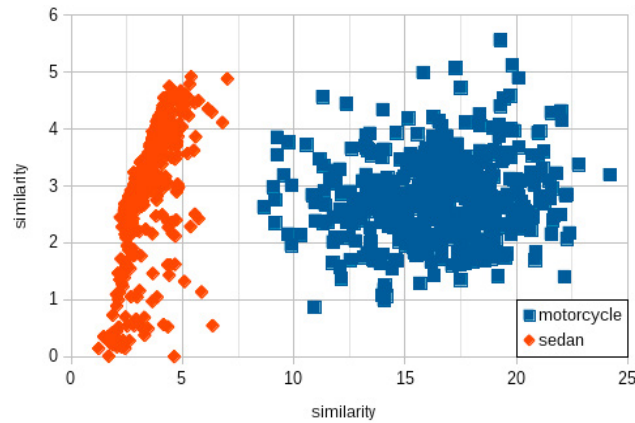


Fig.8.Training set similarity scores

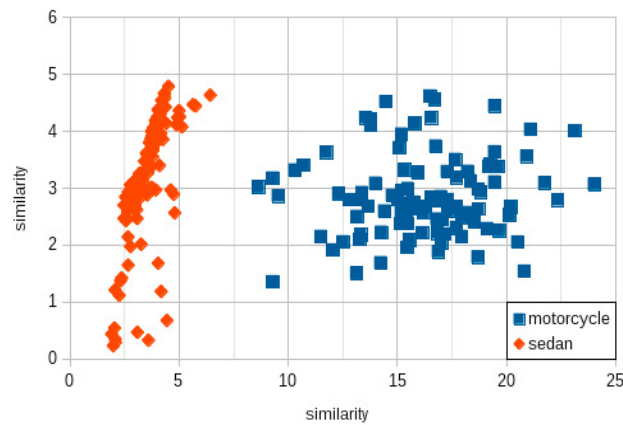


Fig.9.Test set similarity scores

### 3.1. *K*-nearest neighbor (KNN)

KNN is a supervised type of non-parametric method used for both classification and regression. In classification, label is assigned according to the  $k$  number of nearest labels, where  $k$  is a small positive integer (Fig.10). Its simplicity makes KNN a popular machine learning technique. On the contrary, KNN performance is significantly affected by irrelevant samples. In order to avoid this, selection and scaling should be performed initially.

Selection of  $k$  parameter affects classification result. A larger value will reduce impact of noise; on the other hand class boundaries tend to overlap.

For different  $k$  values between 1 and 20, test set is correctly classified without any error.

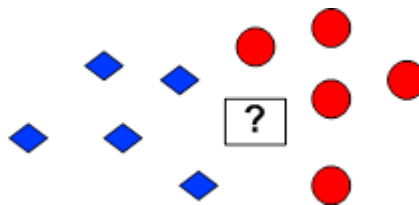


Fig.10.KNN classification

### 3.2. Decision tree (DT)

Decision trees are supervised type of extremely powerful machine learning techniques with the capability of modeling nearly any problem; on the other hand their major drawback is overfitting. In this type of classification, class labels are assigned to leaves and tree branches correspond to conditions.

Using a simple tree as shown in Fig.11, classification can be performed between motorcycle and sedan. Decision trees can be enlarged to further classify different types of vehicles. Resultant tree boundary is given in Table 1. Performance of the classification is given in Table 2.

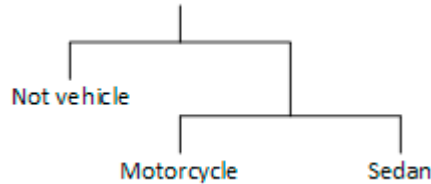


Fig.11.Constructed decision tree

Table 1: Decision tree boundary

$x < 7.009$	sedan
$x > 7.009$	Motorcycle

Table 2: Confusion matrix

		predicted	
		motorcycle	sedan
test	motorcycle	100	0
	sedan	0	135

## 4. Conclusions and future work

In this study, an automated vehicle classification method to distinguish different vehicle types is presented. Classification is performed between motorcycles and sedans. Particularly, classification method is based on image similarity between heat maps generated from the training set. Moreover, machine learning techniques including k-nearest neighbor and decision trees are adapted for comparison.

The results from public motorway tests show that proposed classification method can discriminate motorcycles from sedans. This information can be used to notify traffic operators in real time. However, the proposed method only focuses on motorcycle detection. As an extension, this method can be extended to detect other vehicle types such as SUV, minivan and bus. Because each vehicle type has its own specific shape; a more general system can be modeled with sufficient training data.

From machine learning point of view, feature selection and feature extraction still remains as the most important issue. Selected features affect overall accuracy significantly.

In this study, following future research subjects are possible: (1) detection of different motorcycle types (sports, cruiser, touring, scooter ...) will be studied; (2) detection of different types of vehicles (car, SUV, truck, bus ...); (3) the detection of humans passing by (non-vehicle entries)

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