

# Road Vehicle Classification Based on Extreme Learning Machine

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**Abstract**—Road vehicle classification plays an important role in traffic surveillance, traffic security, and transportation management systems. This paper proposes a novel vehicle classification algorithm based on extreme learning machine. Invariant moments and horizontal edge features are extracted to classify vehicles into sedan, bus and van truck. Experimental results show that the proposed method can satisfactorily achieve vehicle classification at very fast training speed.

**Keywords**- Vehicle classification; Extreme learning machine; Invariant moments; Edge detection

## I. INTRODUCTION

With the increasing traffic pressure, Intelligent Transportation System (ITS) has been a hot research field. An ITS incorporates electronic, computer, and communication technologies into vehicles and roadways for monitoring traffic conditions, reducing congestion, enhancing mobility [1]. Road vehicle classification can be used to compute the percentages of vehicle classes [2], optimize available parking spaces, detect the traffic violation, for example, a sedan is driven on a bus lane.

Many methods of vehicle classification have been put forward in the past. Chen et al. [3] extract a simple silhouette shape vector which includes size, aspect ratio, width and solidity of the vehicle foreground blob, classify vehicles into car, van and HGV using the Support Vector Machine (SVM), and obtain the average type sensitivity of 0.759, the average type specificity of 0.887. Hsieh et al. [1] introduce a new “linearity” feature in vehicle representation, extract vehicle size and linearity to categorize vehicles into car, minivan, van truck, truck. A vehicle classification system based on the rear-side view is proposed in [4]. A feature set of tail light and vehicle dimensions is extracted, and a hybrid dynamic Bayesian network (HDBN) is used to classify a vehicle into one of four classes: sedan, pickup truck, SUV/minivan, and unknown. A classification accuracy of 95.68% is shown in [4]. This method can be employed only when the camera’s field of view is directly behind the vehicle. Ma et al. [5] develop a feature based on edge points and modified SIFT descriptors. The whole set of features forms a rich representation for object classes. However, the method of feature extraction has high complexity, and low real-time. Cretu et al. [6] design a vehicle classification system using a set of images collected from 6 views. A series of binary support vector machines are used to achieve classification

with an average accuracy of 96%. But the approach is not suitable for vehicles on real road because it is difficult to obtain the images of moving vehicles from 6 views on a real road. Different from fixed-model-based methods, a 3-D deformable vehicle model with 12 shape parameters is set up, and a local gradient-based method is presented to estimate the fitness between the projection of the vehicle model and image data [7]. The deformable model is more accurate, efficient and simple than fixed model. A hierarchical classification method is proposed in [8]. Firstly, image set is divided into two groups, small and large, according to the number of edge points. Secondly, the small vehicles are classified as motorbike or car, and the large vehicles are classified as bus or truck using adaptive-KNN based on the feature of Principal Component Analysis (PCA). PCA is also used in [2] in two ways, one is called “Eigenvehicle” inspired by the Eigenface, and the other is called “PCA-SVM” which uses PCA to extract the feature vectors of vehicles and classify them by using Support Vector Machines (SVM).

Extreme learning machine (ELM), proposed by Huang et al., is a simple and efficient learning algorithm for single-hidden layer feedforward neural networks (SLFNs) [9,10]. Traditionally, all the parameters of the feedforward networks need to be tuned, while ELM randomly chooses hidden nodes and analytically determines the output weights of SLFNs [10]. For regression and classification, ELM tends to provide similar or better generalization performance at much faster learning speed (up to thousands times) than traditional SVM and BP [10, 11].

The rest of the paper is organized as follows: In section II we introduce extreme learning machine. In section III we give the method on extracting the feature vectors of invariant moments and horizontal edge features. In section IV we present the experimental results. In section V we conclude the paper.

## II. EXTREME LEARNING MACHINE

The mathematical model of extreme learning machine can be represented as [12]

$$H\beta = T \quad (1)$$

where H is the hidden-layer output matrix

$$H = \begin{bmatrix} h(x_1) \\ \vdots \\ h(x_N) \end{bmatrix} = \begin{bmatrix} h_1(x_1) & \cdots & h_L(x_1) \\ \vdots & \ddots & \vdots \\ h_1(x_N) & \cdots & h_L(x_N) \end{bmatrix}_{N \times L}, \quad (2)$$

$\beta$  is the output weights matrix of order  $L \times m$ , and  $T$  is the target labels matrix of order  $N \times m$ . The output weights can be evaluated as,

$$\beta = H^+ T = H^T (HH^T)^{-1} T. \quad (3)$$

$H^+$  is the Moore–Penrose generalized inverse of the hidden layer output matrix  $H$  [12].

According to ridge regression theory, a positive value can be added to the diagonal of  $HH^T$ , thus (3) can be rewritten as [13]

$$\beta = H^T \left( \frac{I}{C} + HH^T \right)^{-1} T, \quad (4)$$

where,  $C$  is called the regularization factor.

A kernel matrix for ELM can be defined as [11]

$$\Omega_{ELM} = HH^T : \Omega_{ELM,i,j} = h(x_i) \cdot h(x_j) = K(x_i, x_j). \quad (5)$$

The output function of ELM classifier can be written as follows

$$f(x) = h(x)\beta = h(x)H^T \left( \frac{I}{C} + HH^T \right)^{-1} T \\ = \begin{bmatrix} K(x, x_1) \\ \vdots \\ K(x, x_N) \end{bmatrix} \left( \frac{I}{C} + \Omega_{ELM} \right)^{-1} T. \quad (6)$$

In this paper, the Gaussian kernel  $K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$  is adopted, in which  $\gamma$  is the kernel parameter.

### III. FEATURE EXTRACTION AND PROPOSED METHOD

Two types of features are extracted from vehicles in images: invariant moments and horizontal edge features. We put forward a novel approach of extracting horizontal edge feature.

#### A. Invariant Moments

The method of invariant moments is a very useful tool for extracting features from 2-dimensional images [14]. For a digital image  $f(x, y)$ , the  $(p+q)$  order moment is defined as

$$m_{pq} = \sum_x \sum_y x^p y^q f(x, y). \quad (7)$$

The central moments is determined by

$$\mu_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q f(x, y), \quad (8)$$

where  $(\bar{x}, \bar{y})$  is the coordinate of centroid.

The normalized central moment of the image is defined as

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^\gamma}, \quad (9)$$

where

$$\gamma = \frac{p+q}{2} + 1. \quad (10)$$

We employ the following seven moments, defined by Hu, as the feature of invariant moments

$$\begin{aligned} \phi_1 &= \eta_{20} + \eta_{02} \\ \phi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\ \phi_3 &= (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \\ \phi_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\ \phi_5 &= (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 \\ &\quad - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03}) \cdot [3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\ \phi_6 &= (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\ &\quad + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\ \phi_7 &= (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 \\ &\quad - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03}) \\ &\quad [3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \end{aligned} \quad (11)$$

#### B. Horizontal Edge Features

Fig. 1 shows three images of a sedan, a bus and a van truck, and the results of horizontal edge detection.



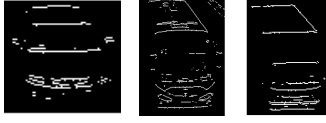


Figure 1. Horizontal edge images of a sedan, a bus and a truck

The key steps for extracting horizontal edge feature of a vehicle image are as follows:

Step 1: Input a gray scale image  $f(x,y)$ , the size of  $f(x,y)$  can be expressed as  $S_1 \times S_2$

Step 2: Compute the horizontal edge image  $f_{edge}(x,y)$  by Sobel edge detector in horizontal direction

Step 3: Calculate the horizontal projection of the horizontal edge image by

$$P(x) = \sum_{y=1}^{S_2} f_{edge}(x,y) / S_2 \quad (12)$$

Step 4: find the indices corresponding to the entries of  $P$  that are greater than a threshold  $th$ ,  $th \in (0,1)$ , and normalize the indices by  $S_1$

Step 5: select 8 largest indices as horizontal edge features.

### C. Proposed Method

Figure 2 presents the block diagram of proposed method for vehicle classification. The method includes feature extraction, training and classification. The invariant moments and horizontal edge features compose the feature vector of a vehicle. In the stages of training and classification, ELM algorithm described in section II is used.

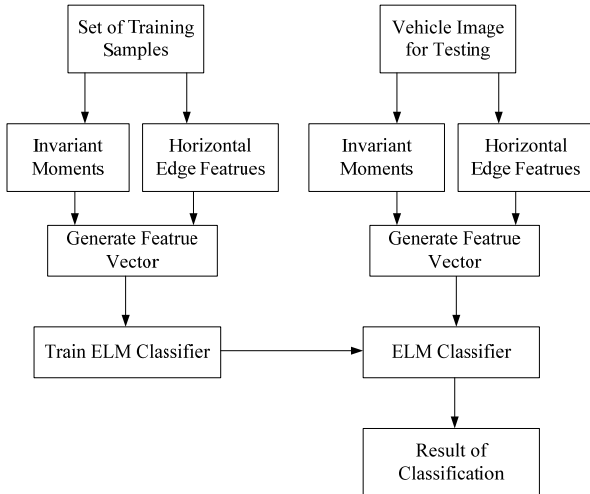


Figure 2. Proposed method block diagram

## IV. EXPERIMENTAL RESULT

The proposed algorithm and experiments is carried out in MATLAB R2010a environment running in PC with a 2.1GHz, Core 2 Duo CPU.

All training samples and test samples are manually obtained from real road videos. The set of training samples includes 50 sedans, 30 buses and 20 van trucks. Fig. 3 shows some samples. There are 30 sedans, 15 buses and 10 van trucks in the set of test samples. In our experiment, the values of regularization factor  $C$  and kernel parameter  $\gamma$  are  $(C, \gamma) = (10, 0.1)$ , threshold  $th$  is set to 0.25. The average training time is 0.0058s. The test results are presented in table I.

## V. CONCLUSION

A new vehicle classification method is presented in the paper. In the feature extraction stage, we introduce a novel approach of extracting edge feature. In the classification stage, ELM is employed as the vehicle classification algorithm for the first time. Experimental results demonstrate that proposed method is a simple, fast and efficient method for road vehicle classification.

In the future work, we intend to work on classifying more vehicle categories and enlarging the set of samples.

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Figure 3. Sample images in database

TABLE I. TEST RESULTS

Vehicle Classes	Number of Training Samples	Number of Test Samples	Right Classification	Accuracy
Sedan	50	30	30	100%
Bus	30	15	14	93.3%
Van truck	20	10	9	90%

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