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A Neural Network based Approach for the Vehicle Classification

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Abstract- **This paper presents a neural network based approach for vehicle classification. The proposed vehicle classification approach extracts various features from a vehicle image, normalises and classifies them into one of the known classes. It is based on structural features and a direct solution training method. The preliminary experiments on training and testing of 4 types of vehicles patterns were conducted. The experimental results are very promising and demonstrate the effectiveness and usefulness of the proposed approach.**

Keywords- Vehicle image classification, neural networks, pattern classification.

I. INTRODUCTION

Automatic techniques for the processing and classification of vehicle patterns are in huge demand because of their applicability to wide variety of real-world applications such as motorway surveillance, fare collection, toll collection, booth gate operator, break-down roadside services, traffic offence detection, war intelligence collection and fight against terrorist activities. There is a need to develop a reliable processing and classification technique which can work under difficult real-world conditions including images affected by weather conditions such as rain and fog, low resolution/contrast, colour/compression format, rotation and distortion.

The main aim of this research is to investigate novel computational intelligence based techniques such as neural networks and genetic algorithms for processing and classification of vehicle patterns. Neural networks are capable of learning and adapting complex non-linear patterns and genetic algorithms are well suited for optimisation of complex problems. The proposed intelligent method will be able to increase the reliability and efficiency of the systems so that they can be used for real world surveillance of motorways. The method for vehicle classification can be applied to various surveillance systems and help in finding criminals, road invaders, toll avoiders, wanted and suspected terrorists.

This paper consists of 5 sections. Section 2 reviews existing literature on vehicle classification, afterwards the Section 3 emphasises on describing the proposed method. The experimental results are presented in Section 4, and finally the conclusions are drawn in Section 5.

II. REVIEW OF EXISTING WORK

There are many researchers and companies [1-8] such as Canal Industrial and Trading Company, MetroCount, Transport Data Systems, Micrologic Systems, Inductive Signature Technologies and IBM involved in development of vehicle classification and surveillance systems. Most surveillance systems currently available are standalone systems and use magnetic loop detectors which can help counting and classifying vehicles. Advanced video monitoring systems and research techniques, such as IBM's real-time video traffic surveillance and UC Berkeley's machine vision based traffic surveillance [3, 8] are being developed to address real-time surveillance of traffic and analysis of traffic on motorways. As mentioned above, several companies are involved in developing traditional vehicle classification systems. There has been also a lot of research in this area and a number of techniques has been recently investigated and published in the literature. In [9], a novel vision based preceding vehicle recognition method is described for vehicle classification. It uses various sample images for training which includes vehicle and non vehicle. In [10], authors describe the multi-clustered modified quadratic discriminant function (MC-MQDF**),** which is able to identify the distribution of vehicle on the basis of their wide range of appearances and features. This approach however is very computationally expensive. Moreover in order to increase the classification rate that required increasing the number of clusters which again increase the cost.

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In [10], authors used inductive loop signatures for vehicle classification in conjunction with two different vehicle classification methods which are implemented on seven vehicle classes. First method uses a heuristic discriminant algorithm for vehicle classification and second method uses Self Organizing Feature Map (SOFM) for recognizing the vehicles. Both vehicle classification methods accept the processed inductive signatures as the input.

In [11], an inductive classifying artificial network (ICAN) is described that is used to explain a self organizing feature map for vehicle classification. The method uses inductive signatures as input. ICAN method did not classify the vehicle according to their number of axles. However it is differentiating between the two- axle vehicles.

In [12], the fuzzy inference system is described for target recognition and vehicle classification in various clutter environments. The fuzzy inference system is less prone to false alarm and provides high recognizing rate. It explains an automatic vehicle classification method which is based on the rules used in the inference engine. However this approach cannot be trained by using various data sets. This approach required certain changes so that it can be adapted to training using sample data values.

In [13], the wireless distributed sensor networks (WDSN) are described for vehicle classification. Whenever the sensor detects the presence of any vehicle the processor will retrieve feature vectors of that particular vehicle based on the acoustic or seismic signal which are sensed by the sensors. WSDN vehicle classification problem consists of two parts which includes local classification and global decision fusion. However this approach is very costly.

In [14], the vision based detection and classification of various vehicles are described. It uses only one fixed camera that captured the different image sequences of traffic running on the road. After capturing the image sequence the system will compute the height and length of the vehicles. It describes the whole system into six stages which includes segmentation, region tracking, and recovery of vehicle parameters, vehicle identification, vehicle tracking and finally vehicle classification. However this approach has certain problems such as error in detection of the particular vehicle class because of noise, poor segmentation, two vehicles persist as a single vehicle if the relative velocity between them is small and all the data related towards the vehicle running on the road only in one direction.

In [15], the distance vectors are used for the real time vehicle classification that are retrieved from the four view directions which includes bottom, top, left and right. To recognise the motion vehicles the system uses normalized correlation methods on the basis of four directions that are depend on the distance vectors. It describes a spatio temporal based arguments as well as distance vectors based spatio temporal data which helps to analyse and recognise the vehicles that are in motion.

In [16-17], the probabilistic neural network method is described for vehicle classification. The system receives data such as number of axles, axle spacing and the weight of the particular vehicle and classifies the vehicle into one of the existing classes.

III. PROPOSED METHOD

The purpose of the proposed method is to automatically classify vehicles into one of the known classes. The method uses a set of features retrieved/extracted from the vehicle. Many different angles are used to view the vehicle that includes all angles of rotation. The data used in this research was collected by JP Siebert [18]. A MLP based classifier with a novel training algorithm (DSM with additional neurons), standard DSM and standard BP is used. The proposed vehicle classification strategy is to successfully differentiate various vehicle classes' such as cars, vans and buses. An overview of the proposed method is shown in Figure 1 below.

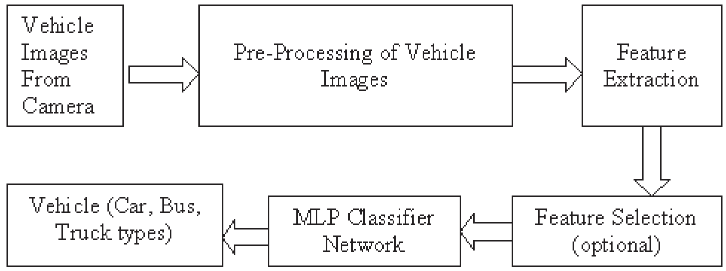

Figure 1. An overview of the proposed method.

The Hierarchical Image Processing System (HIPS) was used to extract all the shape features of the vehicles. The HIPS utilise two measures namely classical moments based measures and heuristic measures [18]. With the help of these two measures the HIPS extracts a collection of scale independent features of the particular vehicle.

All the images of the vehicle were captured through camera. The image was captured from a static angle of altitude which is 34.2 degrees to the horizontal. Before capturing the image of the particular vehicle, they all were positioned on a disperse backlit surface. To improve the quality of vehicle image, 128 by 128 pixels that were quantised to 64 grey levels were used in the proposed system. A radial graticule was placed under the vehicle to calculate their angle of orientation, when the particular vehicles were moving. During motion of the vehicle, 0 and 180 degrees are measured at both front and rear end. In contrast 90 and 270 degrees were measured in opposite direction.

Classifier Network

The proposed method uses a recently developed DSM-AN algorithm and compares the results with standard BP (Back Propagation) and DSM (Direct Solution Method). The main reason for choosing the DSM-AN was that it can produce 100% classification accuracy on training data and has good generalisation abilities.

The DSM-AN consists of training and testing processes as described below.

Training process:

Step 1: Input 18 vehicle features

Step 2: Initialise hidden units to 2.

Step 3: Initialise weights of hidden layer using small random values and the weights of additional hidden neurons using input features.

Step 4: Calculate the weights (W) of the output layer.

- Step 4.1: Feed each feature vector to the network and calculate output of the hidden layer (matrix H).
- Step 4.2: Calculate the O_{tar} using the target value as follows.

  $$O_{tar}=\log(Target/(1-Target)) \quad (1)$$
- Step 4.3: Set a linear system of equations by using H, O_{tar} and W.

  $HW = O_{tar}$ - Use modified Gram-Schmidt method and calculate W
- Step 4.4: Repeat Steps 4.2 and 4.3 for each output.
- Step 4.5: Set weights of additional neurons to +1 and -1 as shown in Fig. 2.

Step 5: Increment the number of hidden units by 1 and repeat Steps 3-4.

Step 6: Select the number of hidden units with the highest classification accuracy on test set and repeat Steps 3-4.

Test process:

Step 1: Input new feature vector.

Step 2: Calculate the output of the hidden layer except the additional neurons using a standard multiplication of inputs and weights (same as in BP).

$$net= x_1w_1+x_2w_2+\ldots+x_{18}w_{18} \quad (2)$$

$$output=f(net)=1/1+\exp(-net) \quad (3)$$

Use a minimum distance function (4) to calculate the output of the additional neurons.

$$net=O_{tar}*(\exp(-\min(\|x-X_{all}\|))) \quad (4)$$

$$f(net) = \begin{cases} net & net >= O_{tar} \\ net*0.49 & net < O_{tar} \end{cases}$$

Step 3: Calculate the output of the network by multiplying inputs to output layer with weights of output layer and passing through the sigmoidal function same as in BP.

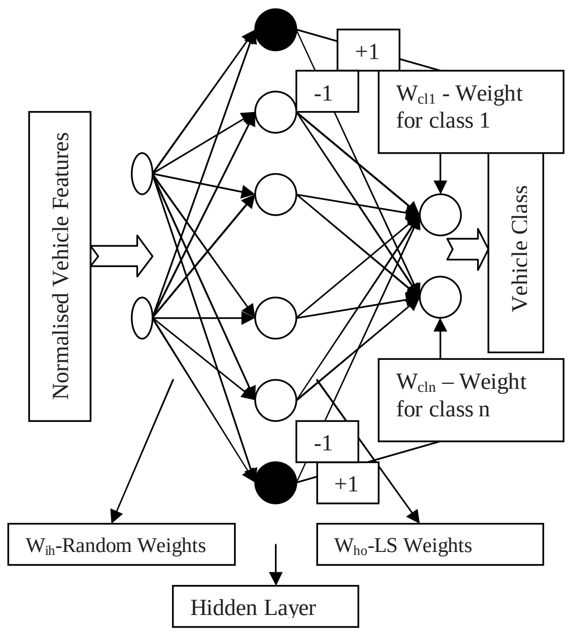

Figure 2. A neural classifier for the proposed approach.

IV. EXPERIMENTAL RESULTS

A. Training Experiments

The proposed method was trained using maximum of 400 different training samples (50, 100, 150, 200 and 400 training samples). All the training pairs belong to four classes which include a double decker bus, Cheverolet van, Saab 9000 and an Opel Mantra 400. The training sample contains various data in the form of numbers that includes features, appearances, weight, size, height, shape etc. of an individual vehicle. All data have been normalised between 0 and 1 and stored in different files in such a format that allows the proposed method to read inputs and outputs and train the method.

Table 1. Results using the proposed approach with 3 different methods.

Training Method	Input Features	Hidden Units	Iterations	Classification Rate [%]	
				Training Set	Test Set
Back Propagation (BP)	18	8	200K	84	50
	18	12	200K	86	51.5
Direct Solution Method (DSM)	18	86	1	80.5	56
	18	108	1	82.50	55
	18	109	1	90	62
DSM with Additional Neurons (DSM-AN)	18	109	55	100	62

Table 1 depicts various parameters for training and testing. It contains various columns; each column contains different values such as first column contains the training methods, second contains number of input features, third contains hidden units, fourth shows iterations and the last column shows the classification accuracy.

B. Testing Experiments

To test the proposed method, 200 different testing samples (50, 60, 100 and 200 testing samples) are used which are not included in the training samples. All 200 testing pairs belong to one of the four classes, which include a double decker bus, Cheverolet van, Saab 9000 and an Opel Mantra 400. Each testing sample contains various information of an individual vehicle which may be a bus, opel, saab or van. As vehicle having different appearances, features and shape therefore, the testing sample used in the proposed method contains 18 inputs that contained all these appearances, features and shape of an individual vehicle. The proposed method accepts these 18 inputs and on the basis of other factors like hidden units, learning rate, RMS error, iteration etc., it produces the desired output.

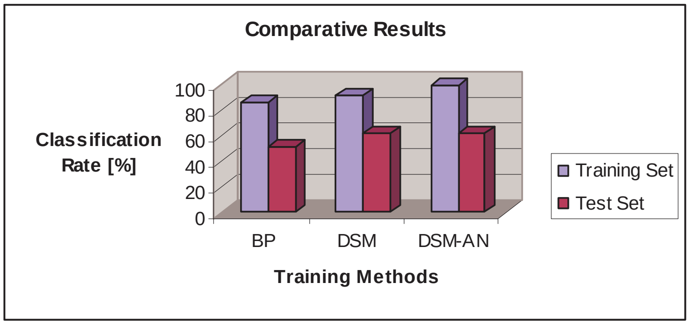

Figure 3. Classification results with the proposed approach using 3 training methods.

Figure 3 depicts the comparative results obtained by using various training methods in conjunction with our proposed approach on training and testing sets. The parameters such as a number of hidden units, number of training pairs, learning rate, momentum, number of iterations, RMS error, etc. have been varied and the best obtained results are presented and compared in Figure 3.

C. Classification Results

The overall classification rates by using the proposed approach are shown in Table 1 and Figure 3. For training set, 400 samples (50, 100, 150, 200 and 400 training samples) of different vehicles were used. Out of 400 training samples, 100 samples are taken from each vehicle class that is van, opel, bus and saab which means (4*100=400 samples). The proposed approach with DSM-AN algorithm has correctly classified 100% samples from training set. The standard BP and DSM have correctly classified 86% and 90% samples from training set.

Other than the 400 training samples, various sets of testing samples (50, 60, 100 and 200 testing samples) were used in the experiments. 200 testing samples contained 50 samples for each class that is (50 * 4= 200 samples). The proposed approach correctly classified 62% samples from testing set as listed in the Table 1. The best three classification rates on test set by using the proposed approach are 51.5%, 56% and 62% as listed in Table 1.

The experimental results on training and testing set for different vehicle classes as shown in Table 1 and Figure 3, demonstrate the effectiveness and usefulness of the proposed method.

V. CONCLUSIONS

We have proposed and investigated a novel neural network based approach for vehicle classification. The proposed approach was implemented and preliminary experiments were conducted. The results are very promising. The best classification rate 100% on training set and 62% on test set was achieved. All methods tested in this research provided low accuracy rate on test data. In our future research, an analysis and further experiments will be conducted to improve the classification accuracy on test set.

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