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GEOMETRICAL FEATURES FOR MULTICLASS VEHICLE TYPE RECOGNITION USING MLP NETWORK

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ABSTRACT

Vision-based vehicle type (model) recognition is a hot topic in the domain of intelligent transportation systems. But it is difficult to recognize the exact type (model) of a vehicle due to the influence of some factors, for example, the view variations. In this paper, we present a robust system of recognition of the type (model) of vehicles from several frontal vehicle images. We use the height of the number plate as a reference to eliminate the zoom effect. From this reference, we extract several geometrical parameters (distance, surface, ratio …) of decision, on bases of images taken in real conditions, were tested and analyzed. Employing this model, a distance error process allows measuring the similarity between an input instance and the data bases classes. The fusion of the three classifiers using the artificial neural networks (ANN) for each parameter allows showing the effectiveness of our process for the identification of the type of vehicle. We obtain taking a threshold of 90% a False Identification Ratio (FIR) of 1.6% and a False Rejection Ratio (FRR) of 3%. The network was tested and it was capable of classifying the type of vehicle of the taken database and a classification ratio of about 97% was obtained. And the minimized error percentages constitute an additional factor for the success of the verification system. According to these parameters, the rate of identification can reach 97% on a basis of a realistic data set of over 1000 images made up of 12 models and 9 classes of the type of vehicles. The results show that this approach achieves very high levels of both identification and verification performance.

Keywords: *Vehicle Type, System Recognition, Image Processing, Features Extraction, Geometrical Parameters, Neural Networks, Fusion Process.*

1. INTRODUCTION

Vehicle type recognition is a relatively new research domain, which begins to interest various laboratories in the world. Various access control systems that use techniques such as biometrics and smart cards are increasingly applied to authenticate and restrict access to users and intruders respectively. Recently, vehicle based access control systems for buildings, outdoor sites and even housing estates have become commonplace. Additionally, various traffic monitoring and control systems that depend on user (man+vehicle) identification, such as congestion charging would also benefit by augmenting existing number-plate recognition with an additional authentication mechanism.

The study described in this communication is dedicated to the identification of the type (model) of the vehicles starting from an image provided by a camera. Given an image containing a frontal view of a vehicle (car), a system is proposed here that determines its exact class (make and model). The aim is to obtain reliable classification of a vehicle in the image from a multitude of possible classes (vehicle types) using a limited number of prior examples (only one per class).

The obvious applications are the monitoring of the carpark or the home-bankings. In a real situation of application, the images at the entries of carpark are primarily tallied so as to make quite visible the number plates. Such a system is useful in many fields and places: parking lots, private and public entrances, border control, theft and vandalism control, etc. The first application has to classify region-of-interest (ROI) in two classes: vehicles or background. Vehicles are localized in an image with 2D or 3D bounding box [2], [3]. The second one can use geometric models in addition to classify vehicles in some categories such sedans, minivans or SUV. These 2D or 3D geometric models are

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defined by deformable or parametric vehicle templates [4, 5, 6].

Instead, most systems either detect (classify vehicle or background) or classify vehicles in broad categories such as cars, buses, heavy goods vehicles (HGVs) etc. [12, 13, 14, 15, 16, 17]. Kato et. al. [12] propose a vehicle detection and classification method based on the multi-clustered modified quadratic discriminate function (MC-MQDF) that is reported to exhibit high levels of detection of a range of vehicle types against road environment backgrounds.

Until recently, vehicle type identification was limited to identifying one of a small set of generic categories, such as a sedan, or a truck [7, 8, 9, 10]. This limitation was removed by Petrovic and Cootes in [11], where the specific vehicle make and model was identified. In that work, a particular region of the car (the front) is used for identification. This region is normalized to a fixed size, and various features capturing the image structure are calculated from it and form a feature vector. Moreover, for this kind of representation, a vector of appearance of great dimension is often necessary, which makes the algorithms of classification used very greedy in memory and computing times.

This paper addresses the identification problem of a vehicle type from a vehicle grayscale frontal image which is a part from a combined system including a plate number reader (Figure 1). The input of the system is an unknown vehicle class that the system has to determine from a data base.

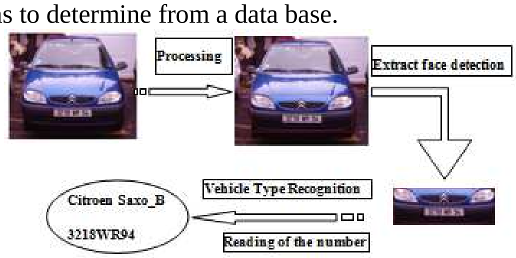

Figure 1.Example of combined system of plate number reader andvehicle type recognition.

In this paper, a multiclass recognition system is developed using a frontal view to identify the instance as the most similar model class in the database. Then, the classification will be based on a several geometrical parameters which have a relation between the width of the plate and the width and the height opposite a vehicle (sizes) (Figure 3). These parameters are differential of a vehicle to another. Each parameter has a different rate of identification, Moreover; we propose the fusion between those parameters make it possible to increase the rates of identification.

Recognition is initiated through an algorithm that locates a reference segment on the object, in this case the front number plate. The location and scale of this segment is used as reference to define a region of interest in the image from which the structure is sampled. A number of feature extraction algorithms that perform this task, including Neural Networks for classification and identification system are investigated. Different system configurations are tested on a realistic data set of over 1000 images and show that this approach achieves very high levels of both identification and verification performance.

In section 2, we explain how we define a model for every class in the data base using several geometrical parameters. In section 3, we describe the geometrical parameters for the identification of the different classes of vehicle. The Neural Networks configuration is detailed in section 4. Experimental results of our proposed system will be presented in the section 5 and we finish with our conclusion.

2. MULTICLASS VEHICLE DATABASES

The scope and complexity of the recognition problem considered in this paper is exemplified by the extensive database of car images, illustrated in figure 2, with 1000 images ordered into 12 distinct models and 9 classes, such as Renault Clio A class, Ford Escort, Peugeot 306 etc. In our experiments, 105 images are used for registration (training) and 890 for evaluation of the proposed system. Otherwise one example-per-class registration set. This approach is considered as more testing for the recognition process compared to using several examples of each class displaying more variation in lighting and pose.

The images in the dataset were obtained over a period of two months and exhibit a variety of weather and lighting conditions. Most are outdoor; although a proportion (10%) were captured in a multi-storey car park and exhibit extreme lighting conditions.

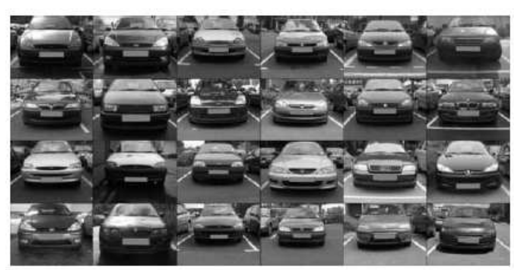

Figure 2: Examples from the data set of frontal car images.

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All contain frontal views of a single vehicle (with no occlusion) captured from varying distance and a height of approximately 1.2 m. However, the camera was not fixed and there is significant variation in both the scale and in-plane rotation of the vehicle in the images. In particular, the horizontal axis is within a range of +− 5 degrees of the image horizontal. The images are 640x480 color pixels; although the proposed system considers only grey level intensities produced using a weighted sum of the color channels.

The recognition system proposed in this paper is based on the principle of locating, extracting and recognizing normalized structure samples taken from a reference image patch on the front of the vehicle, structure Figure 3.

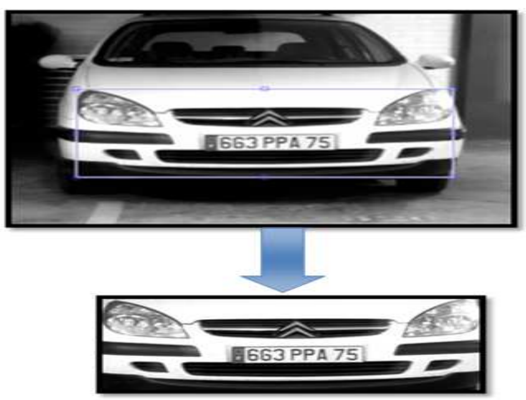

Figure 3.Cut the face of the vehicle of image using the localization of the number plate [1].

We describe now, how to build a model for each prototype of vehicle. Our base of knowledge is made up of 12 models and 9 classes of vehicles. The all database was labeled in order to detect that vehicle which is not partially hidden, only on the vehicles which are in direct link with the vehicle equipped with a camera (potentially dangerous and close vehicle).
The problem is that we have to choose the method of extraction on a basis of images taken for vehicle parking, with the same catch of sight and various lightings. For that, we use our system which localizes the coordinates of the number plate [1].

Table 1: Various models and classes of vehicles type.

Models		Classes
Opel	**Op_Corsa_A (1)**	**4**
	Op_Astra_A (2)	
Mercedes	**Me_200 (1)**	**5**
	Me_250 (2)	
	Me_SLK_A (3)	**5**
FORD	**Fo_Escort_B(1)**	**7**
Honda	**Ho_Pony (1)**	**8**
RENAULT	**Re_Clio_A(1)**	**2**
	Re__Re_Espace_A(2)	**5**
	Re_5_A(3)	
	Re_Clio_C(4)	**9**
	Re_Espace_B(5)	
Mazda	**Ma_2 (1)**	**4**

For each type of vehicle (table 1), we will determine a model single and representative of its class from all the images of vehicles of this type. Indeed, a type is represented in the Base by N prototype. This quantity varies from one type to another. For each type, we take a test on each prototype among N prototype. The creation of the model for the classes is illustrated by the figure 4.

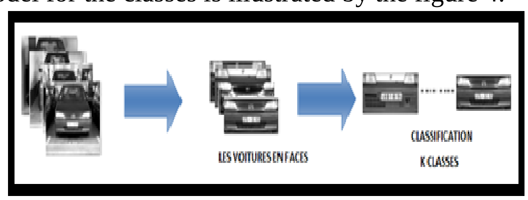

Figure 4.Creation of the different models from the vehicles.

In order to reduce confusion between the models, we introduce a construction on several floors. Also in our construction, we will classify the various cars in several classes and each class is made up of several models (table 1).

3. GEOMETRICAL FEATURES EXTRACTION

Feature extraction from the Region of Interest provides a structure representation used to recognize the object. The system proposed in this paper is based on the principle of locating, extracting and recognizing normalized structure samples taken from a reference image patch on the front of the vehicle (figure 5). The process starts with locating a reference segment on the object (in this case number-plate) and defining a Face Detection relative to it. The Face Detection is processed by the feature extraction element to define a normalized sample of the structure within it. The structure is expressed in a feature vector of pre-defined length that is representative for the vehicle identity. Finally, simple nearest neighbour classification is used to determine the vehicle type associated with each vector.

The location and scale of a reference structure on the object defines a reference frame for the region of interest to be sampled. A RoI defined relative to

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the number-plate is thus independent on the actual location and scale of the vehicle in the image.

Number-plates are highly regular rectangles. To locate them, our system finds all possible righ-angle corners using suitably tuned, separable gradient filters. A hierarchical algorithm for aggregation of corner points into valid rectangular constellations is used to generate hypotheses for the plate location in the image. A number of scale and aspect constraints are used to remove unsuitable candidates, many caused by the characters on the plate and regular vehicle structure features, and of the remaining candidates the one with best corner structure fit to each of its corners is chosen. RoI is defined in terms of number plate width wp relative to its center, as shown on Figure 5.

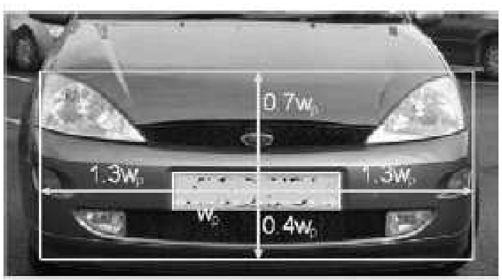

Figure 5.Region of Interest defined relative to vehicle number plate.

The identification consists in associating an example known as of test with a type of the dictionary of the classes. The identification by class is done compared to the geometrical results of the three parameters deduced from figure 5 and 6:

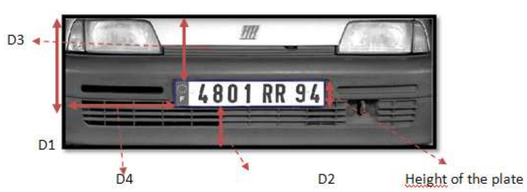

Figure 6. Measures for the different geometrical parameters.

a) The first parameter represents the distance between the beginning of the framework and the beginning of the plate compared to the height of the plate (upwards): D2/height of the plate.

b) The second parameter represents the distance between the beginning of the framework and the beginning of the plate compared to the height of the plate (from top to bottom): D3/height.

c) The third parameter represents the distance between the beginning of the framework and the beginning of the plate compared to the height of the plate (of left in right-hand side): D4/height.

Therefore, if one of parameter is not in arranges or hidden, our system permits to eliminate the parameters that are not in the interval and to identify the type of vehicle by the other parameters.

A. *Analyzing of the first parameter*

We applied our algorithm to several of the examples of the Base. The first parameter identifies correctly like average of rate of identification 92% of the images; what corresponds to the rate of identification which identifies different the type of vehicle.

Table 2 shows the geometrical variation of parameter D2 compared to the height of the plate. It shows also the variation of the rate of identification according to the number of class of work. It is about a compromise between a percentage of correct classifications high and an acceptable computing time.

Table 2: Evolution of the identification rate according of the various classes base on the first geometric parameter.

Parameter1 - Ratio D2/height			
	Models	**D2/height**	**Identification rate**
class 1	**Opel (1)(2)**	2,00690	**92,00%**
class 2	**Mercedes(1)(2)**	2,34760	**89,67%**
class 3	**FORD (1)**	2,49640	**86,67%**
class 4	**Honda (1)**	2,51305	**91,43%**
class 5	**RENAULT(2)(3)**	2,57780	**90,00%**
class 6	**RENAULT (1)**	2,71690	**86,67%**
class 7	**Mazda (1)**	2,74385	**91,67%**
class 8	**Mercedes(3)(**	2,90480	**88,67%**
class 9	**RENAULT(4)(5)**	3,11810	**90,00%**

Figure 7 gives the error in rates of identification which obtained after a study on all classes.

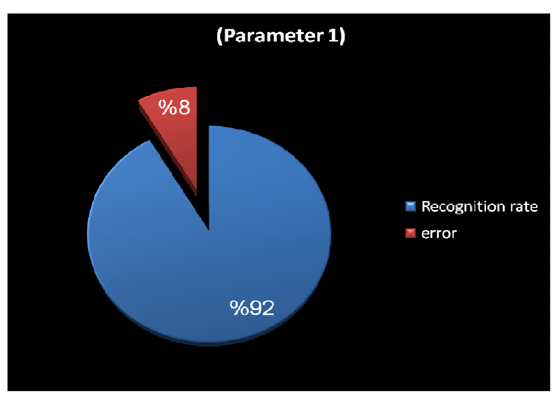

Figure 7.The rate of identification and the error of the first geometrical parameter.

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B. Analyzing of the second parameter

We applied our algorithm to several of the examples of the Base. The second parameter identifies correctly like average of rate of identification 95% of the images; what corresponds to the rate of identification, which identifies different the type of vehicle.

Table 3 shows the geometrical variation of parameter D3 compared to the height of the plate. It shows also the variation of the rate of identification according to the number of class of work. It is about a compromise between a percentage of correct classifications high and an acceptable computing time.

Table 3: Evolution of the identification rate according of the various classes based on the second geometric parameter.

Parameter2 - Ratio D3/height			
	Models	**D3/height**	**identification rate**
class 1	**Opel (1)(2)**	2,93965	95,00%
class 2	**FORD(1)**	3,13795	93,33%
class 3	**Mercedes(1)(2)**	3,39040	93,33%
class 4	**RENAULT(2)**	3,42210	94,67%
	RENAULT(3)	3,53550	
class 5	**RENAULT (1)**	3,75470	92,67%
class 6	**Honda (1)**	3,82700	90,00%
class 7	**RENAULT(4)(5)**	3,89150	96,67%
class 8	**Mazda (1)**	3,94770	93,33%
class 9	**Mercedes(3)**	4,10855	93,33%

Figure 8 gives the error in rates of identification which obtained after a study on all classes.

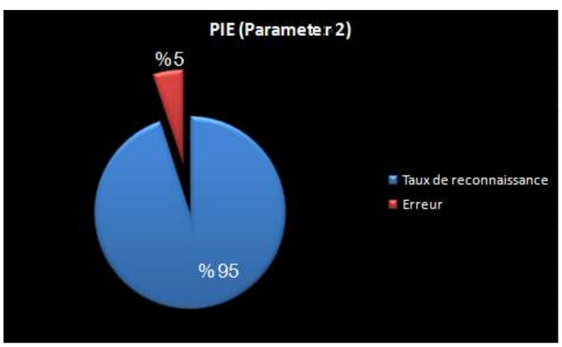

Figure 8.The rate of identification and the error of the second geometrical parameter.

C. Analyzing of the third parameter

We applied our algorithm to several of the examples from the Database. The third parameter identifies correctly like average of rate of identification 84% of the images; which identifies almost type of the vehicle.

Table 4 shows the geometrical variation of parameter D4 compared to the height of the plate. It shows also the variation of the rate of identification according to the number of class of work. It is about a compromise between a percentage of correct classifications high and an acceptable computing time.

Table 4: Evolution of the identification rate according of the various classes based on the third geometric parameter.

Parameter3 - Ratio D4/height			
	Models	**D4/height**	**identification rate**
class 1	**Opel (1)**	3,65495	**96,67%**
class 2	**Mazda (1)**	3,71660	**70,00%**
class 3	**Mercedes(1)**	3,96640	**96,67%**
class 4	**Honda (1)**	4,34120	**83,33%**
class 5	**RENAULT(3)**	4,39910	**80,00%**
class 6	**RENAULT(4)(1)**	4,52780	**86,50%**
class 7	**Mercedes(3)**	4,92435	**87,78%**
	Mercedes(2)	4,93715	
	RENAULT(5)	4,92435	
class 8	**Opel (2)**	5,17305	**73,33%**
class 9	**RENAULT(2)**	5,19080	**76,33%**

Figure 9 gives the error in rates of identification which obtained after a study on all classes.

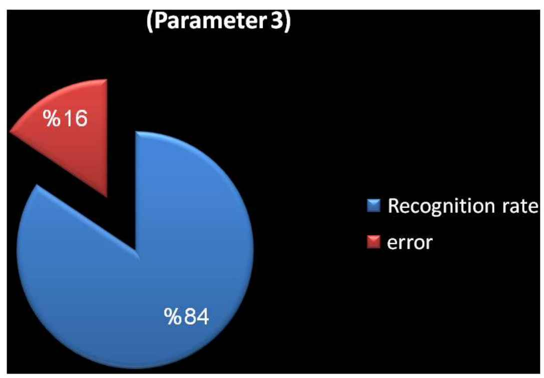

Figure 9.The rate of identification and the error of the third geometrical parameter.

4. NEURAL NETWORKS APPROACH

Artificial Neural Network or ANN resembles the human brain in learning through training and data storage. The ANN is created and trained through a given input/ target data training pattern. It is

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generally difficult to incorporate prior knowledge into a neural network; therefore the network can only be as accurate as the data which is used to train the network.

4-A) General Architecture

We introduce in the general architecture a Neural Networks which is capable after a training phase to classify the type of vehicle. As input of the neural network, we introduce the three geometric parameters extracted from the image (Figure 7).

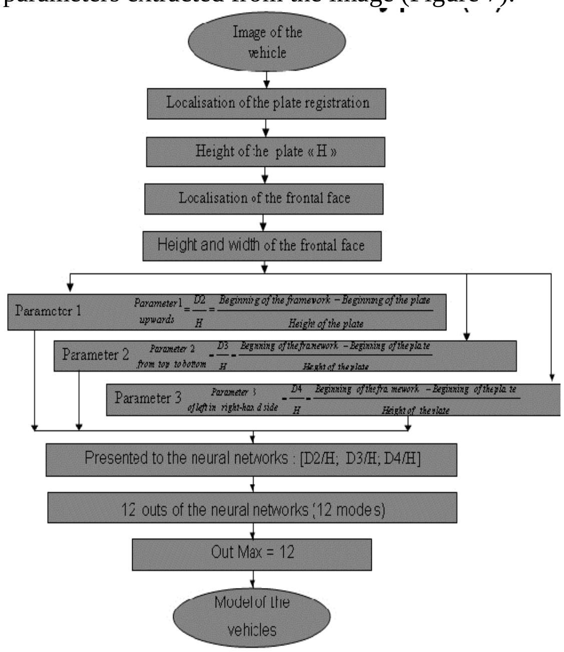

Figure 7.Algorithm of extraction of the different geometrical parameters from a vehicle image and the final decision using the MLP Neural Networks.

A phase of normalization of the input data is necessary (table 5). A linear mapping of the geometrical parameter is performed to cover the range of the Hyperbolic Tangent Sigmoid function. The inputs are then de-correlated by shifting the zero and normalizing so that the mean of the input values and the standard deviation becomes 0.1 and 0.9 respectively.

Table 5: Normalization of the three geometrical parameters.

Parameter1 - Ratio D2/height			
	Models	D2/height	Normalized
class 1	Opel (1)(2)	**2,00690**	0,100
class 2	Mercedes(1)(2)	**2,34760**	0,345
class 3	FORD (1)	**2,49640**	0,452
class 4	Honda (1)	**2,51305**	0,464
class 5	RENAULT(2)(3)	**2,57780**	0,511
class 6	RENAULT (1)	**2,71690**	0,611
class 7	Mazda (1)	**2,74385**	0,631
class 8	**CITROEN(2)**	**2,90480**	0.746
class 9	**RENAULT(4)(5)**	**3,11810**	0.900

Parameter2 - Ratio D3/height			
	Models	D3/height	Normalized
class 1	**Opel (1)(2)**	2,93965	0,100
class 2	**FORD(1)**	3,13795	0,236
class 3	**Mercedes(1)(2)**	3,39040	0,408
class 4	**RENAULT(2)**	3,42210	0,430
	RENAULT(3)	3,53550	0,508
class 5	**RENAULT (1)**	**3,75470**	0,658
class 6	**Honda (1)**	3,82700	0,707
class 7	**RENAULT(4)(5)**	3,89150	0,751
class 8	**Mazda (1)**	**3,94770**	0,790
class 9	**Mercedes(3)**	**4,10855**	0,900

Parameter3 - Ratio D4/height			
	Models	D4/height	Normalized
class 1	**Opel (1)**	3,65495	0,100
class 2	**Mazda (1)**	3,71660	0,132
class 3	**Mercedes(1)**	3,96640	0,262
class 4	**Honda (1)**	4,34120	0.457
class 5	**RENAULT(3)**	4,39910	0.488
class 6	**RENAULT(4)(1)**	4,52780	0,555
class 7	**Mercedes(3)**	**4,92435**	0,761
	Mercedes(2)	**4,93715**	0,768
	RENAULT(5)	**4,92435**	0,761
class 8	**Opel (2)**	**5,17305**	0,891
class 9	**RENAULT(2)**	**5,19080**	0,900

4-B) Training Phase

To choose the number of neurons in the hidden layer, network performance was tested using a varying number from 5 to 250 neurons. Results obtained in terms of speed and errors are presented in table 6. The obtained results show that 150 neurons is the optimum choice to be used in the hidden layer, reporting low validation and test errors. As for the output layer, it consists of 9 neurons, representing each of the 9 classes of the database.

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Table 6: Network performance in function of number of neurons in the hidden layer.

Number of neurons	Training time	Epochs	Train error	Validation error	Test error
5	3.4	57	0.8123	0.782	0.7748
10	3.3	38	0.4925	0.561	0.4799
15	5.6	79	0.0511	0.164	0.1353
20	2.0	19	0.3976	0.498	0.4277
30	8.1	83	0.0100	0.057	0.0902
40	12.4	111	0.0100	0.092	0.0944
50	9.2	73	0.0099	0.087	0.0837
100	9.1	40	0.0098	0.109	0.0658
150	**12.7**	**31**	**0.0096**	**0.055**	**0.0678**
200	237.7	292	0.0177	0.101	0.0841
250	49.3	27	0.1412	0.195	0.1859

Weights and biases are initialized according to the Nguyen-Widrow initialization algorithm which distributes the values randomly within the active region of each neuron in the layer. In order to ensure convergence within a reasonable time, an appropriate learning rate is to be chosen. Experimental results reported that a rate of 0.1 corresponds to the fastest convergence with the same performance for other criterions such as epochs, train error, validation error end test error.

During the learning process [6], the neural network output is compared with the target value and a network weight correction via a learning algorithm is performed in such a way to minimize an error function between the two values.

The mean-squared error (MSE) is a commonly used error function which tries to minimize the average error between the network's output and the target value. And the training is successfully done as shown in Figure 8.

A thousand images (Nine classes) of the type of vehicles train the network and they were enough to give very good results in verification.

Batch training is selected as the training method instead of online training, since the later would favor the minimization of the errors for the classes that have more training patterns. As for the transfer function, differentiable transfer functions in both layers have to be chosen. The performance of the network was tested for different configurations of the *tansig* and log-sigmoid functions for both hidden and output layers. It has been found that choosing *tansig* for the hidden layer and *logsig* for the output layer would be the optimal choice. Cross-validation was used to prevent over-fitting.

After optimizing all the parameters of the network, final architecture is obtained and summarized in table 7.

Table 7: Final configuration of the network: It contains all the information related to the design of the Neural Network. Nine classes of the type are used for training the network.

Number of inputs	3
Number of neurons Hidden Layer	150
Number of neurons Output layer	9
Number of Layers	2
Initial weights	Nguyen-Widrow
Learning rate	0.1
Weight update schema	Batch training
Transfer function first layer	Hyperbolic tangent
Transfer function second layer	Logarithmic sigmoid
Early stopping	Implemented with cross validation, 10 fails allowed
Error function	Mean squared error
Goal	0.0001
Max epochs	1000
Learning method	Levenberg-Marquardt
Momentum Constant	Default
Number of patterns for original classes of the type of vehicles	20
Number of tested of vehicles	180

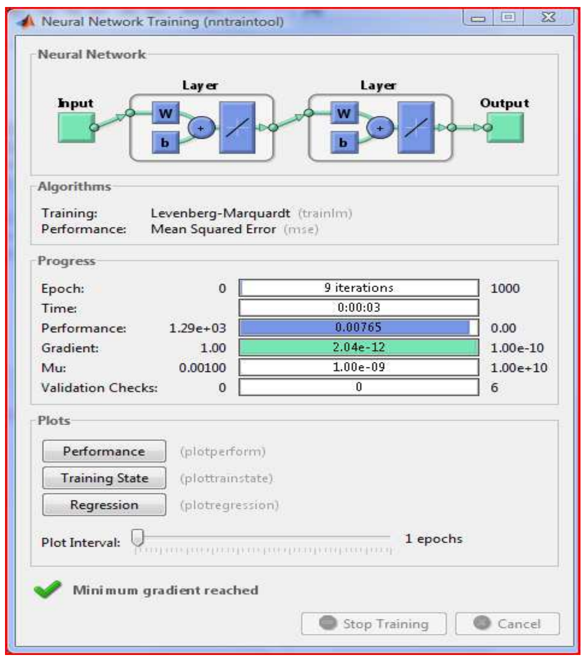

Figure 8.Neural Network Training via Matlab.

4-C) Recognition Performance

The system has been tested for its accuracy and effectiveness on a database of about 10 vehicles from 9 users. All the samples of our database were

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preprocessed and the global features were extracted out. After the detection of face of the car and the determination of the coordinates of the plate, we determine the 3 parameters to recognize the type of vehicle.

Figure 9.The face of one test image.

By realization, one classifies the parameters according to the strategy:

Rate of identification parameter 1: D2/height	Rate of identification parameter 2: D3/height	Rate of identification parameter 3: D4/height
92%	95%	96.67%

Then, compared to the various tests carried out we obtain as result that the type of car is 95% CITROEN. The figure 10 shows the variation of rate of identification of this kind of vehicle according to the different parameters.

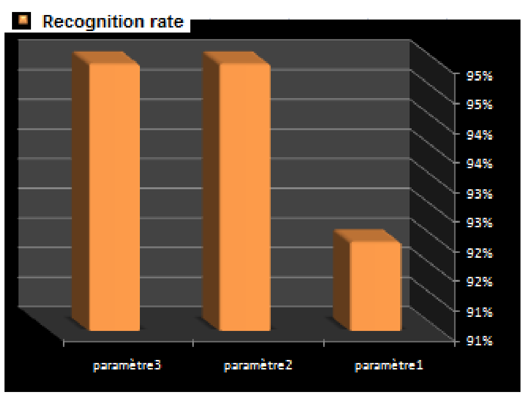

Figure 10.The variation of geometric parameters: first parameter gives 95% OPEL, the second 96.67% OPEL and the third 92% OPEL.

The fusion of the three classifiers using a neural network trained, allows showing the effectiveness of our process for the identification of the type of vehicle.

The data base of about 90 vehicles was tested. The precision of the identification of the type of the vehicle can be expressed by two types of error (FIR and FRR) for a one class chosen (Ci):

False Identification Ratio (FIR): The false identification ratio is given by the number of fake recognition (identified as class Ci) made on the group of image not among the class chosen (Ĉi) identified by the system with respect to the total number of comparisons made.

False Rejection Ratio (FRR): The false rejection ratio is the total number of fake identification for the group of the chosen class (Ci) rejected by the system with respect to the total number of comparisons made.

Both FIR and FRR depend on the threshold variance parameter taken to decide the genuineness of an image. If we choose a high threshold variance then the FRR is reduced, but at the same time the FIR also increases. If we choose a low threshold variance then the FIR is reduced, but at the same time the FRR also increases.

We obtain taking a threshold of 90% a FIR of 1.6% and a FRR of 3%.

The network was tested and it was capable of classifying the type of vehicle of the taken database and a classification ratio of about 97% was obtained. And the minimized error percentages constitute an additional factor for the success of the verification system.

A number of incorrectly recognized vehicles (SM grads) from both datasets are shown in Figure 11. The main modes of failure in the "Parking Lot" data, top row, include severe in-plane rotation and poor lighting conditions. The latter is also a source of errors with "Access Control" data, bottom row, along with severe out-of-plane rotation.

Figure 11:Recognition failures with feature extraction.

5. CONCLUSION

Neural networks have demonstrated their success in many applications due to their ability to solve some problems with relative ease of use and the model-free property they enjoy. One of the main features, which can be attributed to ANN, is its ability to learn nonlinear problem offline with selective training, which can lead to sufficiently accurate response.

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This paper presents an investigation into various feature extraction techniques in a rigid structure approach to automatic recognition of vehicle types. It was shown that a set of geometrical parameters.are capable of accurate and reliable recognition of vehicles from frontal views under a variety of conditions.

This article presented an identification system for an application of identification multi-classes of the type of vehicle based on geometrical parameters using neural network.

Our system of classification makes it possible to distinguish several models from vehicle increasing the rate of identification by 2%.. Our algorithm identifies correctly like average of rate of identification 95% of the 1000 images, which corresponds to the average of the individual rates of identification (for each class).

We obtain taking a threshold of 90% a FIR of 1.6% and a FRR of 3%.

The network was tested and it was capable of classifying the type of vehicle of the taken database and a classification ratio of about 97% was obtained. And the minimized error percentages constitute an additional factor for the success of the verification system.

Further work will be oriented to reduce the influence of the images number used in the model creation process. We propose extending the system to deal with a wider range of viewpoints and in plane rotations as well recognition of more general classes of objects.

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