

Vehicle Authentication from Digital Image Measurements

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Abstract- In this work, it is demonstrated that relatively simple image processing functions based on symmetry measurements can be used to obtain high performance vehicle authentication, creating an “image signature” for every vehicle. On that basis, distinctive parts of the vehicle frontal view such as the headlights and the logo area can be segmented. A novel neural network application, properly trained, provides adequate vehicle manufacturer recognition when used in conjunction with a previously developed license plate recognition module. It is also shown that image processing functions based on Scale Invariant Feature Transform (SIFT) measurements can be used to obtain high performance object features location, creating a keypoint fingerprint for every feature. A grid of SIFT keypoints was drawn and a neural network was used also for vehicle model recognition.

I. Introduction

Vehicle classification in general categories is a task that has been adequately addressed in the literature ([1],[2],[3],[4]). In this paper, a novel system is reported, whose aim is to obtain reliable authentication of a vehicle image from many possible vehicle models using a car model and make database in conjunction with a previously developed license plate recognition module using special image processing techniques [5]. Similar approaches related with vehicle model identification have been published previously with encouraging results. Glandenkov and Belongie [6] utilized Scale Invariant Feature Transform (SIFT) features recently developed by Lowe [7], [8] which are invariant to scale, rotation and even partially invariant to illumination differences, making them suitable for MMR. Petrovic and Cootes [9] presented an interesting approach for vehicle model recognition and verification that displays the best results in respective tasks. Merler [10] presents a car detection system based on color segmentation and labelling, which performs color recognition, but lacks full MMR.

The authentication method proposed in this paper was based on locating the license plate in the vehicle image and defining a characteristic Region of Interest (RoI) in its frontal view. The RoI was processed using image processing routines to provide information concerning segmentation of the vehicle logo, vehicle color and measuring SIFT [7] keypoint vehicle fingerprint. Vehicle manufacturer and vehicle model were estimated using a properly trained Probabilistic Neural Network. The system consists mainly of five modules: 1) Vehicle License Plate Recognition & Segmentation, 2) Color Recognition, 3) Vehicle Manufacturer Recognition, 4) Vehicle Fingerprint Measurement and 5) Vehicle Model Recognition and Color Recognition.

II. Vehicle Make and Model Recognition (MMR)

A. Vehicle License Plate Recognition and Segmentation

Vehicle image is first pre-processed, intensity-equalised and scaled to a 640 x 480 pixel size. Then Licence Place Recognition (LPR) module was applied. LPR uses a Sliding Concentric Window (SCW) segmentation method, Anagnostopoulos et al. [11], masking, binarization with Sauvola method [12], and followed by connected component labelling and binary measurements, which are arranged in sequence. The dimensions of the rectangular RoI (“car mask”) are defined as: $L = 4 \times l$ and $W = 2 \times w$ where L , W are the length and width of the vehicle “mask” and l , w are the length and width of the segmented license plate as shown in Figure 2. We should note, however, that this assumption doesn't hold for cars having non-symmetric frontal license plate placement. In such a case, we rely solely on the total car image symmetry axis location as shown in our previous work [13] and Sun [14].

After the equalisation of the vehicle mask, the distinctive features are identified. In this work, we have implemented a method that is based on phase congruency calculation, Kovessi [15] which is a dimensionless measure to assess the existence of significant features. Values of phase congruency vary from a minimum of zero (indicating no significance) up to 1 (indicating a very significant feature). We used the code provided by Kovessi [15], including the default values proposed in his study and measured a characteristic feature curve for every image, as an “image signature” of the vehicle, which is unique and representative for each of the samples used, see Figure 1. For instance, using the car image of Figure 1(c), the plot was divided in discrete sections that correspond to logo (part A), radiator grille (part B) and headlights (parts C and D) as shown in Figure 2. A comparative knowledge acquisition system, consisting of several object recognition modules for the rear view of vehicles appears in Maemoto et al. [16]. The most important part of the “image signature” is the central region of the vehicle mask, where the manufacturer logo usually appears.

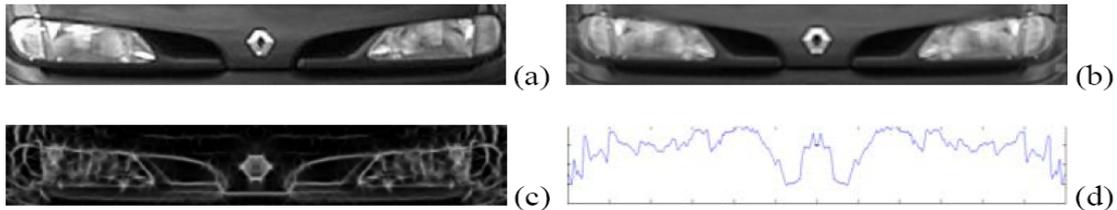


Figure 1. (a) Vehicle “mask” before equalization. The left part of the image is brighter due to sun reflections, (b) after illumination equalization, (c) phase congruency feature map, (d) image signature: horizontal projection of (c)

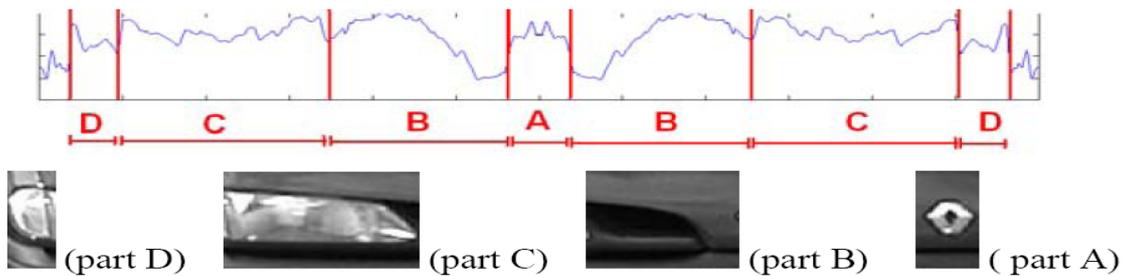


Figure 2. Image signature and vehicle mask segmentation based on phase congruency map gradient threshold.

B. Vehicle Color Recognition

The captured vehicle image is cropped in an area that is over the vehicle mask and covering the bonnet of the vehicle. In order to estimate the vehicle's color we create histograms of the R, G, B components from the segmented bonnet image. Then the peak of each histogram (R_{max} , G_{max} , B_{max}) forms the dominant ROI color. The estimated dominant RGB value was then compared with a given set of 16 standard colors by using the Euclidean metric distance, resulting in a color characterization for the input vehicle image.

C. Vehicle Manufacturer Recognition

A Probabilistic Neural Network (PNN), see Specht [17], was used for classification of the vehicle manufacturer (logo). It is a special type of neural network, which is generally used for the purpose of pattern classification and its goal is to classify an input pattern into one of the predefined classes that were previously presented and trained to by supervised training. The NN is first presented with samples of each pattern that it will be expected to recognize. The PNN learns these classes and calculates the probability that the unknown input pattern is of the same class. The greatest advantage for using a PNN is training and classification speed. Training a PNN actually consists of copying training classes into the network, that is fast and straightforward making it appropriate for real time image processing applications. A disadvantage of PNN is the big network size: the PNN network actually contains the entire set of training cases which is memory expensive and computationally hard but memory size and computer speed become bigger and faster, respectively, every year.

Experimental Part I.

We have used the license plate location information so as to crop the mask of the car, as shown in Figure 1. From a vehicle image database, 110 vehicle images have been selected. We have divided the image set into 11 distinct classes (10 different manufacturers and one 'unknown'). The vehicle license plate was located and the plate number was retrieved for every image. Using the position and dimension of licence plates, then the car mask was segmented. Next, the car manufacturer (logo) area was segmented using the phase congruency calculation, as shown in Figure 2. In order to classify the vehicle manufacturers from the vehicle images, a series of runs for the PNN have been performed, in two phases: a) Training Phase and b) Recognition Phase. PNN was implemented by using code developed in MATLAB.

Training Phase

In the Training Phase, the PNN was fed with sets of classes that represents each car model recognition pattern. Ten classes of car models were tested plus one class for the unknown car model. For every class five sample classes are provided as a training set. The training sample classes are shown in Table 1. The PNN input vector size is $m * n$ pixel values, directly taken from segmented logo image converted to an one-dimensional array. We have tested four different network ($m*n$) resolutions: 25 by 25, 50 by 50, 100 by 100 and 200 by 200 respectively, with 11 classes x 5 samples/class and the total net size (array elements) was : $m*n*55$. We had tried different runs varying the value of spread, σ , from 0.0 to 5.0 and we found that optimum recognition rate was achieved at $\sigma = 0.9$. A Pentium IV at 2.0 GHz was used for the simulations. The PNN setup time versus network size is shown in the following Table 2.

Table 1. PNN Training Data Set

Manufacturer	Samples	Manufacturer	Samples
Alfa Romeo	5	Renault	5
Audi	5	Seat	5
Bmw	5	Toyota	5
Citroen	5	Volkswagen	5
Fiat	5	Unknown/Other	5
Peugeot	5		

Table 2. PNN Setup Time

Size	Setup Time (ms)
25*25	576
50*50	637
100*100	754
200*200	1428

Recognition Phase

During the Recognition Phase, unknown samples segmented from car masks were fed to the trained PNN and the classifier produced the results of Table 3. Ten classes of car models were tested plus one class for the unknown car model. The manufacturer recognition rate was about 87%. The speed of classification versus network size is given in Table 4.

Table 3. PNN Classification Statistics

Manufacturer	Recognition Rate		
	Correct	Mistaken	Not Recognized
Alfa Romeo	6	3	1
Audi	7	3	0
Bmw	10	0	0
Citroen	10	0	0
Fiat	9	1	0
Peugeot	7	2	1
Renault	7	2	1
Seat	9	0	1
Toyota	6	2	2
Volkswagen	9	1	0
Unknown/Other	8	2	0

Table 4. PNN Classification Time

PNN Size	Setup Time (ms)
25*25	154
50*50	221
100*100	287
200*200	793

D. Vehicle Fingerprint Measurements and Vehicle Model Recognition

In parallel to logo image segmentation, a Scale Invariant Feature Transform (SIFT) [7],[8] was applied to a series of vehicle images. SIFT is the state-of-the-art in the field of image recognition and the method of choice for a wide range of applications. It is based on the idea of representing images by a set of descriptors based on gradient orientation histograms. The points of interest (key-points) were located as local peaks in a scale-space search and filtered to preserve only those that are likely to remain stable over transformations. SIFT keypoint descriptor has the following properties : a) Smooth changes in location, orientation and scale do not cause radical changes in the feature vector. b) It is fairly compact, expressing the patch of pixels using a 128 element vector. c) It is resilient to perspective deformations such as those caused by perspective effects and thus be efficient for vehicle recognition in non-controlled conditions. SIFT methodology is also evidenced from vision research in biological systems. In brief, SIFT includes four main steps:

1. Scale-space peak selection: The first stage of computation searches over all scales and image locations to identify interest points that are invariant to scale and orientation. The scale-space $L(x,y,\sigma)$ is defined as the convolution operation of image $I(x,y)$ with a Gaussian kernel $G(x,y,\sigma)$. This is implemented efficiently by constructing a Gaussian pyramid and searching for local peaks (keypoints) in a series of difference-of-Gaussian (DoG) images [7]. The image $I(x, y)$ is blurred progressively with a series of values of $\sigma' = r\sigma$, then the difference between neighboring Gaussian blurred images is calculated. The difference of Gaussian images are then checked for local extrema: A point is considered a minimum or a maximum, if it is by a given threshold higher or lower than its twenty-six neighbors in the difference of Gaussian space.
2. Keypoint localization: At each candidate location, a detailed model is fit to determine location, scale, and contrast. Keypoints are selected based on their stability and were filtered rejecting points with low contrast and those lying along edges [7].
3. Orientation assignment: One or more orientations are assigned to each keypoint based on local image properties. The dominant orientations for each keypoint were identified, based on its local image patch. Gradients are weighted by their distances from the feature point location and ordered in a circular histogram of 36 bins that cover 10 degrees each. The bin with the most points is selected, and the exact orientation is calculated from a parabola fitted to this peak and its 3 closest neighbors. The assigned orientation(s), scale and location for each keypoint enables SIFT to construct a canonical view for the keypoint that is invariant to similarity transforms.
4. Keypoint Descriptor: The local image gradients are measured at a neighborhood region around each keypoint (patch) and transformed into a representation that allows for local shape distortion and change in illumination. This patch has been previously centered about the keypoint's location, rotated on the basis of its dominant orientation and scaled to the appropriate size. The keypoint descriptor is created by sampling the magnitudes and orientations of the image gradient in the patch around the keypoint, and building smoothed orientation histograms to capture the important aspects of the patch. A [4 x 4] array of histograms, each with 8 orientation bins, captures the rough spatial structure of the patch. This 128-element vector [4x4x8] is then normalized to unit length and thresholded to remove elements with small values.

Experimental Part II

For each database image a grid was drawn, see Figure 3 and a set of SIFT descriptors were calculated following the procedure described above. The keypoints then were filtered and selected such that it is only one keypoint per cell. In the case that inside a cell there is no keypoint found, a null keypoint is set with its descriptor calculated at the centre of this cell, exactly as if it was a real keypoint. In such a way all the training images were transformed to a fixed set of 16x9 128-bit descriptors. A Probabilistic Neural Network (PNN) similar to that used in our previous work for logo recognition [13] was trained from these database image descriptors. In the recognition phase, the PNN was fed with descriptors created by exactly the same procedure from query images and the PNN gives the maximum matching probability with a database class. We have used a single car manufacturer database set of images (Volkswagen) and we had tried to recognise the model (make) from the query image as the one which matches best with the database one. The results are shown in Table 5.

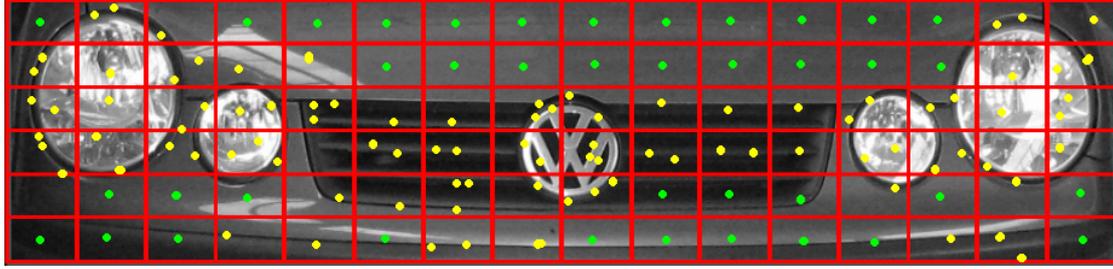


Figure 3 Vehicle mask grid (16 x 6) (real keypoints are in yellow, null keypoints are in green)

Table 5. Model Classification Statistics for a fixed manufacturer (Volkswagen)

Volkswagen (VW) Model	Correct	Model Recognition Rate	
		Mistaken	Not Recognized as VW
Polo II (1990-1994)	4	3	3
Polo III (1994-2000)	6	2	2
Polo IV (2000-2005)	4	4	2
Golf III (1991-1997)	5	3	2
Golf IV (1997-2003)	7	2	1
Golf V (2003-2006)	5	2	3
Bora (1999-2006)	7	2	1
Passat IV (1993-1996)	5	3	2
Passat V (1996-2005)	6	3	1
New Beetle (1998-2005)	4	3	3
Unknown	6	4	0
Total	59 [54%]	31 [28%]	20 [18%]

We should note here, following the results, that the neural network method is not very appropriate for classification and recognition since the true recognition rate was almost 54%. The false recognition rate was 28 % for the query images and moreover, 18% of the query images were not recognized as VW. One possible reason is, that in general the keypoints were not supposed to be uniformly distributed, and also by filtering them so as to have one keypoint per cell, this reduces dramatically the possible matches and hence the true detection rate. In a non-filtered image we can have many keypoints located very near to each another and areas without keypoints at all.

On the other hand, this method is much faster than a conventional nearest neighbour one, since the PNN gives almost an immediate response (less than 1 sec). We are currently working on developing a nearest neighbour technique which gives already some promising preliminary results and there is an active ongoing research in this area.

III. Conclusions

The system demonstrated good performance when applied to a vehicle database in conjunction with a license plate recognition module. In this database, 110 vehicle images were processed with the license plate recognition module and their registration number was identified. Using the plate location, a template for the “image signature” for each captured vehicle has been archived into the database in advance and related with the plate registration number. We digitally modify the original images, switching the registration numbers and forward the modified images to the system. Based on the vehicle license plate, the respective template image was retrieved from the database and then compared to the one acquired during the simulation. A probabilistic neural network is assessed as a classifier for vehicle manufacturer and model recognition. This research was done by using a small set of vehicle models and manufacturers. A similar approach is recently presented in Lee [18] where a 3-layer multi-layered perceptron was used for vehicle model recognition. Moreover, in the original images, the logo section of the vehicle mask was successfully segmented and the car was identified with a good rate. To further improve our performance in classification rates, we actually need to combine several techniques. This involves extending the system to deal with a wider range of viewpoints and in plane rotations as well recognition on more complex scenes and under a wider variety of illumination conditions.

IV. References

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