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Vehicle model recognition using geometry and appearance of car emblems from rear view images

D. F. Llorca, D. Colás, I. G. Daza, I. Parra, M. A. Sotelo

***Abstract*— In this paper a novel vehicle model recognition approach is presented modelling the geometry and appearance of car emblems (model, trim level, etc.) from rear view images. The proposed system is assisted by LPR and VMR modules. Thus, a generic methodology is defined to build a hierarchical structure of car-make-dependent vehicle model classifiers. The emblems location, size and variations are firstly learnt. Then, the appearance of each badge is modelled using a linear SVM binary classifier with HOG features and the outputs of each individual classifier are converted to an estimate of posterior probabilities. A specific probability is computed for each hypothesis (model) integrating the posterior probabilities of all the emblems using the geometric mean. Inference about the most probable car model is finally carried out selecting the model with the maximum probability. We evaluate this approach on a dataset composed of 1.342 images (910/432 for training/test) corresponding to 8 different car makes and 28 different car models (52 considering generations) achieving an overall accuracy of 93.75%.**

***Index Terms*— Vehicle model recognition, emblems, badges, geometry and appearance, HOG, SVM.**

I. INTRODUCTION

Any car enthusiast is able to recognise the make, model and even the year of a car from an arbitrary viewpoint. Actually, any person can perform this recognition task after some training period. However, as stated in [1], to date no computer vision system can mimic this ability. Car model identification is a challenging task due to the amount of car models, including different car manufactures and models depending on the year. In addition, they have large untextured regions and their appearance is often dominated by environmental reflections and highlight lines. On top of that, in some cases the visual differences between some models of a specific manufacturer are almost inappreciable.

Although automatic vehicle model detection is a still unresolved task, the need for a full vehicle identification approach is getting more relevant due to the increased demand for effectiveness and security. Current traffic surveillance applications, speed and access control platforms, automatic tollgate systems, etc., rely on the use of License Plate Recognition (LPR) systems that provide a unique and weak identifier for each detected vehicle: the license plate. A more detailed description of the different parameters of the vehicle would enhance current vehicle identification systems. Besides the license plate [2], vehicle colour [3], plate colour [4], car make [5], [6], and finally, the car model [7], are representative variables of the vehicles. The automatic detection of these variables will open a new horizon of possibilities such as avoiding improper fines to drivers due to LPR errors, detecting fake license plates and suspicious vehicles, ensuring proper toll rates in tollgate systems, etc.

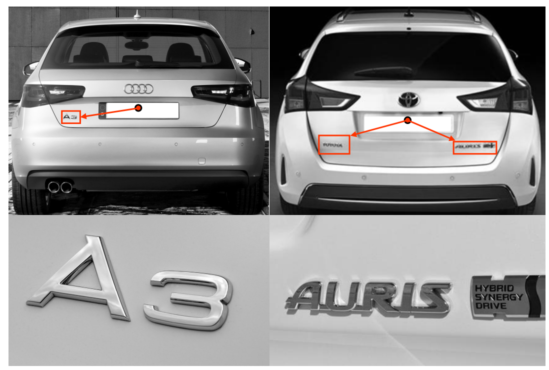

Fig. 1. Vehicle rear emblems representative of the car model. Geometry is defined w.r.t. the license plate.

Most of the work in recognising the exact model of a car involves the simultaneous classification of vehicle manufacturer and model, i.e., Vehicle Manufacturer and Model Recognition (VMMR). Although the reported performance of theses approaches is considerable good, the number of car makes and models used in the experiments is somehow limited. A more realistic approach consists in firstly recognising the car manufacturer [6] and then apply a specific classifier ensemble to select the model. Thus, a more tractable solution can be provided to deal with vehicle model recognition. However, even if the complexity of the multi-classification problem is reduced by independently covering only the models for a specific car manufacturer, the question about what features are more discriminative when learning each car model remains open.

Our paper aims to provide a novel VMMR approach by learning the geometry and the appearance of car emblems (model, trim level, etc.) from rear view images. Rear car emblems provide a valuable source of information related with the model. Their location, size, text and font are specifically defined for each model (see Fig. 1). The geometry of the rear emblems (location and size) is independently learnt for each model. Then, a set of binary discriminative SVM classifiers using HOG features are applied to model the appearance of emblems for each model. Inference is finally carried out by approximating the posterior probability for each model hypothesis using the geometric mean of the posterior probability of all binary classifiers corresponding to that

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TABLE I
SUMMARY OF PREVIOUS WORK.

Ref. Year	Single Class Make-Model	View	Features	Classifier	# samples	# classes	Accuracy
[8], 2004	Yes	Front	Square Mapped Graphs	Nearest Neighbour	1132	77	93%
[9], 2005	Yes	Front	Canny edges	Nearest Neighbour	180	5	97%
[10], 2006	Yes	Front	Texture descriptors	Neural Networks	415	24	94%
[11], 2008	Yes	Front	Oriented contours	Nearest Neighbour	830	50	90%
[12], 2009	Yes	3D free	SIFT	Features matching	≈ 400	36	90%
[13], 2009	Yes	Front	Contourlet transform	SVM	300	25	90%
[7], 2011	No	Front	SIFT	Neural Networks	90	10	54%
[14], 2011	Yes	Front	Harris corners	Naive Bayes	262	74	96%
[15], 2012	No	Rear	Shape context descriptors	Nearest Neighbour	≈ 400	10	70%
[16], 2013	No	Front	DCT, GLCM	SVM	1096	12	97%
[17], 2013	Yes	Front	Square Mapped Graphs	Nearest Neighbour	1000	27	93%
[1], 2014	Yes	3D free	3D curves	3D curve matching	190	8	87%
[18], 2014	Yes	Front	SURF, HOG	SVM	6936	29	98%
Our approach, 2014	No	Rear emblems	HOG	set of linSVM	1342	52	94%

model. The hypothesis providing the maximum probability will be selected as the most probable model.

II. PREVIOUS WORK

Vehicle manufacturer and model have been usually considered as a single class recognition problem. The most relevant contribution was presented in 2004 by Petrovic and Cootes [8]. This work defined the baseline and the methodology for later works. Using frontal images of vehicles, a Region of Interest (ROI) is defined relative to the license plate location. A canonical or reference view is obtained transforming the original images using the limits of the license plate. A set of features are then extracted from the ROI and a nearest neighbour classifier is used as discriminative mechanism. The gradient representation using square mapped graphs without PCA provided a 93% recognition rate using 1.132 images from 77 distinct models.

This structure has been replicated in several works using different features and machine learning approaches. Thus, features such as Canny edges [9], texture descriptors [10], oriented contour points [11], Contourlet transform [13], SIFT features [7], Harris corners [14], shape context descriptors [15], DCT and GLCM [16], SURF and HOG [18] have been used. Considering the machine learning approach, nearest neighbour classifiers [9], [11], [17], neural networks [10], [7], Naive Bayes [14] and SVM [13], [16] have been proposed. Other approaches make use of 3D models [12], [1] to perform vehicle model recognition.

The lack of public and standardised databases has moved researchers to use their own dataset. Accordingly, it is very complicated to establish a performance comparison between the different approaches. In Table I we provide a summary of previous works -including our approach- with details related with vehicle view, features, classifier ensemble, number of samples, number of classes and recognition performance. We pose the problem as a within category object class recognition as in [7] and [15]. A previously developed car make detection approach [6] by means of logo recognition using low resolution images is used here to select a specific intra-manufacturer model classifier ensemble. As a clear contribution we translate the model recognition problem into an emblems classification approach, including their geometry and appearance. Although the rear car emblems are regions defined w.r.t. the license plate as in previous approaches, their number, location, and size is not fixed for all the models. Accordingly, a new generic methodology is needed. Our proposal adapts the main concepts of deformable part-based object detection (implicit shape models, constellation models, DPM, etc.) defining each object class by a set of regions, their appearance and their spatial relations.

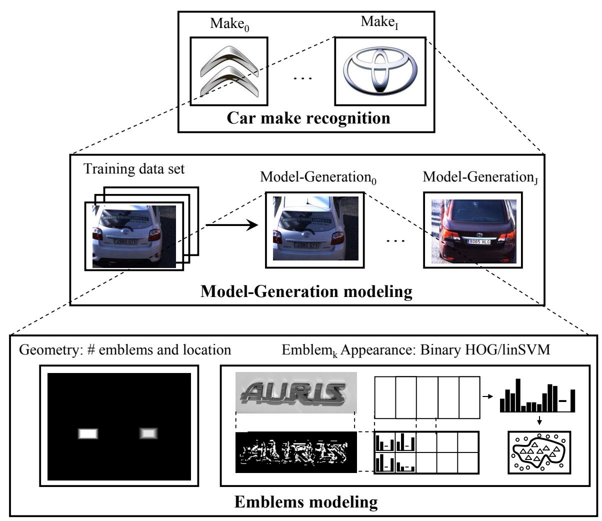


Fig. 2. Overall system layout.

III. SYSTEM DESCRIPTION

A. System Layout

The overall system layout is depicted in Fig. 2. The approach is divided into three different levels. First, a car logo recognition system [6] provides the car make. Model recognition [1] is then carried out within the context of a specific car make, i.e., models from other car manufacturers

[1]Note that by model we mean model and generation which are defined according to the geometry and appearance of rear emblems.

are not considered. A model-generation is defined by the geometry and the appearance of the rear car emblems. Lets consider a car make i and a model-generation j. The geometry model involves the number of emblems $\{NE^i_j\}$, the mean position and size $\{x^{i,j}_k, y^{i,j}_k, w^{i,j}_k, h^{i,j}_k\}$ and the corresponding standard deviation $\{\sigma x^{i,j}_k, \sigma y^{i,j}_k, \sigma w^{i,j}_k, \sigma h^{i,j}_k\}$. These values will be used to define a set of regions around the mean location for each rear emblem to obtain multiple samples from a single image. Appearance is modelled using HOG features and linSVM classifiers. The set of regions will be fed to the classifier increasing the number of training and test samples and obtaining an enhanced representation of the local appearance for each emblem. A similar approach was successfully applied by the authors in the context of logo [6], pedestrian [19], [20] and pavement [21] recognition.

B. Image Normalisation

License plate is firstly recognised in all images by using a LPR system previously developed by our research group. Thus we can use the four corners of the license plate to normalise the scale, rotation and skew of the license plate and hence vehicle rear and emblems location. Images can be mapped to canonical positions using planar homography allowing full $8-$DOF. However, as remarked by [14], a more stable mapping is obtained by restricting the corners of the license plate to be on a parallelogram and performing a $6-$DOF affine mapping. Fig. 3 depicts a sequence of images corresponding to the same vehicle and the result after applying affine transformation.

This normalisation procedure provides accurate results for the region of the license plate. However, the location of the emblems slightly varies since the rear part of the vehicles does not strictly follows the assumption of being at the same plane of the license plate. Accordingly, the recognition problem can be seen as a deformable part-based object recognition problem such as implicit shape models, constellation models, DPM, etc. However, these approaches are not directly applied here since we manage a multi-classification problem in which each class is defined by a different number of regions, with different sizes, and a local appearance that cannot be easily recovered using bag of features.

Fig. 3. Image normalisation example. Upper row: original images. Lower row: results after affine mapping.

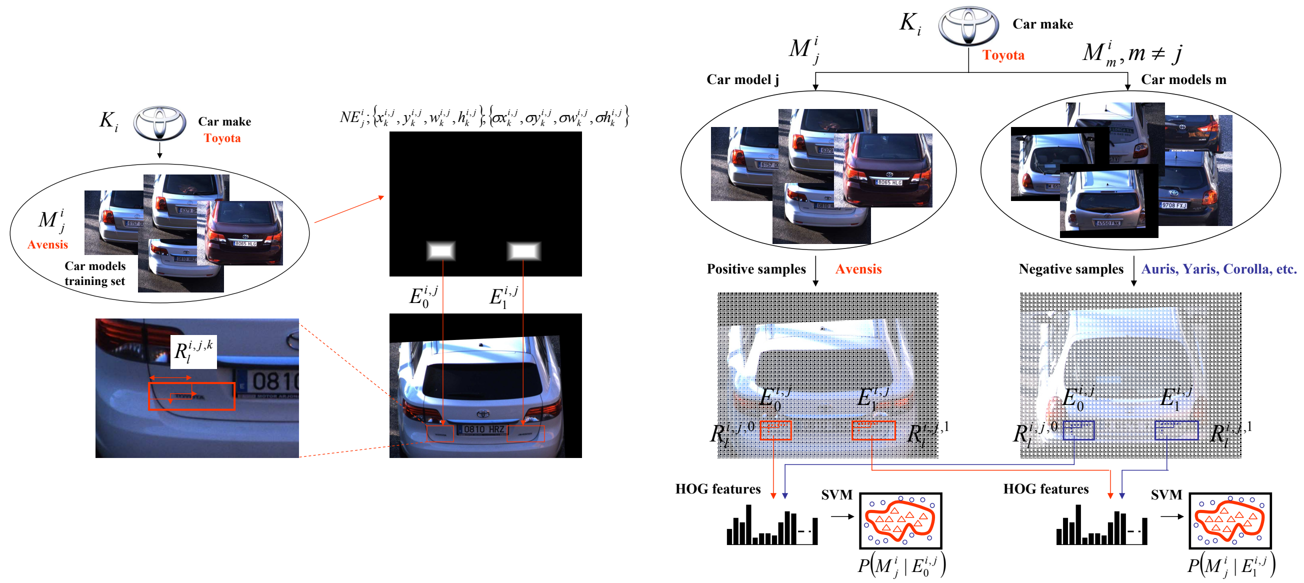
C. Learning Rear Emblems

For vehicle model-generation recognition, we use the set of rear emblems that characterise the specific model considering all the possible models for a specific car manufacturer. Let K_i denote the i-th car manufacturer, with $i = 1, \ldots, T$, being T the number of car makes, and N_i be the number of models for the i-th car make. Let M^i_j denote the j-th model of i-th car make, with $j = 1, \ldots, N_i$, and NE^i_j be the number of emblems corresponding to j-th model and i-th car manufacturer. Given a specific model j from a car make i, $E^{i,j}_k$ denote the k-th rear emblem, with $k = 1 \ldots NE^i_j$, and $NR^{i,j}_k$ denote the number of regions extracted from the average location of emblem $E^{i,j}_k$ using the geometry model (mean position and size and standard deviations). Finally, $R^{i,j,k}_l$ denote the l-th region corresponding to k-th emblem of j-th model and i-th make, with $l = 1, \ldots, NR^{i,j}_k$.

The distribution, location and number of regions $R^{i,j,k}$ for each rear emblem $E^{i,j}_k$ are defined by learning the specific geometry model using a training data set (see Fig. 4(a). The mean position and size, and the corresponding standard deviations for a specific rear emblem $E^{i,j}_k$ are used to define an oversized region of interest that bounds the average location of that emblem. Within the context of this region, a sliding window approach is used to get the set of regions that will be finally fed to the classifier. Different steps are computed for the x- and y-image positions and the *width* of the region. The *height* of each region is automatically computed by using a fixed aspect ratio obtained when learning the geometry model. As an extension of the example depicted in Fig. 4(a), this process is triggered for all the models-generations M^i_j of all the vehicle manufacturers K_i.

The appearance of the emblems is modelled using a HOG descriptor [22]. Fine scale gradients are used ((-1,0,1) masks with smoothing), fine orientation binning (8 bins) and 2×2 blocks of either 8×8 pixels cell. Then, overlapping blocks contrast normalisation (L_2-norm) is applied. Each concatenated feature vector dimension will vary depending on the emblem $E^{i,j}_k$. In order to assure the same feature dimension all the regions $R^{i,j,k}_l$ maintain the same aspect ratio. Thus, we can resize them to a reference region from which the final distribution of cells/blocks can be defined.

In order to learn the HOG feature vector space of each emblem, a discriminative approach is proposed by means of linear SVM [23]. As can be observed in Fig. 4(b) we use the normalised images from the model M^i_j to obtain the positive samples, and the normalised images from the rest of the models $M^i_m, m \neq j$ of the same car manufacturer K_i to obtain the negative samples. Note that we do not include negative samples from other car makes $K_m, m \neq i$, since the proposed approach provides itself much more negatives than positives, i.e., positives correspond to one specific model-generation whereas negatives correspond to the rest of models-generation of the same car manufacturer.



(a) (b)

Fig. 4. Learning rear emblems examples: (a) geometry model and (b) appearance model.

D. Inference

Given a sample image I from which we already know the license plate position and the car make K_i by means of logo recognition [6], we firstly transform the image into a reference view following the normalisation procedure described in Section III-B. Then, the model recognition problem is translated into a multi-class recognition problem considering all the possible models and generations M_j^i, with $j = 1,\ldots,N_i$, of the specific car make K_i. Let $P(M_j^i|I)$ denote the posterior probability estimate for class M_j^i given the image I and the car make i. We make a Bayesian decision and assign image I to the class with highest posterior probability:

$$M^i_{model} = arg\,max_{M_j^i} P(M_j^i|I) \tag{1}$$

As depicted in Fig. 4(b), the discriminative approach is built using a set of binary classifiers that represents each emblem $E_k^{i,j}$. Let $E^{i,j} = \{E_0^{i,j},\ldots,E_{NE_j^i}^{i,j}\}$ denote the vector of emblems for the j-th model of i-th car make. We represent the posterior probability $P(M_j^i|I)$ as the posterior probability of class model M_j^i given its emblems $E^{i,j}$, i.e., $P(M_j^i|E^{i,j})$. We assume that all individual classifier responses are independent. Then, this posterior probability is approximated by using the geometric mean of the posterior probabilities of each one of the emblems for a specific class model M_j^i:

$$P(M_j^i|E^{i,j}) \approx \sqrt[NE_j^i]{\prod_{k=1}^{k=NE_j^i} P(M_j^i|E_k^{i,j})} \tag{2}$$

This approximation is mainly considered here due to its simplicity and efficiency when assembling different posterior probabilities that represents different feature vector spaces with different dimensions [24]. In addition, this way of computing a global score is independent from the number of emblems and thereby comparable across different hypotheses [25].

Following the same procedure, we approximate the posterior probability for an emblem $E_k^{i,j}$, by combining all the posterior probabilities (SVM outputs) of each one of the regions $R_l^{i,j,k}$ of k-th emblem of j-th model of i-th make, taking their geometric mean:

$$P(M_j^i|E_k^{i,j}) \approx \sqrt[NR_k^{i,j}]{\prod_{l=1}^{l=NR_k^{i,j}} P(M_j^i|R_l^{i,j,k})} \tag{3}$$

Finally, in order to estimate the posterior probability of a model class M_j^i given a region $R_l^{i,j,k}$ (defined according to the geometric model) we convert the SVM decision value $f_{SVM}(p_{R_l^{i,j,k}})$ (distance to the hyperplane) to a posterior probability using a sigmoidal mapping or logistic function with parameters A and B learned from the training set by maximum-likelihood [26]:

$$P(M_j^i|R_l^{i,j,k}) \approx \frac{1}{1+exp(A\cdot f_{SVM}(p_{R_l^{i,j,k}})+B)} \tag{4}$$

By solving Eqs. (4), (3) and (2) for all the possible car models M_j^i corresponding to a vehicle manufacturer K_i previously recognised [6], and evaluating Eq. (1) we finally obtain the model class with highest probability for one specific image sample I.

IV. EXPERIMENTS

A. Experimental Setup

The presented approach has been tested using real world traffic images regarding VMMR recognition performance. A digital camera with a resolution of 1280×960 pixels and a

TABLE II

NUMBER OF MODELS-GENERATION AND TRAINING/TEST SAMPLES FOR EACH VEHICLE MANUFACTURER.

Car Make	# Models-Generation	# training/test samples
Citröen	8	170 / 78
Peugeot	5	99 / 47
Ford	7	127 / 59
Opel	9	117 / 60
Renault	10	162 / 70
Seat	7	144 / 74
Toyota	2	30 / 13
Volskwagen	4	61 / 31
TOTAL	**52**	**910 / 432**

variable focal length of 10-50mm was placed at one road bridge pointing to one specific lane from which vehicles are driving away. The focal length is fixed to maximise the size of the rear part of each vehicle projected into the image plane, assuring that large vehicles are totally visible. The images were captured in one day under different lighting conditions (from sunny to cloudy). The sequences comprise a total of 1.342 images corresponding to 8 different car makes and 28 different car models (52 considering generations). The number of models-generation and training/test samples for each vehicle manufacturer are depicted in Table II. An approximate ratio of $2/3$ of the samples for training (910) and $1/3$ for test (432) has been used, assuring that test samples correspond to vehicles not appearing in the training dataset.

In order to only evaluate the performance of the proposed approach to deal with vehicle model recognition, both logo (car manufacturer) and license plate locations (parallelogram) are manually marked. Thus, the logo recognition errors and the license plate location inaccuracies do not affect the evaluated performance.

B. *Classification Performance*

The evaluation of the proposed inference approach is carried out separately on each car manufacturer test data set. Results are given in Tables III-X. Each Table depicts the model-generation identifier and years, the number of emblems (SVM models) of each one of the models, and the accuracy. An overall accuracy of 93.75% is obtained. Most of the errors provided by the system are mainly due to classes with similar geometry and appearance. In addition, we can expect lower accuracy in real conditions due to errors in the car make recognition system, which can be considered as a critical error, and errors in the license plate location system, which will produce inaccurate normalisation transformations. This global analysis is out of the scope of this paper.

V. CONCLUSION

In this paper we have proposed a novel approach to deal with vehicle model recognition by modelling the rear emblems that are very representative of the vehicle model. The problem is translated into a multi-classification problem within the context of one specific vehicle manufacturer (a previously developed logo recognition system [6] provides

TABLE III

CITRÖEN RESULTS.

Models-Generation	# Emblems/SVM	Accuracy
C2_I (2003-2009)	2	9/9 (100.00%)
C3_I (2002-2010)	2	12/12 (100.00%)
C4_Ia (2004-2010)	2	4/4 (100.00%)
C4_Ib (2004-2010)	2	8/8 (100.00%)
C4_II (2010-2014)	2	4/4 (100.00%)
SAXO_I (1996-2003)	2	9/9 (100.00%)
XSARA_I (1997-2003)	2	7/7 (100.00%)
XSARA_II (1999-2010)	2	25/25 (100.00%)
TOTAL	**16**	**78/78 (100.00%)**

TABLE IV

PEUGEOT RESULTS.

Models-Generation	# Emblems/SVM	Accuracy
206_I (1998-2011)	2	16/16 (100.00%)
207_Ia (2006-2012)	2	8/9 (88.89%)
306_I (1993-2001)	2	9/10 (90.00%)
307_Ia (2000-2007)	2	6/6 (100.00%)
307_Ib (2000-2007)	2	6/6 (100.00%)
TOTAL	**10**	**45/47 (95.74%)**

TABLE V

FORD RESULTS.

Models-Generation	# Emblems/SVM	Accuracy
Fiesta_III (2002-2008)	1	1/9 (11.11%)
Focus_C-MAX_I (2003-2010)	2	9/9 (100.00%)
Focus_I (1998-2004)	1	7/7 (100.00%)
Focus_II (2004-2009)	1	12/12 (100.00%)
Mondeo_I (1993-2000)	1	5/5 (100.00%)
Mondeo_IIa (2000-2007)	1	15/15 (100.00%)
Mondeo_III (2007-2013)	2	2/2 (100.00%)
TOTAL	**9**	**51/59 (86.44%)**

TABLE VI

OPEL RESULTS.

Models-Generation	# Emblems/SVM	Accuracy
Astra_II (1998-2004)	1	7/7 (100.00%)
Astra_III (2004-2010)	2	11/11 (100.00%)
Astra_IV (2010-2014)	1	9/9 (100.00%)
Corsa_II (2000-2006)	2	3/3 (100.00%)
Corsa_III (2006-2014)	2	7/7 (100.00%)
Vectra_II (1995-2002)	2	4/4 (100.00%)
Vectra_IIIa (2002-2008)	2	6/6 (100.00%)
Zafira_I (1999-2005)	2	9/9 (100.00%)
Zafira_II (2005-2010)	1	4/4 (100.00%)
TOTAL	**15**	**60/60 (100.00%)**

TABLE VII

RENAULT RESULTS.

Models-Generation	# Emblems/SVM	Accuracy
Clio_II (1998-2005)	1	8/8 (100.00%)
Clio_III (2005-2010)	2	4/4 (100.00%)
Clio_IV (2010-2014)	2	5/5 (100.00%)
Laguna_IIa (2000-2008)	1	4/4 (90.00%)
Megane_Ia (1995-2002)	2	0/4 (0.00%)
Megane_II (2002-2008)	1	14/14 (100.00%)
Megane_III (2008-2014)	1	11/11 (100.00%)
Scenic_I (1996-2003)	2	7/7 (100.00%)
Scenic_II (2003-2009)	1	8/8 (100.00%)
Scenic_III (2009-2014)	2	5/5 (100.00%)
TOTAL	**15**	**66/70 (94.29%)**

TABLE VIII

SEAT RESULTS.

Models-Generation	# Emblems/SVM	Accuracy
Altea_XL_I (2006-2008)	1	2/10 (20.00%)
Altea_XL_II (2009-2014)	1	3/3 (100.00%)
Cordoba_IIa (1999-2009)	2	6/6 (100.00%)
Ibiza_II (1996-2006)	2	18/19 (94.74%)
Ibiza_III (2003-2014)	1	20/20 (100.00%)
Leon_I (1999-2005)	2	0/4 (0.00%)
Leon_II (2003-2014)	1	12/12 (100.00%)
TOTAL	**10**	**61/74 (82.43%)**

TABLE IX

TOYOTA RESULTS.

Models-Generation	# Emblems/SVM	Accuracy
Auris_I (2007-2013)	2	9/9 (100.00%)
Avensis_II (2003-2014)	2	4/4 (100.00%)
TOTAL	**4**	**13/13 (100.00%)**

this estimate). Each vehicle model is represented by the geometry (number of emblems, location and size) and the local appearance (HOG/linSVM) of each one of the rear emblems. A specific probability is computed for each hypothesis (model) by integrating the posterior probabilities (SVM outputs) of all the emblems using the geometric mean. Inference about the most probable car model is finally addressed selecting the model with the maximum probability. We obtain an overall accuracy of 93.75% which clearly validates the discriminative power of the proposed combination of geometry and appearance of emblems to deal with vehicle model recognition.

Future works are mainly conceived to extend the training and test dataset, including new samples captured from different locations, and a higher number of models and vehicle manufacturers.

VI. ACKNOWLEDGMENTS

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TABLE X

VOLKSWAGEN RESULTS.

Models-Generation	# Emblems/SVM	Accuracy
Golf_II (1997-2003)	2	7/7 (100.00%)
Golf_III (2003-2014)	2	8/8 (100.00%)
Passat_II (1996-2005)	2	3/3 (100.00%)
Passat_IIIa (2005-2010)	2	13/13 (100.00%)
TOTAL	**8**	**31/31 (100.00%)**

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