Front. Electr. Electron. Eng. China 2010, 5(1): 77–84
DOI 10.1007/s11460-009-0072-4

RESEARCH ARTICLE

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Size-self-adaptive recognition method of vehicle manufacturer logos based on feature extraction and SVM classifier

Abstract Besides their decorative purposes, vehicle manufacturer logos can provide rich information for vehicle verification and classification in many applications such as security and information retrieval. However, unlike the license plate, which is designed for identification purposes, vehicle manufacturer logos are mainly designed for decorative purposes such that they might lack discriminative features themselves. Moreover, in practical applications, the vehicle manufacturer logos captured by a fixed camera vary in size. For these reasons, detection and recognition of vehicle manufacturer logos are very challenging but crucial problems to tackle. In this paper, based on preparatory works on logo localization and image segmentation, we propose a size-self-adaptive method to recognize vehicle manufacturer logos based on feature extraction and support vector machine (SVM) classifier. The experimental results demonstrate that the proposed method is more effective and robust in dealing with the recognition problem of vehicle logos in different sizes. Moreover, it has a good performance both in preciseness and speed.

Keywords vehicle manufacturer logo recognition, feature extraction, support vector machine (SVM), size-self-adaptive

1 Introduction

Vehicle manufacturer logos can contain important information about the vehicles besides their decorative purpose. A vehicle logo can provide not only the identity of the manufacturer, but also the information for vehicle verification, identification, and recognition. For example, a manufacturer logo of a certain type of vehicle appears in a fixed location. It could indicate a problem if the logo appears at a wrong location. Association of a manufacturer logo with a license plate can be used for vehicle verification. Manufacturer logos can also be used as an index to search a vehicle, e.g., we can search for “a red Toyota sedan” or “a black Ford SUV”. Both “Toyota” and “Ford” can be identified from their manufacturer logos. Therefore, detection and recognition of vehicle manufacturer logos have many potential applications. However, unlike the license plate, which is designed for identification purposes, vehicle manufacturer logos are mainly designed for decorative purposes and hence they may be embedded into surrounding objects or have low contrast against the background, as shown in Fig. 1. From a detection and recognition point of view, the differences between a license plate and a manufacturer logo are as follows:

1) While all license plates are installed in the specified locations (e.g., in the central part of the front and/or back of a vehicle), locations of vehicle logos can differ between manufacturers. For example, as shown in Fig. 1(a), Mercedes Benz logo is almost separated from the main body of the car with the windshield glass as its background, which creates a great challenge for detection and recognition. The vehicle logo in Fig. 1(b) is surrounded by the grille while the vehicle logo in Fig. 1(c) is embedded into the body.

2) While the shape, text, and color of license plates are standardized by the authority, a manufacturer has the freedom in designing the appearance of a logo which results in a great variation in appearances of different logos. Some logos are even very similar, e.g., a Honda logo versus a Hyundai logo, as shown in Figs. 1(d) and 1(e).

3) While it is illegal to mask or modify a license plate, the regulations on manufacturer logos are much loser. A vehicle logo can be occluded by other objects, as shown in Fig. 1(f).

4) While the content of a license plate consists of letters

Received June 25, 2009; accepted September 6, 2009

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and digits within a rectangular plane, the manufacturer logo can contain letters, digits and any symbols on complex surfaces, as shown in Figs. 1(b) and 1(c).

Moreover, in practical applications, because vehicles are moving on the road, the sizes of vehicles captured by a fixed camera are not all the same. Therefore, it is very

Fig. 1 Illustration of some challenging cases for manufacturer logo detection and recognition. (a) Separated from the body; (b) surrounded by grille; (c) embedded into body; (d) Honda logo; (e) Hyundai logo; (f) partial occlusion

difficult, if not impossible, to robustly recognize vehicle manufacturer logos in real world applications. What is worse, because of the above essential differences between a license plate and a vehicle logo, we cannot utilize the existing mature technologies of license plate recognition (LPR) to recognize vehicle logos directly. Fortunately, with the development of statistical learning theory (SLT) in recent years, it is possible to recognize vehicle manufacturer logos based on support vector machine (SVM) which is a realization of SLT. This is the classification method we propose in this paper. In addition, we adopt the strategy of block division in order to deal with the recognition problem of vehicle logos in different sizes. First, we divide the input gray logo image into some non-overlapping subregions, and extract the features of texture and edge gradient orientation respectively. Then we compute the histograms of each block respectively. Finally, we concatenate the histogram values of all the logo image regions into feature vector with uniform dimensions, which is used for the input of SVM to classify and discriminate which type this logo belongs to. The experimental results demonstrate that the proposed method is more effective and robust in dealing with the recognition problem of vehicle logos in different sizes, and moreover, it has a good performance both in preciseness and speed.

The rest of this paper is organized as follows. Section 2 presents some related works. Section 3 illustrates how to extract features of texture and edge gradient orientation of logos in different sizes to form feature vector with uniform dimensions, which is used for the input of SVM and the design of SVM classifier. Section 4 discusses experimental results. Section 5 concludes the paper.

2 Related works

Vehicle manufacturer logo detection and recognition is a relatively new research area that was just introduced in recent years, which has little previous existing work whether at home or abroad. In addition, manufacturer logos that are not designed for identification purposes might lack discriminative features themselves, so there is almost no effective algorithm available to be used in manufacturer logo detection and recognition at present, especially size-self-adaptive algorithm.

Object recognition, as one of the most important studies in computer vision and pattern recognition, has formed a series of mature technologies, and has been widely applied in the fields of intelligent transportation systems (ITSs) [1,2], security inspection [3,4], information retrieval [5], staff registration and management, manipulation [6], and object verification. Currently available methods for object recognition can be categorized based on template matching, artificial neural network (ANN) and type of SVM classifiers.

Most of the current commercial systems for object recognition are almost exclusively based on template matching and there are some successful methods [7,8]. Reference [7] proposed a novel paradigm to reconstruct face templates from match scores using a linear approach. Reference [8] presented a method to extract representative stroke templates automatically from a text image, which contains characters of the same typeface. Recognition methods based on template matching are effective for some fixed occasions where the environment can be controlled easily and where object pose and illumination are constant. However, it will become computationally infeasible when the object is mutative in scale and illumination. Moreover, when the object has regional distortion or the image is defaced, efficiency decreases significantly, accompanied by slow speed, a high miss rate and false alarm rate, which cannot satisfy the requirement of recognition.

Besides methods based on template matching, methods based on ANN are also exploited [6,9]. Reference [6] developed a virtual reality based on driving training system of self-propelled gun (SPG), which uses back propagation (BP) neural network to recognize the hand gestures that exist in the raw sensor data of the CyberGlove. Reference [9] presented an automatic target recognition (ATR) of aircrafts using translation invariant features derived from high range resolution (HRR) profiles and multilayered neural network. These methods can effectively tackle many complex nonlinear problems and have been successfully used in some engineering applications. However, there are still some important issues in ANN which are not solved in theory. In practical applications, therefore, there are still many factors that need to be determined by experience, such as how to select the number of units of hidden layers, original weight values, etc. In addition, local minima, overfitting and stopping criterion are common problems in many methods based on ANN, which have restricted the development of theories and applications of ANN to a large extent.

Fortunately, people have already done more in-depth studies in object recognition to solve these issues, such as the theories of statistical learning. Statistical learning theory is a specialized small sample statistical theory that provides a better theory frame for solving the above problems of ANN. As we all know, traditional statistical methods of pattern recognition are mostly researched under the premise of enough training samples. That is to say, the performance of these methods can be guaranteed in theory only if the number of training samples tends to infinity. In practical applications, however, the number of training samples is limited so that many methods have difficulty achieving ideal results. During the 1960s, Vapnik et al. began to research the theory of machine learning under the condition of limited training samples [10]. In the mid 1990s, Vapnik formed a matured theoretical system—statistical learning theory [10]. Based on it, one of the new methods of pattern recognition named SVM [11,12] was born. SVM projects the original data into a high dimensional feature space, where linear algebra and geometry may be used to separate data that are only separable with nonlinear rules in the input space. Since then, SVM has won a wide range of popular applications due to its attractive abilities and better performances in the fields of small samples, nonlinear and high dimensional pattern recognition compared to other traditional learning machines [13]. Thus, in order to recognize vehicle manufacturer logos accurately, we need to adopt a size-self-adaptive method that not only provides fast and precise classification of vehicle logos but also has a strong robustness. In order to achieve this goal, we adopt the recognition method based on feature extraction and SVM classifier [14,15] in this paper, which will be described in Sect. 3.

3 Size-self-adaptive recognition method of vehicle manufacturer logos

Vehicle manufacturer logo recognition is based on preparatory works on logo localization and image segmentation, which have provided a solid foundation for manufacturer logo recognition. In this paper, we focus on further vehicle manufacturer logo recognition only. Figure 2 shows the flow chart of the processing.

3.1 Size-self-adaptive method of feature extraction

As mentioned above, a manufacturer has the freedom in designing the appearance of a logo, which results in a great variation in the appearances of different logos, such as the size and the shape. Moreover, in practical applications, because vehicles are moving on the road, the sizes of vehicles captured by a fixed camera are not all the same. Therefore, based on preparatory works on logo localization and image segmentation, we obtained the logo images in different sizes. In order to make it possible that all the feature vectors extracted from different logos are comparable, we need to make uniform the dimensions of the feature vectors of all the logos in different sizes.

3.1.1 Extracting features of texture using ALBP operator

The original local binary pattern (LBP) operator has been proven to be a powerful texture descriptor [16]. However, it demands a little more time and storage space. Thus, in this paper, we adopt a more powerful and low-computation advanced local binary pattern (ALBP) operator [17] to extract the features of texture of logos. As shown in Fig. 3, the operator labels the pixels of an image with the binary thresholding result of 3×3 neighborhood of each pixel with the center value. The ALBP operator only uses the right and bottom pixels of the original LBP operator and then the histograms of the labels can be used as texture descriptor [18]. The expression of the ALBP operator is

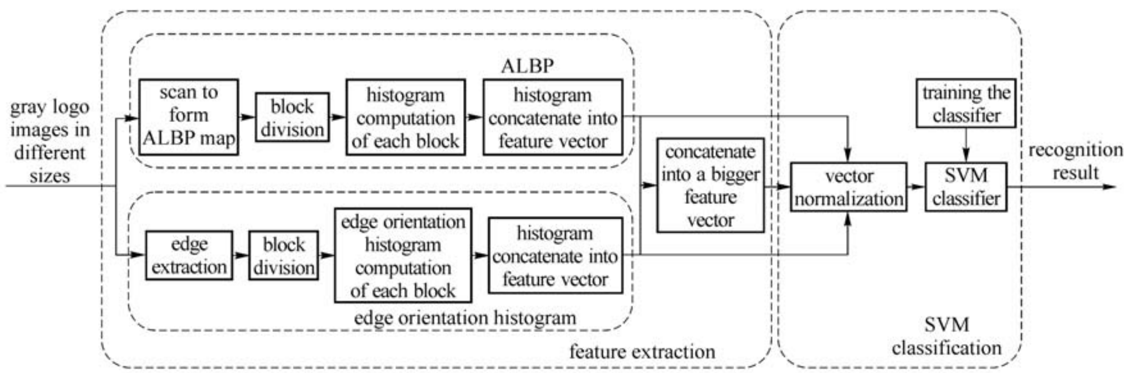

Fig. 2 Flow chart of size-self-adaptive vehicle logo recognition method based on feature extraction and SVM classifier

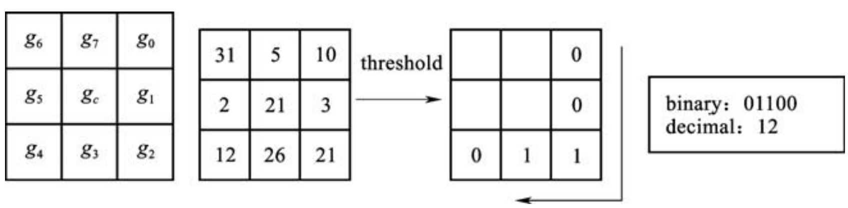

Fig. 3 Example of ALBP operator

$$\mathrm{ALBP} = \sum_{p=0}^{4} s(g_p - g_c)2^p, \tag{1}$$

where

$$s(z) = \begin{cases} 1, & z \geqslant 0, \\ 0, & z < 0. \end{cases}$$

Taking the Audi logo as an example, as shown in Fig. 4, we scan the gray logo image input with a 3×3 sub-window to get the ALBP map. Then, no matter what size it is, we divide the map into m (in this paper, we choose the value of m as 2×4) non-overlapping sub-regions, and compute the histogram for each block. Finally, we concatenate the histograms of all image regions into a feature vector, which will be used for the input of the SVM classifier to classify and discriminate which type this logo belongs to. In this paper, the dimensions of feature vector of ALBP are 256 (2×4×32).

3.1.2 Extracting features of edge orientation histogram

Like Sect. 3.1.1, after using a gray logo image as input, we extract its edge by Canny operator first. No matter what size it is, we divide the edge image into n (in this paper, we choose the value of n as 3×5) non-overlapping sub-regions, thus a sequence of sub-regions $N_0, N_1, \ldots, N_{n-1}$ are generated. After that, we compute the edge orientation histogram which is formed from the gradient orientations of each block. In the end, we concatenate the histogram value of all the logo image regions into a feature vector, which will be used for the input of the SVM classifier also. If we use c (in this paper, we choose the value of c as 8) to represent the statistical number of gradient orientations, the dimension of this feature vector is $n \times c$. Taking the Audi logo as an example also, Fig. 5 shows the flow of the feature extraction of edge gradient orientation.

Therefore, no matter what size the logo image is, and no matter whether the shape of the logo is square, rectangular or round, the dimensions in the feature vectors that will be used for the input of SVM are equal, which makes it possible that all the feature vectors extracted from logos in different sizes are comparable.

Feature vectors extracted from multiple logos under real conditions form a distribution in high dimensional space. Using SVM method and without dimensionality reduction, our system directly gives extracted feature vectors to the SVM classifier. Space is lacking for a detailed description of the basic theory introduction of SVM, but more details about the SVM classifier can be obtained from Refs. [11,12]. Here, only the design of the SVM classifier will be described in detail.

3.2 Design of SVM classifier

As we all know, SVM is a binary classification whose main idea is maximizing the margin between the classes and minimizing the classification error. Given a set of labeled training examples as

$$A = \{(x_i, y_i),\ i = 1,2,\ldots,n \mid x_i \in \mathbb{R}^d,\ y_i \in \{+1,-1\}\}, \tag{2}$$

where $\{x_i, y_i\}$ for $i = 1,2,\ldots,n$ denote the training data set, x_i represents the training data in A, y_i is the target output for the training data x_i, $y_i \in \{+1,-1\}$ is the category label. The resulting optimal function of classification can be shown as

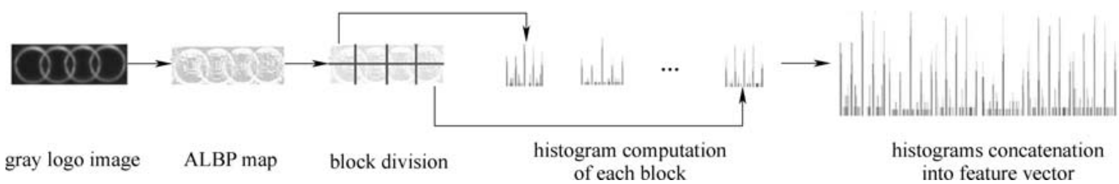

Fig. 4 Flow chart of feature extraction of ALBP

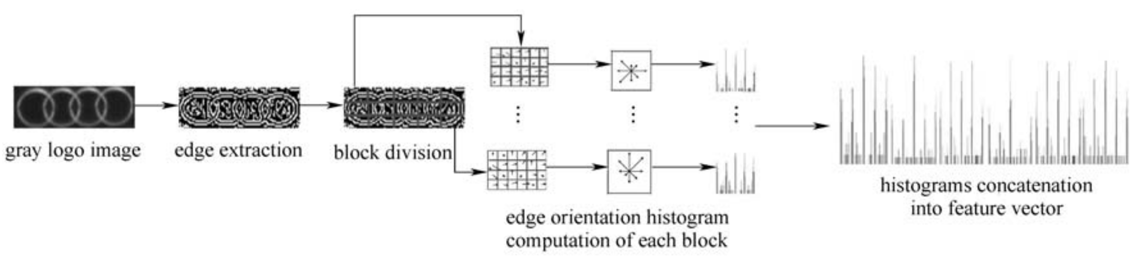

Fig. 5 Flow chart of feature extraction of edge gradient orientation

$$f(x) = \operatorname{sgn}(w^* \cdot x + b^*)$$
$$= \operatorname{sgn}\left[\sum_{i=1}^{n} \alpha_i^* y_i K(x_i,x_j) + b^*\right], \tag{3}$$

where α_i^* is the non-zero Lagrange multipliers and $K(x_i,x_j)$ is the kernel function.

However, the original SVM was designed for binary classification, thus it can only apply to the two class classification problems. How to effectively extend the original SVM classifier to multi-class classifier is still an ongoing research issue. Currently, available methods for multi-class classification are mainly in two types. One is the direct method which considers all data in one optimization formulation. This method modifies the objective function directly, combining the parameters solution of several hyperplanes into one optimization problem, by solving the optimization problem to carry out the issue of multi-class classification one-time. This approach appears to be simple, but in fact, it is difficult to achieve and only suitable for small problems due to its high computational complexity. The other is the indirect method which can be divided into the following two types: one-against-all (OAA) and one-against-one (OAO) [19]. OAA is also called one-against-rest or one-against-remaining, which constructs and combines several binary classifiers to separate one of the classes from others. k different classes of samples need k original binary SVM classifiers. OAO designs an original binary SVM classifier between random two classes of samples, and it needs $k(k–1)/2$ original binary SVM classifiers. The trait of OAA is that the boundary is always stringent with respect to each class, hence it would lead to refusal to classify in some cases.

We use OAO method to design the SVM classifier in this paper. In addition, we use a voting strategy in classification: each binary classification is considered to be a voting where votes can be cast for all the data points; in the end, point is designated to be in a class with maximum number of votes. The sketch map of the designed SVM classifier is shown in Fig. 6.

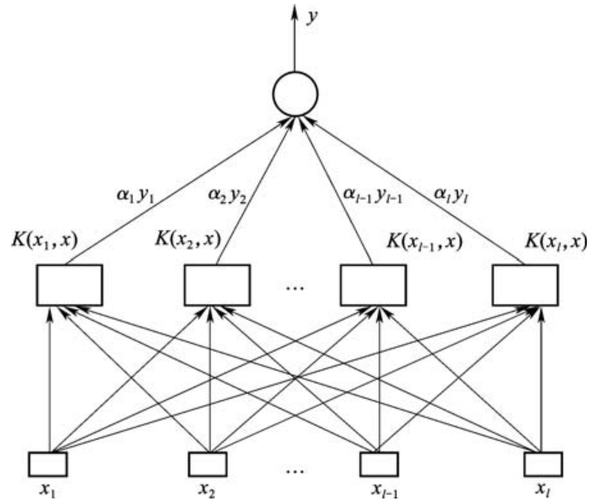

Fig. 6 Sketch map of designed SVM classifier

According to the basic theory introduction of SVM, we know that the selection of an appropriate kernel function plays a crucial role in SVM classification since the kernel function defines the feature space in which logo image data are classified. In this paper, we adopt the following several kernel functions and compare their classification results:

1) Linear kernel:

$$K(x_i,x) = (x_i \cdot x), \quad i = 1,2,...,l; \tag{4}$$

2) Polynomial kernel with degree d:

$$K(x_i,x) = [(x_i \cdot x) + 1]^d, \quad i = 1,2,...,l; \tag{5}$$

3) Gaussian radial basis function (RBF) kernel with tuning parameter σ:

$$K(x_i,x) = \exp\left(-\frac{||x_i - x||^2}{2\sigma^2}\right), \quad i = 1,2,...,l; \tag{6}$$

4) Sigmoid kernel with parameters b and θ:

$$K(x_i,x) = \tanh[b(x_i \cdot x) - \theta], \quad i = 1,2,...,l. \tag{7}$$

4 Experimental results

In order to evaluate our method, we use an image database with 1350 color vehicle images in various real life applications. It includes nine different classes (Audi, Honda, Buick, Volkswagen, Toyota, Suzuki, Xiali, Hyundai, Citroen) and each class includes 150 images (100 images are used for training set and 50 images are used for testing set). In this paper, SVM implementation was done by using a library for support vector machines (LIBSVM, http://www.csie.ntu.edu.tw/~cjlin/libsvm).

Because of the size of our data set, we perform k-fold cross-validation in the design of the SVM classifier in order to select the optimal parameters and train the effective SVM classifier. In k-fold cross-validation, all the data in the data set is divided into k subsets of equal size. SVM classifier is trained k times, each time leaving out one of the subsets from training, but using only the omitted subset to compute the accuracy of SVM classifier. This process is repeated until all the subsets have been used for both training and testing, and the computed average recognition accuracy was used as the performance measure for the designed SVM classifier.

Our experiments are divided into three parts. First, we choose optimal block divisions of ALBP and edge orientation histogram respectively. Second, we convince the validity of features we extract in this method. Third, we compare the recognition accuracy of vehicle manufacturer logos using different kernel functions.

4.1 Experiment of optimal block division of ALBP and edge orientation histogram

According to the method of feature extraction, we know that one of the most important parameters to determine the performance of the SVM classifier is method of block, which directly determines the dimension of the feature vector used for the input of the SVM classifier. Based on preparatory works on logo localization and image segmentation, the logo images we obtained in our experiments are in different sizes. In our data set, the size of the biggest logo image is 111×59 and the size of the smallest logo image is just 16×9. Taking 3×3 ALBP operator into account, we adopt the following eight ways of block. In Figs. 7 and 8, using kernel function of RBF, we draw the recognition accuracy and speed of different block ways by extracting the features of ALBP and edge orientation histogram, respectively, where the time consumption represents the total process time of 1350 images (Pentium (R) 4, CPU 2.80 GHz, 1.99 GB Memory).

From Figs. 7 and 8, we know that the more the number of block divided is, the more time it consumes. In Fig. 7, at the size 2×4 of block division point, we get the best recognition accuracy, while the time consumption can be acceptable. In Fig. 8, on one hand, the size of 2×2 blocks only reaches 89.7778% recognition accuracy, because coarseness division block results in loss of some usable gradient information; on the other hand, it is not robust in terms of logos with low-resolution and heavy noise. In a word, we need to find an appropriate division method. Taking recognition accuracy and time consumption into account, we choose 3×5 division in feature extraction of edge orientation histogram.

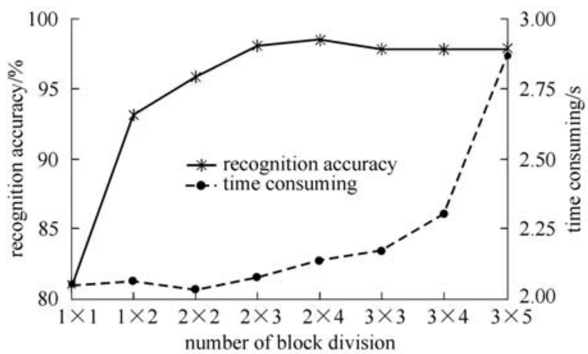

Fig. 7 Comparisons of different blocks division ways of ALBP in recognition accuracy and time consuming

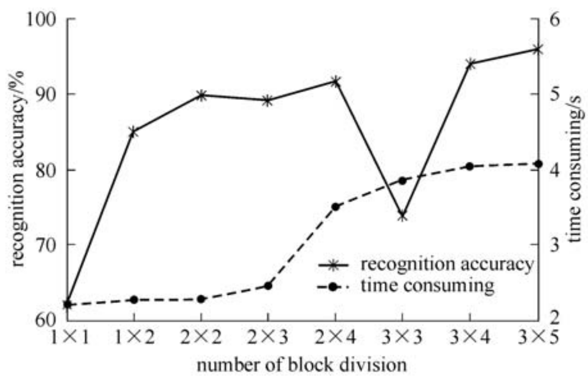

Fig. 8 Comparisons of different blocks division ways of edge orientation histogram in recognition accuracy and time consuming

4.2 Experiment comparison of several features

Table 1 gives a comparison on vehicle logo recognition accuracy and number of support vectors of several features using kernel function of RBF.

1) Only using the feature of ALBP to form the feature vector as the input of SVM classifier, mark as ALBP(2×4);

2) Only using the feature of edge orientation histogram (EOH) to form the feature vector as the input of SVM classifier, EOH(3×5) for short;

3) Combining the features of ALBP and EOH by concatenating their feature vectors to form a bigger vector as the input of SVM classifier, A(2×4)+ E(3×5) for short.

Table 1 Comparison on vehicle manufacturer logo recognition accuracy and number of support vectors of several features

features	penalty coefficient C	-g (i.e., σ)	recognition accuracy/%	number of support vectors
ALBP(2×4)	32	0.03125	98.4444	589
EOH(3×5)	32	0.12500	95.7778	535
A(2×4) + E(3×5)	8	0.03125	99.5556	502

As shown in Table 1, the accuracy of vehicle manufacturer logo recognition of the size-self-adaptive method combining the features of ALBP and edge orientation histogram performs better and more effectively than the methods only using one feature (ALBP or EOH). In addition, the method combining these two features together has lower computational complexity, because the computational complexity of the SVM classifier depends on the number of support vectors, as shown in Eq. (3).

4.3 Experiment comparison of different kernel functions

Table 2 gives the important parameters and recognition results for the testing set of 450 logo images in different sizes, using linear, Polynomial, RBF, and sigmoid kernel functions, respectively (-t is the type of different kernel functions).

It can be noted that we are able to correctly classify nine classes of vehicle manufacturer logos in different sizes. No matter what kernel function we adopt, the method

Table 2 Important parameters and recognition accuracy of vehicle logos using different kernel functions

features	penalty coefficient C	-g (i.e., σ)	recognition accuracy/%			
			-t 0 linear	-t 1 polynomial ($d=3$)	-t 2 RBF	-t 3 sigmoid
ALBP(2×4)	32	0.03125	98.4444 (443/450)	51.5556 (232/450)	98.4444 (443/450)	78.6667 (354/450)
EOH(3×5)	32	0.12500	94.0000 (423/450)	61.5556 (277/450)	95.7778 (431/450)	63.3333 (285/450)
A(2×4)+ E(3×5)	8	0.03125	99.3333 (447/450)	97.7778 (440/450)	99.5556 (448/450)	99.3333 (447/450)

combining these two features together performs better and more effectively than the methods only using one feature. Moreover, Table 2 shows that the RBF kernel we adopt in this paper performs better than other kernel functions.

5 Conclusion

The main contribution of this paper is to have successfully proposed a size-self-adaptive method to recognize vehicle manufacturer logos in different sizes accurately. In this paper, we adopt the features of ALBP and EOH which is suitable for vehicle logo recognition, and performs effectively both in time saving and recognition accuracy. Experimental results indicate that the proposed method based on feature extraction and SVM classifier not only performs well in recognizing multi-size vehicle logos captured in various real life applications, but also is robust against environmental changes. In addition, the method combining these two features also has lower computational complexity. Therefore, it can provide rich information for vehicle verification and classification in many applications, such as security and information retrieval.

Acknowledgements This work was supported by the National High Technology Research and Development Program of China (No. 2007AA01Z417), and the 111 Project (No. B08004).

References

1. For W K, Leman K, Eng H L, Chew B F, Wan K W. A multi-camera collaboration framework for real-time vehicle detection and license plate recognition on highways. In: Proceedings of 2008 IEEE Intelligent Vehicles Symposium. 2008, 192–197
2. Arth C, Limberger F, Bischof H. Real-time license plate recognition on an embedded DSP-platform. In: Proceedings of IEEE Conference on Computer Vision and Pattern Recognition. 2007, 1–8
3. Han X, Niu W L, Li Z Y. Application of fingerprint recognition on the laboratory management. In: Proceedings of the 9th International Conference on Signal Processing. 2008, 2960–2963
4. Liu C. Gabor-based kernel PCA with fractional power polynomial models for face recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2004, 26(5): 572–581
5. Bagdanov A D, Ballan L, Bertini M, Bimbo A D. Trademark matching and retrieval in sports video databases. In: Proceedings of the International Workshop on Multimedia Information Retrieval. 2007, 79–86
6. Xu D Y. A neural network approach for hand gesture recognition in virtual reality driving training system of SPG. In: Proceedings of the 18th International Conference on Pattern Recognition. 2006, 3: 519–522
7. Mohanty P, Sarkar S, Kasturi R. From scores to face templates: a model-based approach. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2007, 29(12): 2065–2078
8. Sun H M. Multi-linguistic optical font recognition using stroke templates. In: Proceedings of the 18th International Conference on Pattern Recognition. 2006, 2: 889–892
9. Guo Z H, Li S H, Xie W X. Automatic target recognition of aircrafts using translation invariant features and neural networks. In: Proceedings of the 9th International Conference on Signal Processing. 2008, 2271–2274
10. Vapnik V N. The Nature of Statistical Learning Theory. London: Springer-Verlag, 1995
11. Cortes C, Vapnik V. Support-vector networks. Machine Learning, 1995, 20(3): 273–297
12. Cristianini N, Shawe-Taylor J. An Introduction to Support Vector Machines and Other Kernel-based Learning Methods. Cambridge: Cambridge University Press, 2000
13. Burges C J C. A tutorial on support vector machines for pattern recognition. Data Mining and Knowledge Discovery, 1998, 2(2): 121–167
14. Benabdeslem K, Bennani Y. Dendogram based SVM for multi-class classification. In: Proceedings of the 28th International Conference on Information Technology Interfaces. 2006, 173–178
15. Ge G Y, Bao X Z, Ge J. Study on automatic detection and recognition algorithms for vehicles and license plates using LS-SVM. In: Proceedings of the 7th World Congress on Intelligent Control and Automation. 2008, 3760–3765
16. Ojala T, Pietikainen M, Maenpaa T. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2002, 24(7): 971–987
17. Wang Y, Zhang H G, Fang X, Guo J. Low-resolution Chinese character recognition of vehicle license plate based on ALBP and Gabor filters. In: Proceedings of the 7th International Conference on Advances in Pattern Recognition. 2009, 302–305
18. Wang X J, Gong H F, Zhang H, Li B, Zhuang Z Q. Palmprint identification using boosting local binary pattern. In: Proceedings of the 18th International Conference on Pattern Recognition. 2006, 3: 503–506
19. Milgram J, Cheriet M, Sabourin R. "One against one" or "one against all": which one is better for handwriting recognition with SVMs? In: Proceedings of the 10th International Workshop on Frontiers in Handwriting Recognition. 2006