Proceedings of the 2017 IEEE International Conference on Applied System Innovation
IEEE-ICASI 2017 - Meen, Prior & Lam (Eds)

A Hierarchical License Plate Recognition System Using Supervised K-means and Support Vector Machine

Wei-Chen Liu and Cheng-Hung Lin

Department of Electrical Engineering, National Taiwan Normal University, Taipei 106, Taiwan
Email: chien0928@gmail.com; Tel: +886-928-178846
Email: brucelin@ntnu.edu.tw; Tel: +886-2-7734-3432

Abstract

In recent years, the use of license plate recognition technology in traffic monitor has attracted a lot of attention because it can be used in a smart city to do criminal investigation and traffic detection. License plate recognition technology has been widely used in parking lot management systems which has fixed shooting angle and lighting environments. The license plate recognition used in traffic monitor will encounter difficulties in character recognition due to factors such as shooting angle, vehicle speed and environment light and shadow. Aiming at the blurred and skewed character images caused by the above factors, this paper presents a hierarchical architecture combining supervised K-means and support vector machine. The supervised K-means is used to classify characters into subgroups. The characters of subgroups can be further classified by support vector machine. The advantage of the proposed approach is to reduce the classes of characters in each subgroup to further reduce the number of SVMs and their complexity, and thus improve the accuracy of character recognition. Experimental results show that our proposed hierarchical architecture achieves an accuracy of 98.89% in character recognition. Compared with the license plate recognition technology using SVM alone, we get a 3.6% improvement in recognition rate.

Key words: License plate recognition, character recognition, support vector machine, K-means

Introduction

License plate recognition technology is an important part to realize a smart city, mainly for criminal investigation and prevention, such as stolen car investigation and vehicle tracking. License plate recognition system has been widely and successfully applied to parking lot management system and highway toll system which have fixed shooting angle and lighting environments. In parking lot management systems, template matching [2][3][4][5][6][7][8] becomes one of the most commonly used character recognition techniques since license plate images have specific shooting angles, size, and brightness. Template matching prepares samples as templates for every character, and then calculates the distance between the character to be identified and the character template, for example, Hamming distance to judge the identification result. However, template matching has some limitations, such as templates and characters to be identified must be the same font. In addition, template matching cannot successfully identify tilt characters, blurred images with noise and dirt, or incomplete characters. For traffic monitoring, template matching encounters the following difficulties and challenges, including variable light and shade, vehicle movement, dirty license plates, font differences, approximate characters and poor image resolution, etc. For example, Fig. 1 shows blurred license plates caused by (a) motion blurred effect, (b) excessive light, (c), poor illumination, (d) plate contamination, and (e) low resolution.

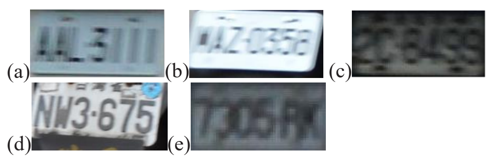

Fig. 1 Different blurred license plate images

To overcome the difficulties, [9] proposed to improve template matching by the expansion of the template for each character, including different angles and different types of tilt, and other font types. Different from the template matching directly using original images for comparison, another part of the literature attempts to identify character patterns in ways that try to avoid the effects of tilting, different fonts, or incomplete characters. Projection features is proposed in [11][12] to use the projection in horizontal and vertical directions as character features for recognition. The character edges and contour features are used in [13] [14] [15] [16] as character features.

In addition, support vector machine (SVM) [19][20][21] [22] is also applied to license plate character recognition due to its high accuracy and superior performance. SVM is a supervised learning method used for classification and regression. However, traditional SVM classification scheme is only classified for two different classes, and its extension to deal with multi-class classification is not straightforward. The reason comes from the fact that for multi-classification, either one-against-rest (OAR) [19], one-against-one (OAO) [19], or Binary tree [22] frameworks must use a larger number of SVM classifiers. In addition, the SVM classifiers for multi-classification need to face the classification of various kinds of samples. The diversity of samples increases the complexity of SVM classifiers and affects its accuracy.

In this paper, we propose a novel hierarchical character recognition scheme based on supervised K-means and Support Vector Machine (SVM) to recognize blurred license plate images.

 ISBN 978-1-5090-4897-7

The supervised K-means is used to classify characters into subgroups which only contains ambiguous characters. The characters of subgroups are further classified by support vector machine. The advantage of the proposed approach is to reduce the classes of characters in each subgroup to further reduce the number of SVMs and their complexity, and thus improve the accuracy of character recognition. Experimental results show that the proposed hierarchical architecture achieves 98.89% accuracy of character recognition. Compared with state-of-the-art approaches using SVM [19][20][21][22], our proposed approach achieves an average of 3.6% improvement.

Review of SVM Classifier

Since license plates include a plurality of letters of the alphabet and numbers, the extensions of SVM for multi-classification, such as OAR, OAO and SVM Binary Tree are proposed to do license plate character recognition. Under OAR framework, in order to distinguish the 34 license plate characters A-Z (I and O excluded) and 0-9, we must train 34 binary classifiers, each trained to separate one class from the others in the cluster. Input images must pass the 34 SVM binary classifiers to determine the final results. Since the SVM classifier built by OAR is used to distinguish a particular one character from the others of which variance is too large, it is difficult to find the best classification decision (hyperplane) in training, and therefore the classification effect is limited. In our experiments, the OAR only obtains 79.6% of accuracy.

To improve the disadvantage of OAR, the OAO is proposed to create an individual SVM classifier for any two characters within the group. Input characters must be passed through all SVM classifiers, and finally the classification results are decided by maximum voting. The advantage of OAO is that it is much easy to find the best classification decision (hyperplane) for classifying two distinct classes and therefore the accuracy is better than OAR. However, in order to distinguish 34 different characters, we have to create 34(34-1)/2= 561 classifiers which leads to too long classification time. The method of SVM Binary Tree builds SVM classifier for binary classification. However, the binary tree relies on the accurate classification path, and the classification path will influence the identification result. The classification path rule needs to be tested many times to find the best classification path of the whole recognition rate. An integration of OAR with binary tree is proposed in [20] where some characters can be identified with fewer classifiers. It improved the traditional OAR where an input image must go through all SVM classifiers. Furthermore, through the order of priority in a binary tree, the method reduces the amount of system computation by identifying the use of higher priority license plate characters, such as 1 and A.

Hierarchical Character Recognition Scheme

In this section, we propose a novel hierarchical character recognition scheme based on supervised K-means and SVM as shown in Fig. 2 where the supervised K-means trains the clustering model by using pre-labeled training samples, and then using the clustering model to cluster the samples into multiple subgroups. K-means clustering method can quickly group a large number of samples; but cannot distinguish between subtle differences in samples. So some of groups will contain a number of similar characters. Table I shows the subgroups which cannot be classified using K-means. For example, 0, D and Q are assigned to the same group. Then, we build a corresponding SVM classifier for each subgroup to further classify the similar characters.

For the subgroup containing only two kinds of characters, we can build a SVM classifier while for the subgroups containing more than two kind of characters, we adopt the OAO approach which creates an individual SVM classifier for any two characters within a subgroup. For example for the group containing H, M, and N, we create three SVM classifiers for recognize H and M, M and N, and N and H, respectively. When an unknown character is classified by two classifiers into the same character, the classification is completed. For example, when an unknown character image is judged to be H by H-M and N-H classifiers, it is recognized that the character is H. We would like to mention that because supervised K-means reduces the kinds of characters to 2~3 characters per set, the OAO is the best choice to do further classification which has better accuracy than OAR without the sacrifice of execution time.

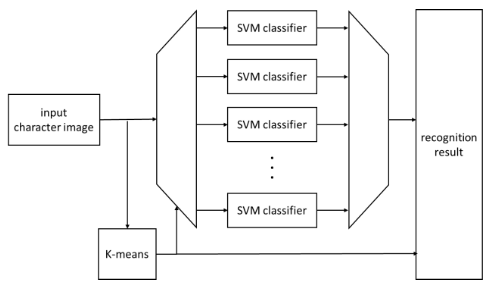

Fig. 2 Hierarchical character recognition scheme

TABLE I: The Results of Clustering Using K-means

subgroup	subgroup
0, D, Q	4, 6
1, 7, Y	8, B
2, Z	9, S, V
3, 5	H, M, N

This architecture mainly uses K-means to classify the samples first, so that easily recognizable samples can be directly identified by K-means, while the ambiguous characters which cannot be recognized by K-means clustering is forwarded to SVM classifier. The method of combining K-means and SVM has two main advantages as follows.

1. Reduce execution time for multi-classification.

   For multi-classification, OAR, OAO or Binary tree frameworks must use a larger number of SVM classifiers. The proposed architecture combined with K-means and SVM effectively reduces the number of classifiers to save computation time.

2. Reduce the complexity of SVM classifiers

For multi-classification, SVM classifiers including OAR, OAO or Binary tree frameworks need to face the classification of various kinds of samples. The diversity of samples increases the complexity of SVM classifiers and affects its accuracy. The proposed architecture effectively reduces the sample diversity by K-means clustering and thus reduce the complexity of SVM classifiers.

Experimental Results

In this paper, we use the license plates of Taiwan as the target of identification. As with most countries, characters on the license plates are composed of letters (A-Z) and Arabic numerals (0-9). Taiwan's license plate has been eliminated using the English alphabet I and O, because I and O are similar to the Arabic numerals 1 and 0. For comparison, we implement a traditional OAR SVM classifier for 34 character classes using histogram of oriented gradients (HOG) as training features. In each character classifier, the positive samples are all samples of that kind of character, and the negative samples use other remaining samples of rest characters. The classification results by the 34-layer SVM classifier for a total of 1530 test samples is shown in Table II. Experimental results shown that the recognition accuracy is only 79.08% and up to 18.56 % of samples cannot be recognized.

TABLE II: The Results of OAR SVM Classifier

	Number	Ratio
# of SVM classifiers	34	
# of training samples	14,626	
# of testing samples	1530	
# of Identification error	36	2.35%
# of Unrecognized	284	18.56%
# of Correct Identification	1210	79.08%
Average recognition time	1,600 ms	

The implementation of the proposed hierarchical architecture has two steps. First, we train a clustering model using supervised K-means algorithm. We pre-label the 1,530 training samples into 34 classes, including A-Z (O and I excluded) and 0-9. In our experiments, each class contains 45 samples and a random sample in each class is selected as the initial center. Table III shows the results of K-means clustering. The accuracy is 76.21% because K-means is not capable of classifying ambiguous characters. Therefore, we group the classes containing ambiguous characters into a subgroup. Table I shows the eight subgroups, including {0, D, Q}, {1, 7, Y}, {2, Z}, {3, 5}, {4, 6}, {8, B}, {9, S, V}, and {H, M, N}. The ambiguous characters in the eight subgroups will be further identified by SVM classifiers. Except for the ambiguous characters in the eight sets, the other explicit characters can be directly identified by the supervised K-means without forwarding to SVM classifiers. In addition, the calculation time per sample is only 1.18ms, more than 1300 times faster than the OAR SVM classifier.

After K-means clustering, we train eight SVM classifiers for the eight groups {0, D, Q}, {1, 7, Y}, {2, Z}, {3, 5}, {4, 6}, {8, B}, {9, S, V}, and {H, M, N}, respectively. For the subgroup containing only two kinds of characters, we can build a SVM classifier while for the subgroups containing more three characters, we adopt the OAO approach which creates an individual SVM classifier for any two characters within a subgroup. For example for the group containing H, M, and N, we create three SVM classifiers for recognize H and M, M and N, and N and H, respectively.

The results of the eight SVM classifiers are shown in Table IV. Experimental results show that the proposed method achieves significant improvement of accuracy for recognizing the ambiguous characters in the eight sets. Compared with the 34-layer OAR SVM classifier, the computation time is reduced from 1600ms to 58.93ms and 17.03ms. Furthermore, it solves the problem that the OAR SVM classifier cannot recognize some characters.

TABLE III: The Results of Clustering using K-means

	Number	Ratio
# of samples	1530	
# of Grouping error	364	23.79%
# of Correct grouping	1181	76.21%
Average execution time	1.18 ms	

TABLE IV: The Results of the Eight SVM Classifiers

Group	# of Samples	Correct	Wrong	Accuracy	Time per sample
{0, D, Q }	135	135	0	100%	58.93ms
{1, 7, Y}	135	133	2	95.56%	58.93ms
{2, Z}	90	90	0	100%	17.03ms
{3, 5}	90	90	0	100%	17.03ms
{4, 6}	90	90	0	100%	17.03ms
{8, B}	90	90	0	100%	17.03ms
{9, S, V}	135	135	0	100%	58.93ms
{H, M, N}	135	135	0	100%	58.93ms
	900	898	2	99.78%	

The overall performance of the proposed hierarchical architecture combining with supervised K-means and SVM is shown in Table V. For blurred and tilt license plate characters, the proposed approach can achieve 98.89% of accuracy. Table VI shows the comparison with state-of-the-art license plate recognition approaches. The proposed approach achieves an average of 3.6% improvement on recognition accuracy.

TABLE V: Overall Performance of the Hierarchical Architecture

	Number
# of testing samples	1530
# of Correct Identification	1513
# of Identification error	17
Accuracy	98.89%
Average recognition time	26.24 ms

 ISBN 978-1-5090-4897-7

TABLE VI: Comparison with State-of-the-Art License Plate Recognition Approaches

Method	#of testing samples	Pattern of Samples	Accuracy
template matching [3]	1176	various scene and condition	93.1%
template matching [4]	180 pairs of images	N/A	95.7%
template matching [7]	2340	different weather and illumination	98.6%
multi-template matching [9]	400 video clips	N/A	97.2%
Kirsch edge detection [13]	2000	outdoor, Stopped vehicle	92.7%
SVM-binary tree [19]	300	outdoor, Stopped vehicle	95.2%
SVM-OAR+binary tree [20]	260	N/A	91.9%
SVM[21]	1000	N/A	98.2%
SVM-binary tree [22]	700	N/A	96.0%
Our proposed hierarchical architecture	1530	roadside, moving vehicle	98.9%

Conclusion

We have proposed a hierarchical character recognition scheme combined with supervised K-means and SVM for blurred and tilt license plate recognition. The advantage of this method is to reduce the characters of each subgroup and further reduce the number of SVMs and their complexity, and thus improve the accuracy of character recognition. Experimental results show that the proposed architecture achieves significant improvement on accuracy and computational complexity.

References

[1] S. Du, M. Ibrahim, M. Shehata, and W. Badawy. Automatic license plate recognition (alpr): A state-of-the-art review. Circuits and Systems for Video Technology, IEEE Trans. on, 23(2):311–325, 2013

[2] M. Sarfraz, M. J. Ahmed, and S. A. Ghazi, “Saudi Arabian license plate recognition system,” in Proc. Int. Conf. Geom. Model. Graph., 2003, pp. 36–41.

[3] [Online].Available:https://www.research.ibm.com/haifa/research.shtml

[4] H.-J. Lee, S.-Y. Chen, and S.-Z. Wang, “Extraction and recognition of license plates of motorcycles and vehicles on highways,” in Proc. Int. Conf. Pattern Recognit., 2004, pp. 356–359.

[5] K. Miyamoto, K. Nagano, M. Tamagawa, I. Fujita, and M. Yamamoto, “Vehicle license-plate recognition by image analysis,” in Proc. Int. Conf. Ind. Electron. Control Instrum., vol. 3. 1991, pp. 1734–1738.

[6] E. R. Lee, P. K. Kim, and H. J. Kim, “Automatic recognition of a car license plate using color image processing,” in Proc. IEEE Int. Conf. Image Process., vol. 2. Nov. 1994, pp. 301–305.

[7] P. Comelli, P. Ferragina, M. N. Granieri, and F. Stabile, “Optical recognition of motor vehicle license plates,” IEEE Trans. Veh. Tech.,vol. 44, no. 4, pp. 790–799, Nov. 1995.

[8] S. Tang and W. Li, “Number and letter character recognition of vehicle license plate based on edge Hausdorff distance,” in Proc. Int. Conf. Parallel Distributed Comput. Applicat. Tech., 2005, pp. 850–852.

[9] T. Naito, T. Tsukada, K. Yamada, K. Kozuka, and S. Yamamoto, “Robust license-plate recognition method for passing vehicles under outside environment,” IEEE Trans. Veh. Tech., vol. 49, no. 6, pp.2309–2319, Nov. 2000.

[10] M.-S. Pan, J.-B. Yan, and Z.-H. Xiao, “Vehicle license plate character segmentation,” Int. J. Automat. Comput., vol. 5, no. 4, pp. 425–432, 2008.

[11] C. A. Rahman, W. Badawy, and A. Radmanesh, “A real time vehicle’s license plate recognition system,” in Proc. IEEE Conf. Adv. Video Signal Based Surveillance, Jul. 2003, pp. 163–166.

[12] J. A. Sethian, “A fast marching level set method for monotonically advancing fronts,” Natl. Acad. Sci., vol. 93, no. 4, pp. 1591–1595, 1996.

[13] S. N. H. S. Abdullah, M. Khalid, R. Yusof, and K. Omar, “License plate recognition using multicluster and multilayer neural networks,” Inform. and Commun. Tech., vol. 1, pp. 1818–1823, Apr. 2006.

[14] S. N. H. S. Abdullah, M. Khalid, R. Yusof, and K. Omar, “Comparison of feature extractors in license plate recognition,” in Proc. Asia Int. Conf. Modeling Simul., 2007, pp. 502–506.

[15] M.-A. Ko and Y.-M. Kim, “Multifont and multisize character recognition based on the sampling and quantization of an unwrapped contour,” in Proc. Int. Conf. Pattern Recognit., vol. 3. 1996, pp. 170–174.

[16] S. Z. Wang and H. J. Lee, “A cascade framework for a real-time statistical plate recognition system,” IEEE Trans. Inform. Forensics Security, vol. 2, no. 2, pp. 267–282, Jun. 2007.

[17] N. Dalal B. Triggs "Histograms of Oriented Gradients for Human Detection" Proc. IEEE Conf. Computer Vision and Pattern Recognition vol. 2 pp. 886-893 2005-June.

[18] Y. Yao Y. Liu Y. Yu H. Xu W. Lv Z. Li X. Chen "K-SVM: An Effective SVM Algorithm Based on K-means Clustering" J. Computers vol. 8 Oct. 2013.

[19] Yang Guang, “License Plate Character Recognition Based on Wavelet Kernel LS-SVM”, inComputer Research and Development (ICCRD) 3rd International Conference, Shanghai, pp. 222 - 226, 2011.

[20] Haiyan Zhao; Chuyi Song; Haili Zhao; Shizheng Zhang; , "License plate recognition system based on morphology and LS-SVM," GrC. 2008. IEEE Int. Conf. pp.826-829, 26-28 Aug. 2008.

[21] Liuy Ongchun and Yang Jing, “Research of license plate character features extraction and recognition,” 2nd International Conference on Computer Science and Network Technology, pp.2154–2157, 2012.

[22] G. Guangying, b. Xinzong, and g. Jing, "study on automatic detection and recognition algorithms for vehicles and license plates using ls-svm," intelligent control and automation, 2008. Wcica 2008. 7th world congress on, 2008, pp. 3760-3765