A Novel and Robust Algorithm for License Plate Location Using Perceptual Salient Features

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Abstract—**License plate location (LPL) plays an important role in license plate (LP) recognition systems. Most existing methods can only deal with LPL well in fixed environment such as stable illumination, simple background or constant distance between cameras and vehicles. And the successful rate of LPL is quite affected by those non-LP objects in the background that share similar features with license plate regions. To overcome these problems, in this paper, we propose a novel LPL method using perceptual salient features, which is based on the visual attention mechanism to choose the most salient features for license plate. The proposed approach consists of two main steps. Firstly, candidate license plate regions consistent with the visual perception are detected based on perceptual salient features from the saliency map. Then, the candidate license plate regions are sifted to distinguish a license plate from background, using salient features which are selected and organized by minimizing probability of error. The proposed algorithm was tested with 1942 real images captured in various conditions and achieved an average accuracy of 98.51%. The experiment result shows that our algorithm is robust to the interference of non-LP objects as well as the change of illumination, view angle, position, size and color of license plates.**

Keywords-license plate location; visual saliency; feature extraction; minimum probability of error

I. INTRODUCTION

A typical system for license plate recognition (LPR) is composed of four parts: obtaining an image of the vehicle, license plate location, character segmentation and recognition. The performance of the locating operation is crucial for the entire system, because it directly influences the accuracy and efficiency of the subsequent steps. Many methods of LPL were proposed in the literature [1~11], and these methods generally include two steps: candidate LP regions formation and sifting out LP regions.

In the first step, the methods of segmenting the candidate LP regions from the vehicle image can be roughly divided into three categories. As the license plate is designed to be rectangular, the first kind of method uses Hough transform (HT) to detect all the rectangles considered as candidate LP regions in the image [1,2]. However, this approach has difficulty in extracting license plate regions when the boundaries of the license plates are distorted and not clear or the images contain lots of vertical and horizontal edges [3].

The second kind of method considers those regions that have higher feature density than other parts of the image to be candidate LP regions, because the license plates are designed to be featured by colors [4], edges [5], corners [6], strokes [7] or some other features [7]. But the location rate would be affected by the increased number of candidate LP regions in the background which may share similar features with the license plate. The third kind of method adopts a trained classifier to classify parts of an image within a search window with a fixed size based on some high level features such as Haar-like [9], EOH [10], TO-MACH [11]. Yet, it is not scale invariant since the size of windows is not adaptive to the change of LP's size in an image.

In the second step, the candidate LP regions are filtered according to the extracted features inside the candidate LP regions such as color, aspect ratio, edge density, corner distribution, projection property, etc. Since the license plate can hardly be picked out from the candidate LP regions by only one feature, multiple features are combined to improve the location effect of the license plate [2,4,6,8,10]. However, as the selected features may not make the biggest distinction between the license plate and the candidates in the background, the location effect is affected by the selection and organization of every single feature.

To address the mentioned problems, we propose a novel method to locate the license plate in various conditions using perceptual salient features, which is based on the visual attention mechanism to choose the most salient features of a license plate. From [12,13], it is known that people's attention is apt to be attracted by those salient locations which are much different from their surroundings in color, intensity, orientation. As a license plate is designed in a way that the color and intensity contrasts between characters and background in the license plate are very strong, the license plate in a vehicle image is supposed to be saliency enough to attract people's attention. Moreover, the computational saliency models, which have been well developed since the year 1998, make it possible to indicate the salient parts of the image. Hence, we are inspired to segment salient regions in the vehicle image as the candidate LP regions. After that, the candidate LP regions are sifted using the features which have been selected and organized based on the saliency of every single feature.

There are several advantages of our method. Firstly, since the pixels in the possible LP regions are highlighted while

suppressed in most of the non-LP regions in the saliency map, the candidate LP regions can be reduced dramatically, which is helpful to sift candidate LP regions. Secondly, it can automatically adapt to the different size of the license plate as the rough size of the candidate LP regions can be estimated from the segmented saliency map. Thirdly, only most salient features are selected and organized, it contributes to achieve high detection accuracy.

The rest of this paper is organized as follows. In Section II, the modules and their goals are presented and the process of locating the license plate within an image is described in detail. Section III shows experimental results. Conclusions and some remarks are given in Section IV.

II. LICENCE PLATE LOCATION

Like previous algorithms, the proposed method in this paper is also divided into two image processing phases: candidate LP regions formation and sifting out the license plate. Firstly, a saliency map is calculated using graph-based visual saliency (GBVS) [13]. Secondly, possible LPs are sifted to remove false LPs through the extraction of salient features which are selected on the basis of the feature-saliency theory. The feature that makes most distinction between the license plate and backgrounds is regarded as the most salient. And inspired by [2], we select and organize salient features on the base of the minimum probability of error, which makes use of the prior information of every single feature saliency acquired from training samples. The overall process of the license plate location is depicted in Fig.1, and the details are presented as follows.

A. Saliency Analysis

Considering the observation that license plates are very salient to human visual perception, we take saliency map to describe the objects that attract our attentions. As for the saliency model, though much work has been done to the center-surround difference model which highlights the objects different from their surroundings, graph-based visual saliency (GBVS) [13] offers a more encouraging result in which the license plate is more salient than other parts of the image.

In the implementation of the algorithm GBVS, there are two basic parameters needed to be preset: the feature channels and the weights of them. We have three feature channels for options: color, intensity, orientation. In our experiments, the color and intensity feature channels are selected, since according to our observation, it is the color and intensity contrast between characters and background that attracts attentions most. Moreover, the license plate in an image is much more salient than other parts when the weight of color feature is set to be twice as that of intensity feature. Fig. 2 gives the saliency maps produced by GBVS as well as the saliency maps produced by some other approaches proposed in [14,15,16].

B. Candidate LPs Segmentation

Several regions can be segmented with OTSU in the saliency map. But in some cases, the threshold is not big enough to separate LP from backgrounds. As shown in Fig.3, the LP region sticks to the radiators and head lights using the OTSU threshold. Hence, we take 1000 images to estimate saliency probability distribution of license plates and backgrounds. And from the result shown in Fig.4, a segmentation threshold th_0 can be selected as follows:

$$th_0 = m - \sigma , \qquad (1)$$

where m, σ is the mean value and standard deviation of the license plate saliency respectively. According to m and σ (149.6 and 51.3 respectively) which can be calculated from the saliency set of LPs, the optimal th_0 we get is 98. When the segmentation is set to 98, as we can see from Fig.4, about 81% license plate regions can be retained while the background regions reduced tremendously. However, the detected license plate regions would be decreased to an
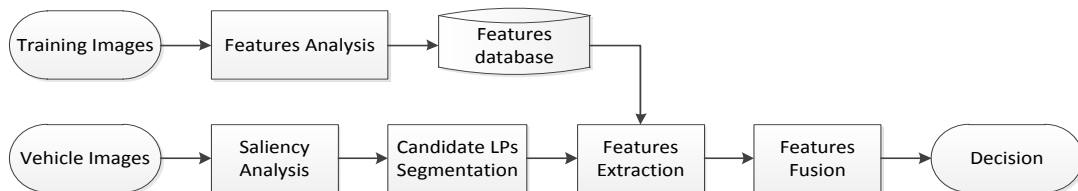

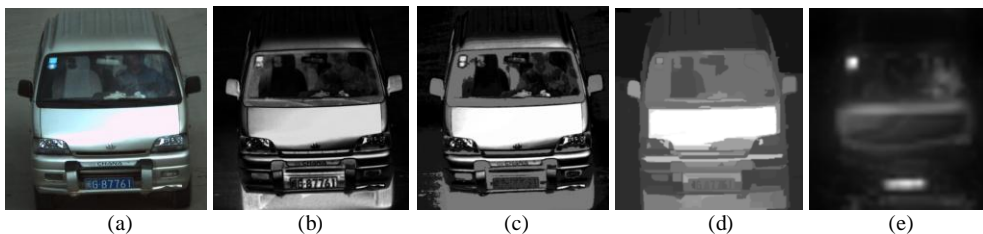Figure 1. Process of License Plate Location

Figure 2.   Typical saliency maps computed by different state-of-the-art methods. (a): Original image. (b): FT (Frequency-tuned) method in [14]. (c): CH (Color-Histogram) method in [15]. (d): RC (Regional-based contrast) method in [16]. (e): GBVS (graph-based) method in [13].

unacceptable level as increasing th_0 .Therefore, by combining OTSU and saliency probability distribution, the final segmentation threshold th is calculated as:

$$th = \max(th_0, th_1),\qquad(2)$$

where th_1 is the segmentation threshold produced by OTSU. By using th, the license plate region is able to be separated from backgrounds shown in Fig. 3(d).

Then, several segments can be obtained as the candidate LP regions. If the camera is rolled or pitched with respect to the license plate, slant detection and correction are very critical. And this can be solved by the method proposed in [17] based on principal component analysis (PCA). Finally, in consideration of lost parts of candidate LP regions in segmentation, the length and width of the minimum enclosing rectangle (MER) of the candidate LP regions are supposed to be extended with a certain percentage.

C. Sifting Candidate LPs with Global Features

In some cases, some irrelative objects such as the radiators or bumpers share similar textures with the plates. Then global features are required to remove them. Therefore, based on minimum probability of error for feature selection, we analyze the saliency of the shape, texture and color features, since these features of license plate are more salient than others such as length, area, etc.

In Fig.5, the salient features are able to make great distinction between objects and background. And the most salient feature means to get the greatest distinction while minimum probability of error in classifying [2]. As for classification, p_f is hoped to be statistically least.

$$p_{fx} = \int_{\Omega_1} p(\omega_2)dx + \int_{\Omega_2} p(\omega_1)dx \rightarrow \min,\qquad(3)$$

$$S_{fx} = 1 - P_{fx},\qquad(4)$$

where $p(\omega_1)$ and $p(\omega_2)$ are the prior probability of feature x of license plates and backgrounds, respectively. S_{fx} is defined as the saliency of feature x. Suppose the threshold of feature x is given, then the probability of error P_{fx} can be known and it contains the probability of what is classified as the license plate while it is the background and the probability of the contrary situation.

The contour feature of a license plate is extensively used in LP recognition since the length-to-width ratio is fixed. Here we define AR as the aspect ratio of length-to-width, obtain the AR probability distribution and probability of error p_{fA}.

The edge image is the basic feature of a license plate which contains rich edges. According to the texture structure feature of a license plate, we mainly concern about the vertical edge information rather than the horizontal. And we choose Sobel operator to detect the vertical edge image.

We define G as the gradient edge density in the candidate license plate. After obtaining the gradient property (GP) probability distribution, the probability of error p_{fG} can be got.

Because the characters on a plate license have enough corners which are distributed intensively, a feature of corner property (CP) is introduced for license plate location. Harris corner detection is implemented using the method proposed in [6]. We define C as the corner density in the candidate license plate, obtain the CP probability distribution and the
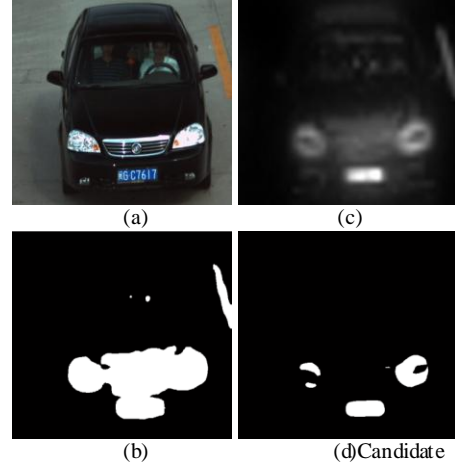

(a)   (c)

(b)   (d)Candidate LPs segmentation. (a)Original image. (b)Saliency map of (a). (c)Segmentation result of (b) using OTSU.(d) Segmentation result of (b) using (2).
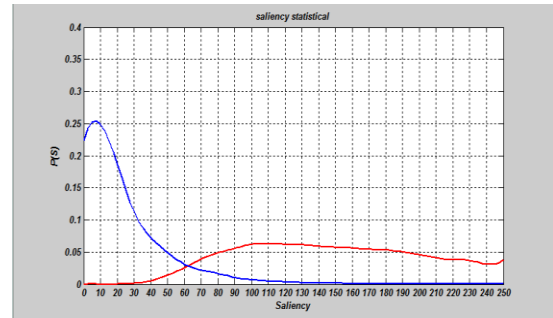

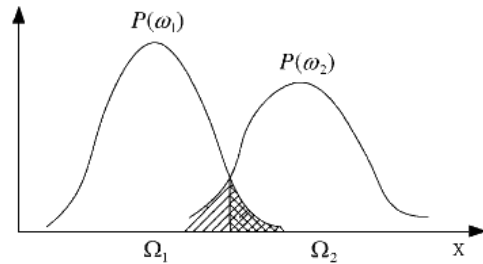Figure 4. Saliency probability distribution (blue for backgrounds and red for license plates)

Figure 6. Feature probability distribution of LPs and background.

Samples	Description	Plate size(pixel)	Images
Sample set 1	road, toll stations or parking places; daylight, nonmoving	various	1097
Sample set 2	road entrance or freeways; daylight, moving	$54 \times 18 \sim 82 \times 27$	378
Sample set 3	road; night, flash, nonmoving	various	78
Sample set 4	parking places; slant location, angle: -30 °~30 °, nonmoving	various	168
Sample set 5	road, interferences: other characters or dirt, nonmoving	various	122
Sample set 6	toll stations, parking places; uneven illumination, nonmoving	various	99
Total images number	1942		

Image Sets	Location rate	Average time
1	1083/1097 (98.72%)	
2	372/378 (98.41%)	
3	76/78 (97.44%)	
4	166/168 (98.81%)	413 ms
5	119/122 (97.54%)	
6	97/99 (97.98%)	
Overall	(1913/1942)98.51%	

probability of error p_{fC}.

It is found that color information (CI) can be very useful to finally decide whether a certain region is a vehicle plate or not. However, extracting robust color features from RGB images can be difficult, since even for a single color, its RGB values may vary considerably due to different illumination. Therefore in the proposed algorithm, the input images are converted from RGB color space to HSL color space which provides more robust color features. In HSL space, H and S element are actually sufficient to represent the color information for a pixel. Also, we can obtain the CI probability distribution and the probability of error p_{fT}.

The characters are organized with obvious equal spacing between them. Therefore, the projection strategy is widely used to describe this arrangement of a license plate. After the candidate license plate is binarized using OTSU, a histogram of the numbers of white pixels are formed by scanning every column of the candidate license plate. If numbers of peaks and valleys belong to a certain range, the candidate is considered as a license plate. We define P as the projection property (PP) in the candidate license plate, then the PP probability distribution and probability of error p_{fP} are able to be obtained.

A set of 1000 images is used for the training procedure. From the experiment, we know that $S_{fA} = 0.981$, $S_{fG} = 0.952$, $S_{fC} = 0.953$, $S_{fT} = 0.963$ and $S_{fP} = 0.717$ by computing the probability of misclassification with five different features. It is obvious that the shape feature is more salient than others while the projection property is the least salient. And corner property is a little more salient than gradient property, but its time consumption is much more than that of the latter. Therefore, we adopt the AR, CI and GP as the global salient features for sifting LP candidates.

III. EXPERIMENTAL RESULTS

The purpose of this paper is to locate the vehicle license plates from an image containing a vehicle. In our experiments, the central processing unit with AMD Athlon Dual-Core processor 2.20GHz and 1GB memory is employed for the performance test. 1942 different images of size 640×480 are collected for testing. The license plates in these images have a resolution of at least 54×18 pixels or more. Table I indicates the composition of the image database and briefly described the properties of these images. Table II depicts the performance of the proposed method in every sample set. The location rate and average time consumption are presented. Though sample set 1 and 2 were acquired under various scenes and surroundings, the successful rates of 98.72% and 98.41% were achieved, respectively. Since sample set 3 were captured by cameras with flashlights at night, of these 78 images, 76 images are successfully located. In sample set 4, with multiple angles of orientation, the license plates in the images are located with angles fluctuating from $-30^0 \text{ to} 30^0$. However, the successful performance achieved were 98.81%, in which the slant correction turned out to be effective. For sample set 5, some similar characters may share similar characters with license plates such as CP or GP, but they can be distinguished by using CI and AR. Moreover, sometimes parts of the license plate were interfered by something like dirt, but as long as the difference between characters and background is acceptable, it is still treated as a LP by using AR, GP and CI. Hence, the location rate was 97.54%. In sample set 6, with exposure and shadow involved, the license plates were still more salient than other parts and the performance achieved was 97.98%. It is also reported in Table II that the average time of locating the plate in every vehicle image was 413ms. Some examples of segmentation result are shown in Fig. 6.

The performance comparison with existing methods is shown in Table III. It is obvious that the proposed method maintains better location performance. As for the speed, it can satisfy most applications, but may not suit rigidly high-speed applications because GBVS is not fast enough. This problem can be solved by using new computation algorithms.

TABLE III. COMPARISON OF PERFORMANCE USING DIFFERENT LPL ALGORITHMS

Method	Boundary-based Method Using HT[1]	Edge-based Method Using Morphological Operation[5]	Method Using Gabor Filter[7]	Method Using AdaBoost[9]	Proposed Method
Location Rate	93.12%	95.34%	95.07%	95.89%	98.51%

Figure 6. Examples from sample sets and segmentation results. Left: original images, Middle: saliency images, Right: results.

IV. CONCLUSION

A novel and robust automated vehicle LPL system was presented in this paper. The operation of this system includes two basic image processing steps. In the first step, a saliency map is calculated using GBVS in order to provide clues of candidate LP regions. In the second step, possible LPs are sifted through the extraction of AR, CI and GP features selected according to the feature-saliency theory. The algorithm was tested with 1942 real images captured in various conditions. And the license plates were successfully located and segmented with an average accuracy of 98.51%, which outperforms the existing methods. The proposed system is mainly intended for the location of Chinese license plates. However, it can easily be extended to the location of license plates of other languages or characters.

REFERENCES

[1] T. D. Duan, T. L. Hong Du, T. V. Phuoc, and N. V. Hoang, "Building an automatic vehicle license plate recognition system," in Proc. Int. Conf. Comput. Sci. RIVF, 2005, pp. 59–63.

[2] Z. X. Chen, C. Y. Liu, F. L. Chang and G. Y. Wang, "Automatic License-Plate Location and Recognition Based on Feature Salience, " IEEE Trans. Vehicular Technology, Vol. 58, no. 7, pp. 3781-3785, 2009.

[3] Christos-Nikolaos E. Anagnostopoulos, Ioannis D. Psoroulas, Vassili Loumos, "License Plate Recognition From Still Images and Video Sequences: A Survey," IEEE Trans. Intell. Transp. Syst., vol. 9, no. 3, pp. 377– 391, Sep. 2008.

[4] S. L. Chang, L. S. Chen, Y. C. Chung and S. W. Chen, "Automatic license plate recognition," IEEE Trans. Intell. Transp. Syst., vol. 5, no. 1, pp. 42–53, Mar. 2004.

[5] H. Mahini, S. Kasaei, F. Dorri, and F. Dorri, "An efficient features–based license plate localization method," in Proc. 18th ICPR, Hong Kong, 2006, vol. 2, pp. 841–844.

[6] R. Wang, G. Y. Wang, J. G. Liu and Z. H. Wang, "A fast method for two-stage precise license plate location based on fusion of corner feature and gray level jumps," in American Journal of Engineering and Technology Research, 2011, Vol.11, No.9, pp. 2695–2700.

[7] F. Kahraman, B. Kurt, and M. Gökmen, "License plate character segmentation based on the gabor transform and vector quantization," in Lecture Notes on Computer Science, vol. 2869, A. Yazici and C. Sener, Eds. New York: Springer-Verlag, 2003, pp. 381–388.

[8] C. Anagnostopoulos, I. Anagnostopoulos, E. Kayafas and V. Loumos, "A license plate recognition system for intelligent transportation system applications," IEEE Trans.Intell. Transp. Syst., vol. 7, no. 3, pp. 377– 392, Sep. 2006.

[9] L. Dlagnekov, "License Plate Detection Using AdaBoost," Mar. 2004, San Diego, CA: Comput. Sci. Eng. Dept., Univ. California, San Diego.

[10] X. Sheng, S. T. Li, "License plate detection based on improved Real Adaboost," in Proc. Conf. ICVES, 2011, pp. 169-173.

[11] J. B. Liu, J. Liu, W. D. Jin, "Robust Vehicle License Plate Localization Using TO-MACH Filter," in Proc. Conf. ICCSE, 2010, pp. 1106-1109.

[12] L. Itti, C.Koch, and E. Niebur, "A model of saliency-based visual attention for rapid scene analysis," IEEE Trans. Pattern Anal. Mach. Intell., vol. 20, no. 11, pp. 1254–1259, Nov. 1998.

[13] J. Harel, C. Koch, P. Perona, "Graph-Based Visual Saliency," Advances in Neural Information Processing Systems, 2007.

[14] R. Achanta, S. Hemami, F. Estrada, and S. Süsstrunk, "Frequency-tuned salient region detection," in CVPR, pp. 1597–1604, 2009. 1, 2.

[15] Y. Zhai and M. Shah, "Visual attention detection in video sequences using spatiotemporal cues," in ACM Multimedia, pp. 815–824, 2006.

[16] M. M. Cheng, G. X. Zhang, "Global Contrast based Salient Region Detection," in CVPR, pp. 409-416, 2011.

[17] D. H. Wu, C. H. Zhu, "A Novel License Plate Slant Correction Method Based on Principal Component Analysis," in Journal of Highway and Transportation Research and Development, vol. 23, no. 8, pp. 143-146.