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Localization of car license plate using adaptive Euler-template matching method

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Abstract: License plate (LP) detection plays an important role in intelligent transportation systems smart traffic control systems of today. Although it is simple and easy to implement for LP detection, traditional template matching method is less favorable compared to state-of-the-art methods due to its processing cost. Thus, this study proposes an innovative template matching method called "adaptive Euler-template matching method" for detection of LP. Two different models of Euler-template and a new matching concept are proposed. The proposed method is evaluated by detecting LP in a total of 150 test images. Then, the performance of proposed method is compared with the performances of some exiting methods. The proposed method gives accuracies of 96% using Euler-template(model-A) and 96.7% using Euler-template(model-B). The average processing time of proposed method is 0.303 s. The results show that Euler-template(model-B) is more effective for LP detection. More distinct observations are presented and finally recommendations for further works are given in this study.

Keywords: euler-template; adaptive template matching; license plate localizing; smart traffic control; automatic recognition system

1. Introduction

Intelligent transportation systems and smart traffic control systems are drawing the growing interest of today society in the age of the 4th Industrial Revolution (IR4.0). Here, the Internet of Things (IoT) technology and automatic recognition systems are very essential to practically implement the intelligent transportation systems and smart traffic control systems in smart cities [1]. As demonstrated in Figure 1, a smart traffic control system consists of traffic light, traffic camera, roadside speed sensor, car-arrival sensor, stationary processing unit, gate-bar and mobile monitoring system. According to the IoT concept, all these components are wirelessly connected through gateways and cloud. An IoT-based smart traffic control system can handle multiple tasks such as recording over-speed vehicles, controlling traffic access to the toll, recording license plate (LP) information of the vehicles passed through the toll gates. Thus, license plate recognition (LPR) plays an important role in smart traffic control systems [2].

In order to recognize a LP, there are three main steps as shown in Figure 2; localizing LP on the vehicle, segmentation (fragmentation) of plate characters and recognizing each character [3]. Also, there could be some image-enhancement steps optionally if the quality of images obtained is low. Thus, it is understandable that localization of LP is the first key step in LPR processes. If the LP is not correctly detected and localized, the next consequential steps cannot be performed. Thus, the whole process will fail.

1. Traffic light
2. Traffic camera
3. Roadside speed sensor
4. Car arrival sensor
5. Processing unit
6. Gate bar control unit
7. Mobile user

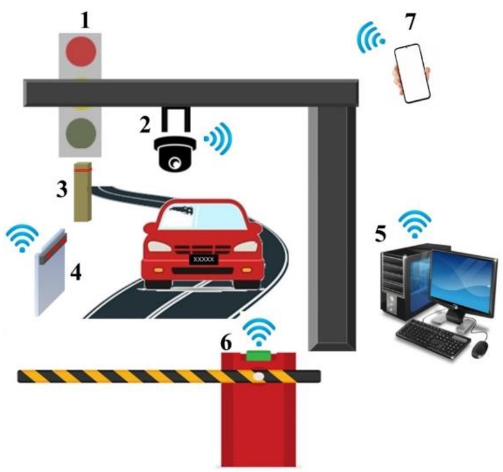

Figure 1. A smart traffic control system

Indeed, localizing or detecting a car LP in a given image is a tricky and challenging step [4]. The reason is that license plates in most countries LPs are in rectangle shape and they are very similar to front mirror, back mirror, car lamps, radiator-cover and even car-wheels which are also forms as rectangle shape in two-dimensional (2D) view images. Also, in natural environment, it can be misrecognized with similar rectangle-shape objects such as windows, brick-walls, signboards and so on.

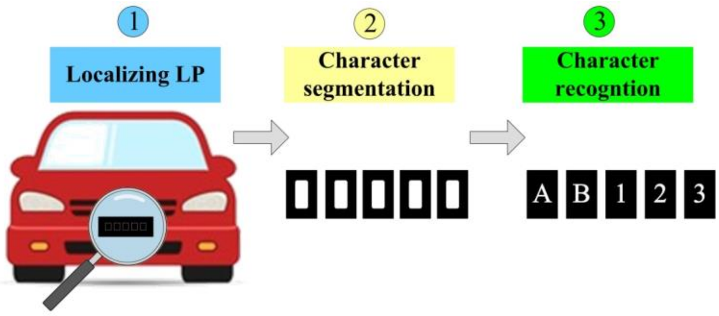

Figure 2. Three main steps in LPR

For this reason, there have been a number of studies in which researchers attempted to propose different innovative approaches to localize LP. In early years, LP localizing methods were based on edge features, colour features and region features. Then in later years, more innovative approaches using wavelet transform were developed. Today, updated technologies, such as deep neural network, become popular and these methods are being used by many researchers for detection and recognition of LP [5], [6], [7], [8], [9]. Although the accuracy of deep neural networks is attractive, these approaches are known to require a huge amount of training data.

In these days, template matching method is also attractively applied in many different areas [10], [11], [12], [13]. The main advantage of template-based methods is that it is simple yet effective and easy to implement. On the other hand, template matching method still has some limitations to be overcome. The first one is that it needs an appropriate template. Thus, template should be designed. The second one is that operation of template matching needs a similarity measure. Due to the difference of one pixel position, the whole temple can be mismatched. The third one is that the template needs to be

manually updated and it has high execution cost. Thus, main challenge of the template matching approach is to keep the search computationally feasible and fast while still being robust with respect to measurement errors or partiality.
In this regard, the aim of this study is to propose an adaptive Euler-template matching method for LP detection. The new contributions of this proposed LP detection method are-

a. Introduction to Euler-Template. A template called "Euler-Template" is introduced in this study. It is very simple and easy to design.
b. Less processing time due to the application of adaptive Euler-Template. It is not necessary to perform matching by shifting the template pixel by pixel.
c. New calculation approach for similarity metrics in template matching

2. Material and methods

2.1 License plate localization in previous works

As described in previous section, a number of researches have been conducted to propose innovative methods for localizing car license plate. In some countries, license plates have distinct and clear colour. Thus, LP's colour is one effective feature to use in detection of LP. HSL (Hue, Saturation, and Lightness) colour model was used in [14]. However, the colour-based detection is less preferable if LPs have multiple colours depending on vehicle types. For example, in Myanmar, five different colours (black, red, yellow, blue and white) are used for LPs to differentiate application types of cars. Also, some vision systems do not support colour imaging.

The other potential features of car LP are vertical edges and horizontal edges because the plate area is rich of edge information. Thus, in [15], both horizontal and vertical edges in the image were detected and then erosion and dilation processes were applied to detect the LP region. In other work [16], also used contour algorithm to find enclosed contour regions. hen, the authors used Hough transform to search two interacted parallel lines that were considered as a plate-candidate. In these days, deep-learning becomes a favorite tool for classification and recognition [9], [10], [17], [18], [19], [20]. Indeed, deep learning neural networks need to be constructed with multiple layers which commonly require thousands of training data. The introduction of new plate format will require re-collecting sufficient data and re-training process. Thus, an innovative template matching methods are still favorable for those who are seeking approaches which are simple, easy and fast to implement while maintaining the efficiency. Thus, it is very potential use template matching approach for LP localization. However, traditional template matching method will not be much efficient. Therefore, Euler-template is introduced in this study and its performance in LP locations is evaluated in comparison with existing methods.

2.2 Proposed method: Euler-template matching method

2.2.1 Euler-number

A distinct term called "Euler-Template" is introduced in this study. Before explaining Euler-Template, it is worth to describe Euler number. Mathematically, the Euler number of a binary image is defined as

$$E = N - H \tag{1}$$

where, *E* is the Euler number, *N* is the number of connected foreground regions and *H* is the number of holes (isolated regions of the image's background) [21]. As demonstrated in Figure 3, there are two holes in one connected foreground object. Thus, for this sample image, the Euler number is -1 since there are two holes in a single foreground object.

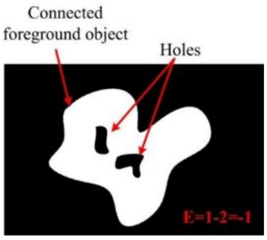

Figure 3. Demonstration of Euler number

2.2.2 Developing Euler-template

Some samples of Myanmar LPs are shown in Figure 4-(a), Figure 4-(b) and Figure 4-(c). The red colour LPs are used for service car, the black colour LPs are used for family car and the blue ones are used for tourism transportation. Then, the binary version of a LP is shown in Figure 4(d). Here, the character colour is changed as black hole and the plate's background colour is converted as white colour so that Euler-number can be calculated.

Figure 4. (a) Service car LP (b) Tourist car LP (c) Family car LP (d) Binary version of LP

Since this Euler number concept is not only simple but also easy to implement, it is used to innovate the conventional template matching method. Thus, a binary image, which has single foreground object and multiples holes, is developed as shown in Figure 5. It is proportional to car LP. Since proposed template is based on binary values and it has a certain Euler number, it is termed as "Euler-Template" in this study. Thus, it is different from Harr-like features or Harr-like patterns which are based on gray intensity and for which Euler number cannot be calculated. Thus, a binary pattern images which are properly arranged to be able to calculate Euler number can termed as Euler-Templates.

Here, as shown in Figure 5(a)-(b), two different Euler-templates proposed for localizing of LP. The first Euler-template(model-A) consists of rectangle holes which generally represent the characters while the second Euler-template(model-B) has digit-shape holes. The holes (black rectangles) are designed to have the width and height propositional to the characters on LP. The first model (model-A) is proposed because the characters sometimes cannot appear properly in their own shape when the image has very low resolution or twisted. In that condition, rectangle holes can generally represent deformed characters. Thus, full rectangle holes which have proportional dimensions to the widths and heights of the characters on LP are created. The second model (model-B) is useful when the image resolution is high and the characters clearly and properly appear in their own shape. In model-B, the holes are created as general digit shapes proportional dimensions to the widths and heights of the characters on LP. Thus, the effectiveness of proposed Euler-templates are also compared. Here, the main advantages of proposed Euler-templates are-

a. Euler-templates are easy and fast to develop since it is just based on binary colours and general shapes.
b. It is independent of the colours of LPs. Thus, it is not necessary to handle multiple templates with different colours. After detecting the LP, its colour can be identified if needed.
c. Euler-templates are proportionally resizable to adaptively match with LP candidate regions

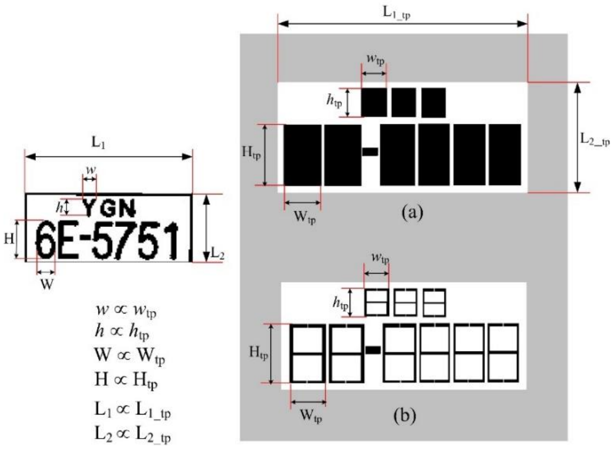

Figure 5. Proposed Euler-templates (a) Euler-template model-A (b) Euler-template model-B

2.2.3 Flow chart of proposed method

Figure 6 shows the flow chart of proposed method. It can be briefly explained since the detailed explanation of each process is given in the following sections. First, car image is acquired as RGB colour image. In processing stage, it is converted to gray-scale image and in turn changed as binary image. Then, the properties, especially Euler-number and aspect ratio of binary regions collected. Then, non-potential candidate regions are filtered out. After that, each candidate region is matched with adaptive Euler-template and the score is recorded. Finally, the score is analyzed to ensure the existence of LP and localize the LP. If LP is detected, its centroid and bounding box are extracted.

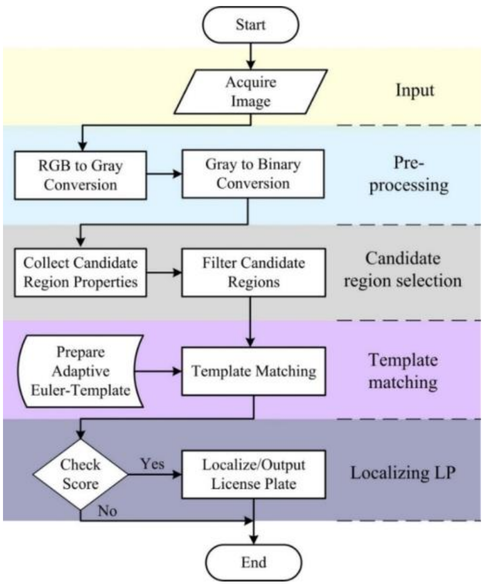

Figure 6. Flow-chart of proposed method

2.2.4 Pre-processing

In this step, the RGB image is converted to gray scale. Here, our own gray-scale conversion model given in Equation 2 is used.

$$I_g = 0.3 \times G - 10 \tag{2}$$

where, I_g is gray-intensity image, R=I(:,:,1), G=I(:,:,2), B=I(:,:,3) are red, green and blue intensities. According to Equation 2, the R intensity and B intensity are totally removed in gray scale conversion so that LP region with any of red, blue and black backgrounds will change as black colour. Only the characters remain with relatively higher intensities as shown in Figure 7 (a)-(b). Thus, this concept is independent of LP's colour during detection. Then, the gray image is converted to binary format by using the following threshold scheme.

$$I_{bw}(i,j) = \begin{cases} 1 & if\, I_g(i,j) < 10 \\ 0 & else \end{cases} \tag{3}$$

where, I_{bw} is binary image. Figure 7(c) shows the resulted sample image in which LP region is formed as a connected foreground object with character holes, from which Euler number is calculated.

2.2.5 Candidate region selection

As discussed in earlier sections, there are many regions that resemble LP in shape in front view and back view of a car. However, non-potential regions must be filtered out so that template matching time can be significantly reduced. The filter is designed with two different parameters; Euler number and aspect ratio. For Myanmar LP, the Euler number is -9 (see Figure 4-(d)). However, due to the possibility of the existence of fastener or other noises, it could be less than -9. Then, the aspect ratio (Width/Height) of Myanmar LP is 2.3. Also, there could be variation of aspect ratio in the image due to possibility of perspective in image. Thus, the following filter is used.

$$f_R = \begin{cases} True & if\;\; E > -30\, \&\, E < -3\, \&\, WH > 1.5\, \&\, WH < 3 \\ False & else \end{cases} \tag{4}$$

where, f_R is candidate region, E is Euler number and WH is aspect ratio. Thus, the meaning of Equation 4 used is that it will collect the regions as a candidate region if its E is greater than -30 or less than -3 and its aspect ratio is greater than 1.5 and is less than 3. After filtering, the candidate regions are collected for template matching in next step.

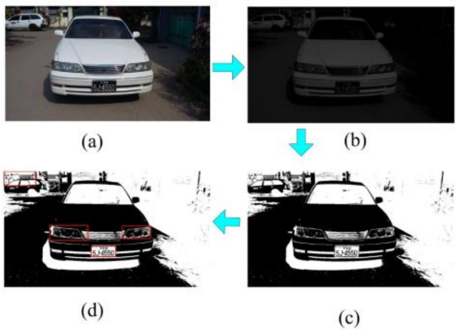

Figure 7. Processes in proposed method (a) True colour image (b) Gray scale image (c) Binary image (d) Candidate regions

2.2.6 Adaptive Euler-template matching

In traditional template matching method, the target is searched by shifting the template throughout the image. This is the main reason of much time consumption in traditional template matching method. Thus, in this study, only potential candidate regions are collected and adaptive Euler-template is used. For each candidate region in the image, the same size of Euler-template is created by adaptively resizing the original Euler-template. When performing matching between the target and the Euler-template, different similarity measures can be used. The most common similarity measures are absolute difference (SAD), sum of squared difference (SSD), maximum absolute difference (MaxAD) [22]. The other popular similarity measures are cross-correlation, normalized cross-correlation [22] and cumulative sum [10]. In most similarity measures, exact pixel-wise match is important. However, sometimes it can result in a big error due to only one position mismatching as shown in Figure 8(a). Thus, it significantly reduces the accuracy of template matching method.

Thus, a new concept of matching is proposed in this study. It is to calculate regional average at each pixel of template and target. Typically, a region of 3×3 or 5×5 can be used. It gives a more robust similarity measures (SAD or SSD) at each pixel. The existence of LP in the image is checked by using the following threshold.

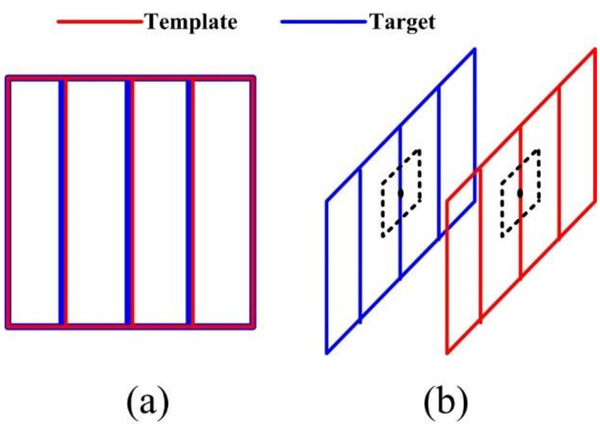

Figure 8. (a) Mismatching of target and template (b) Proposed matching concept

The existence of LP in the image is checked by using the following threshold.

$$R_{LP} = \begin{cases} True & if\ Minium\ error < \rho \\ False & else \end{cases} \tag{5}$$

where, R_{LP} is detected LP region, ρ is the threshold value. According to Equation 5, LP is identified and located if the minimum average error of candidate LP is less than the specified threshold. Otherwise, it is to reject all candidate LP regions.

2.3 Experimental evaluation of proposed method

The performance of proposed method is evaluated by experimentally testing with more than a hundred of test images. The test images include front views or back views of cars which includes LPs. The images taken are in JPEG format. The test images are prepared in higher and lower resolutions. In test images, the largest resolution is 720×960 and the smallest resolution is 309×318. The test scenarios are shown in Table 1.

Table 1. Information of test images and test scenarios

Test scenario	Number of test images	Template used
I	150	Proposed Euler-template(model-A)
II	150	Proposed Euler-template(model-B)
III	10	Proposed Euler-template(model-B)

In scenario-I, a total of 150 images are tested using proposed Euler-template(model-A). In test scenario-II the same images are tested using proposed Euler-template(model-B). In the last test scenario, a total of 15 Chinese family car LP are detected using proposed Euler-template(model-B). The proposed method is implemented using MATLAB 2014 software installed in a computer with a CUP of Intel(R) Core (TM) i5-7500 @ 3.40GHz 8 GB RAM. The performance of proposed method is evaluated in two metrics; accuracy and processing time. The accuracy of the LP detection is calculated by using the following equation [23].

$$Precision = TP/\ (TP+FP) \tag{6}$$

where, *TP* is true positive (the number of correct LP detections), *FP* is false positive (the number of incorrect LP detection). The processing time is automatically recorded by the software. Then, the performance of proposed method is compared with the performances of some existing methods in the literature.

3. Results and discussion

3.1 Detection using Euler-template (model-A)

Figure 9 (a)-(j) shows the detected Myanmar LP in some test images using proposed Euler-template(model-A). In each image, candidate LP regions are marked with red colour and the detected LP is marked with green box. Both font view and back view of car images are tested. As shown in Figure 9(a), Figure 9-(b), Figure 9 (c), Figure 9-(d), Figure 9-(f) and Figure 9(h), one can see that multiple candidate regions are formed due to front mirror, back mirror, front lamps, back lamps and surrounding objects that are similar in shape and aspect ratio of LP. However, the proposed Euler-template matching method can exactly detect the correct LP region from multiple similar regions. Also there are some conditions in which only LP region is found as candidate region as shown in Figure 9 (e).

One can also notice that the proposed method works well in different background environments and for different car colours as shown in Figure 9-(g), Figure 9(i) and Figure 9(j). Moreover, the proposed method is still robust even if the LP is twisted at a certain degree due to perspective view. As one can see in Figure 10 (a)-(b), the proposed method still gives correct detection of LP as long as inclination is just about 15°. By using proposed method, false positive (incorrect detection) occurs when candidate regions cannot be achieved before template matching. A sample of false positive (incorrect detection) detection is shown in Figure 11. It happens when the LP region is connected to neighboring large region, which makes it out of region selection criteria.

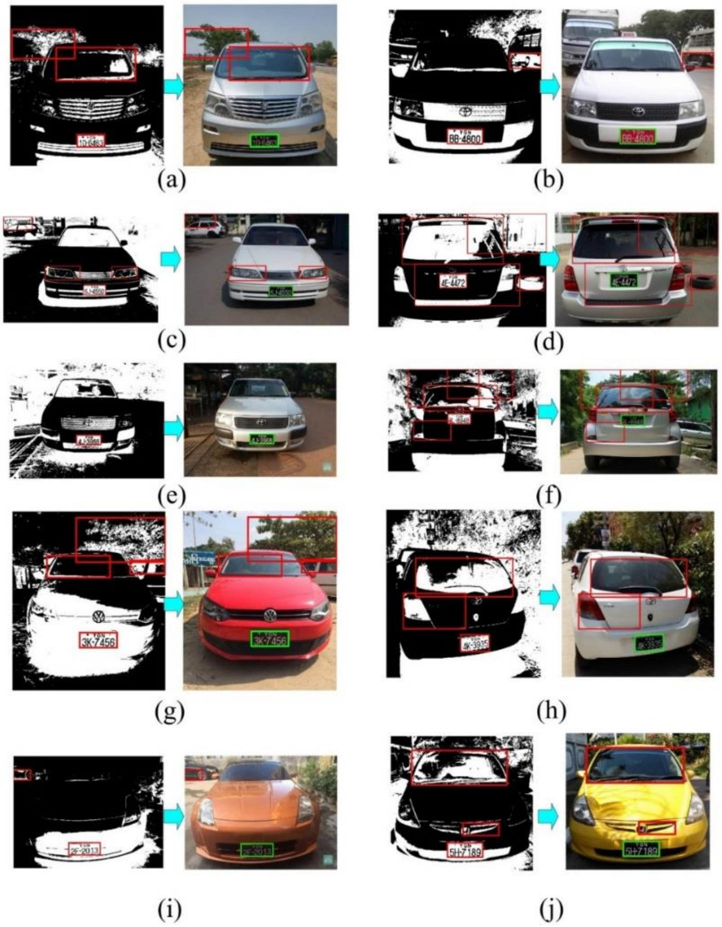

Figure 9. (a)-(h) Detected LP in sample test images

3.2 Detection using Euler-template (model-B)

The performance of Euler-template(model-B) is also evaluated by using the same test images. The SSD score and accuracies from Euler-template(model-A). Compared to Euler-template(model-A), a slightly better detection rate is achieved by using Euler-template (model-B). Table 2 shows the comparison of SSD score using Euler-template(model-A) and Euler-template (model-B) for some test images. The significant difference is that Euler-template(model-B) produces smaller SSD score compared to Euler-template (model-A). It means that Euler-template (model-B) is more effective than model-A.

In the proposed method [24], the segmented character is resized to get the size of template. It can change the image resolution and character formation. Thus, in our approach the template is resized to get the same size as targeted object, it is more flexible and durable to resizing.

Figure 10. (a)-(b) Correct LP detections in perspective views

Figure 11. Incorrect detection of LP

Table 2. Comparison of SSD score using proposed Euler-templates

Test image	SSD score using Euler-template (model-A)	SSD score using Euler-template (model-B)
Test image-1	2258	1814
Test image-2	1336	1158
Test image-3	3286	2513
Test image-4	4208	3238
Test image-5	1044	834

The accuracy of proposed method is shown in Table.3. Out 150 test images, a total of six false positive images occur by using Euler-template(model-A). Thus, the accuracy is 96.0%. Meanwhile, the proposed method using Euler-template(model-B) gives an accuracy of 96.7% with five false positive images. However, processing time is the same for both template models. It should be noted that the processing time shown in Table 3 is average processing time.

Table 3. Performance of proposed method (model-A and model-B)

Template used	Total test images	TP	FP	Precision (%)	Processing Time (s)
Euler-template(model-A)	150	144	6	96.0%	0.303 s
Euler-template(model-B)	150	145	5	96.7%	0.303 s

For testing a different license plate version, Euler-template(model-B) is developed for Chinese car LPs as shown in Figure 12. The aspect ratio of Chine family car LP is 3.14. The Euler-number is also less than -9. Then, the detected LPs in five test images are shown in Figure 13. It can be seen that there are multiple candidate regions due to different font appearance of the car. Even in such conditions, the proposed method still gives a robust detection of LP.

Figure 12. Euler-template(model-B) for Chinese car LP

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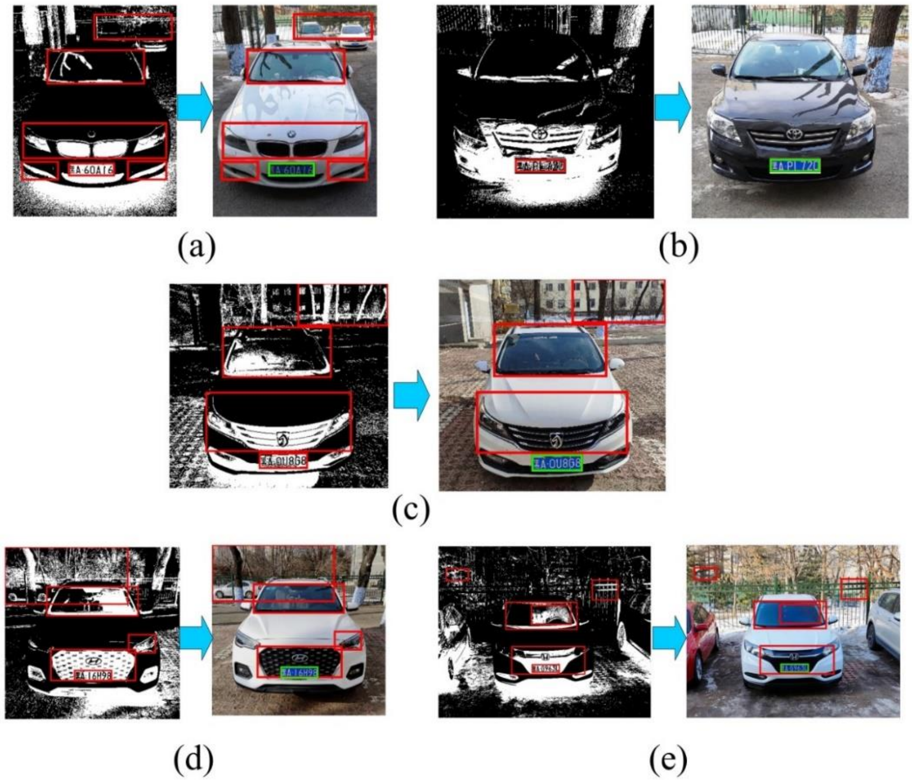

Figure 13. (a)-(h) Detected LP in Chinese car images using Euler-template(model-B)

Table 4. Performance comparison proposed method with previous methods

Method	Accuracy (%)	Processing time (s)
Canny edge detector and morphological operation [14]	92.0	0.3
Vertical edge detection algorithm [15]	84.8	<0.5
Hough transform and contour algorithm [16]	99.0	0.650
Text localization and extraction technique [25]	90.0	NA
Horizontal scan of repeating contrast changes [26]	96.8	1.200
Kernel density method [27]	98.1	0.452
Proposed Euler-template matching method	**96.7**	**0.303**

The performance of proposed method is also compared with the performance of existing methods in previous works as shown in Table 4. The accuracy of proposed method is relatively higher compared to some methods and somewhat lower compared to some other methods. When comparing in the perspectives of processing time, the proposed method is favorable compared to most of previous methods. However, it should be noted that the processing time is much dependent of image size, the number of candidate regions founded and speed of processing device. Indeed, in addition to accuracy and processing time, the complexity of algorithm and practicality in real-time applications are also important measures to be considered in the performance.

The performance of the method in [16] is very high. However, in [16], the location of LP was identified by searching character elements in a region. When the number and size of elements searched in a region are as expected, the rectangle region was identified as car license plate. It took much time and increased complexity compared to ours. In our proposed method, it is not necessary to find out the properties of characters. The proposed method is much simple in step-by-step processing. It enhances the processing time. The method in [26] showed a very slightly higher performance than our proposed method. The aspect ratio of LP was used for searching rectangular objects. due to multiple steps including wavelet edge detection and morphological operation, it took a long processing time of 1.2 s. It is a big longer time compared to the processing time required by our proposed method.

4. Conclusion

In this study, adaptive Euler-template matching method is proposed for car LP localization. Two different models of Euler-template and a new matching concept are proposed. The proposed method is evaluated by detecting LPs in 150 test images and by comparing with the performance of some previous works. This study contributes an innovative template matching method for localizing LP with the following remarkable characteristics.

a. The proposed Euler-template is very simple binary template and easy to implement by following the general pattern of targeted LP. It is independent of LP colour and LP size. The proposed method significantly reduces processing cost since it does not need to shift the template throughout the images. It does not need to handle multiple templates with different colours and different sizes.
b. The proposed method works in different outdoor environments and with different image resolutions. The proposed method can still give correct detection of LP even for some perspective view of LP as long as the inclination is around 15°.
c. The proposed Euler-template(model-B) is more effective than proposed Euler-template(model-A) by showing a slightly larger accuracy and smaller SSD score. The proposed method gives an accuracy of 96.7% with average processing time of 0.303 s.

This study still has some limitations and further investigations are needed for advancement of proposed method. The proposed Euler-template should be tested more with different LP formats from different foreign countries. The performance of Euler-template should be tested in other general object detection (for example, road signs). Also, its performance should be tested with image resolutions lower than 300×300 and real-time application. The effective of Euler-template (model-A) and Euler-template (model-B) could be dependent of pattern of targeted object.

Author’s declaration

Author contribution

Nay Zar Aung developed the main idea of Euler-template matching method, designed the research and prepared the research paper. The research was supervised and guided by **Li Songjing** and **Peng Jinghui** implemented MATLAB coding. **Khin Cho Tun** contributed for finding dataset and implemented experimental tests.

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Data availability

The data is owned by the authors. For data accessibility for further research, permission of authors is needed.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical clearance

This study did not involve human subjects; therefore, approval from the ethics committee was not required.

AI statements

This article is the original work of the author without using AI tools for writing sentences and/or creating/editing table and figures in this manuscript.

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Researcher and Lecturer Society as the publisher and Editor of Innovation in Engineering state that there is no conflict of interest towards this article publication.

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Nomenclature

L_1	Width of license plate
L_2	Height of license plate
W, w	Width of character
H, h	Height of character
L_{1_tp}	Width of Euler-template
L_{2_tp}	Height of Euler-template
W_{tp}, w_{tp}	Width of holes in Euler-template
H_{tp}, h_{tp},	Height of holes in Euler-template
E	Euler number
N	Number of connected foreground regions
H	Number of holes
I_g	Gray intensity value
R	Red intensity value
G	Green intensity value
B	Blue intensity value
I_{bw}	Binary image
f_R	Candidate region
WH	Width-height ratio
R_{LP}	License plate region
ρ	Threshold value
TP	True positive
FP	False positive