Adaptive License Plate Detection Algorithm Under Varying Conditions: Postprint

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Abstract

License plate detection (LPD) constitutes a primary step in automatic license plate recognition (ALPR). To address the issues of slow detection speed and low detection accuracy under various conditions, this paper proposes an improved license plate detection algorithm based on adaptive morphological closing and opening operations. The algorithm first applies local histogram equalization to license plate images, then utilizes adaptive morphological closing operations to smooth all grayscale regions. Subsequently, local adaptive threshold processing is introduced to obtain smoothed images and separated license plates. Finally, morphological opening operations are employed to separate external regions from the connected components of license plate characters. Experimental results demonstrate that the proposed method achieves higher detection accuracy compared to other algorithms while also exhibiting a lower average detection time, rendering it suitable for real-time license plate detection under diverse conditions.

Full Text

Adaptive License Plate Detection Algorithm for Different Conditions

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Abstract: License plate detection (LPD) is a crucial step in automatic license plate recognition (ALPR). To address the problems of slow detection speed and low accuracy under varying conditions, this paper proposes an improved license plate detection algorithm based on adaptive morphological closing and opening operations. The algorithm first employs local histogram equalization to preprocess license plate images, then uses adaptive morphological closing to smooth all grayscale regions. Subsequently, local adaptive thresholding is introduced to obtain smoothed images with separated license plates. Finally, morphological opening operations are applied to separate connected components between external regions and license plate characters. Experimental results demonstrate that the proposed method achieves higher detection accuracy and shorter average detection time compared to other algorithms, making it suitable for real-time license plate detection under diverse conditions.

Keywords: license plate detection; local histogram; adaptive morphological closing operation; local adaptive threshold; morphological opening operation

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0 Introduction

Intelligent transportation systems (ITS) represent a vital component of traffic management, playing a significant role in reducing transportation costs [1,2]. Automatic license plate recognition (ALPR) constitutes a primary step within ITS [3-5], with applications spanning traffic monitoring, security management, public and private parking systems, and stolen vehicle tracking. Since every vehicle possesses a unique, standardized license plate number without requiring additional technologies or materials, visual ALPR systems offer simpler and more cost-effective upgrades compared to alternative technologies [6-8].

Most ALPR systems comprise three main components: license plate detection, character segmentation, and character recognition. Among these, license plate detection is the most critical step [9,10], as the accuracy of subsequent character segmentation and recognition directly depends on the quality of the initial detection. If license plate localization can precisely detect the plate without extraneous regions or pixels, the accuracy of character segmentation and recognition will improve accordingly.

Numerous algorithms have been proposed for license plate detection. Reference [11] introduced a method combining edge density and covariance SVM, which uses edge density to detect candidate plate regions, employs chain code tracking and morphological erosion to eliminate overly long or short edges while preserving broken plate edges caused by edge detectors, and finally validates candidate sets using a linear support vector machine with covariance features for rapid and accurate video-based detection. Reference [12] applied frequency filters and a novel contrast enhancement method for license plate detection under hazardous conditions such as rainy or foggy weather, low-contrast environments, and backgrounds similar to license plates. Reference [13] proposed a corner feature-based approach that first removes non-corner points by selecting large gradient thresholds, then uses an improved Harris corner classifier with clustering to find candidate regions, and finally reduces thresholds and detects corners within these candidates. Reference [14] developed a robust method based on wavelet transform and empirical mode decomposition (EMD) analysis to locate license plates, extracting horizontal and vertical details through wavelet transform, applying EMD to find plate positions, and using Hilbert transform to extract plate features.

Despite these advances, license plate localization remains challenging due to factors including environmental lighting variations, occlusions, motion blur, plate distortion, and weather conditions. Building upon existing methods, this paper proposes an adaptive license plate detection algorithm that first applies adaptive morphological closing (AMC) to smooth grayscale images, introduces local adaptive thresholding to obtain smoothed images with essentially separated license plates, and finally performs morphological opening (MO) to separate plate data from external regions, thereby achieving accurate plate detection.

1 License Plate Detection Algorithm Using Improved AMC and MO

The flowchart of the proposed license plate detection method is shown in [Figure 1: see original paper]. This approach improves adaptive morphological closing operations and introduces local adaptive thresholding between the closing and opening operations, resulting in smoother and clearer license plate detection.

1.1 Improved Adaptive Morphological Closing Operation

The preprocessing method in this paper employs improved histogram equalization to enhance image contrast. Histogram equalization stretches pixel values to the range [0, L-1] as shown in Equation (1):

$$s_k = \frac{\sum_{i=0}^{k} n_i}{N}, \quad k = 0, 1, 2, \dots, L-1$$

where s_k represents the new transformed pixel value, N denotes the total number of pixels, and n_i indicates the number of pixels with value equal to i.

While histogram equalization performs well under uniform and adequate lighting conditions, its accuracy degrades with non-uniform illumination or reflection. To address this limitation, the proposed method adopts local histogram equalization, which divides the license plate image into different overlapping blocks and performs operations within each block. [Figure 2: see original paper] compares the detection effects of standard histogram equalization versus local histogram equalization. The original image in (a) exhibits low contrast and appears dark. Applying standard histogram equalization yields image (b), where the entire image is enhanced but some regions become oversaturated. Local histogram equalization, shown in (c), resolves this issue by processing overlapping blocks independently.

Morphological closing aims to fill features and smooth license plate regions. Conventional morphological closing uses a fixed structuring element (SE) whose size and shape cannot be adapted, representing a significant limitation for applications where scaling is important. While using multiple fused SE features is one solution, it substantially increases computational cost. Adaptive morphological closing overcomes this by employing a set of SE features for the closing operation.

For image A and structuring element B, the basic morphological erosion and dilation operations are defined as:

$$A \ominus B = \min_{(i,j)\in B} A(i+t_1, j+t_2)$$
$$A \oplus B = \max_{(i,j)\in B} A(i-t_1, j-t_2)$$

where $\ominus$ denotes erosion, $\oplus$ denotes dilation, and (t_1, t_2) represents the translated pixel values of set B. Based on these operations, closing is defined as:

$$A \bullet B = (A \oplus B) \ominus B$$

Closing operations eliminate narrow breaks and long, thin gaps, fill small holes, and bridge discontinuities in images. The proposed adaptive morphological closing replaces the 串联 of multiple closing operations by using adaptive structuring elements. [Figure 3: see original paper] illustrates the AMC operation using a set of SEs, where d represents one of the base elements in the set. This approach saves memory and other computational resources.

Following AMC, local adaptive thresholding is applied. The proposed method uses rectangular windows instead of traditional square windows, enabling detection of more pixels while reducing computation time. The pseudocode for the local thresholding procedure is as follows:

```
procedure AdaptiveThreshold(in, out, m, n, w, h)
    for i = 0 to w do
        sum $\leftarrow$ 0
        for j = 0 to h do
            sum $\leftarrow$ sum + in[i, j]
            if i = 0 then
                intImg[i, j] $\leftarrow$ sum
            else
                intImg[i, j] $\leftarrow$ intImg[i-1, j] + sum
            end if
        end for
    end for

    for i = 0 to w do
```

```
        for j = 0 to h do
            x1 $\leftarrow$ i - s/2
            x2 $\leftarrow$ i + s/2
            y1 $\leftarrow$ j - s/2
            y2 $\leftarrow$ j + s/2
            count $\leftarrow$ (x2 - x1) $\times$ (y2 - y1)
            sum $\leftarrow$ intImg[x2, y2] - intImg[x2, y1-1] - intImg[x1-1, y2] + intImg[x
            if (in[i, j] $\times$ count) $\leq$ (sum $\times$ (100 - t)/100) then
                out[i, j] $\leftarrow$ 0
            else
                out[i, j] $\leftarrow$ 255
            end if
        end for
    end for
```

where `in` represents the input image, `out` represents the output image, `intImg` is the integral image, m and n denote license plate width and height, w and h are input image dimensions, and t is the threshold value.

1.2 Morphological Opening Operation

Vehicle components such as radiators, grilles, and bumpers often connect to license plate regions. Morphological opening operations, which perform erosion followed by dilation, can disconnect weakly connected regions. Based on erosion and dilation, opening is defined as:

$$A \circ B = (A \ominus B) \oplus B$$

Opening operations smooth object contours, disconnect narrow breaks, and eliminate thin protrusions. [Figure 4: see original paper] demonstrates the separation of connected regions using morphological opening. Sample images (a) and (b) show buffers attached to license plate regions, while (c) and (d) display the successfully separated regions after opening.

Both morphological opening and closing operations use a $K \times K$ matrix on license plate images. For an input image of size $w \times h$, the computational complexity is $O(w \times h \times K \times K)$. In license plate detection, the minimum and maximum values of m and n are determined by spatial factors or distance between vehicle and camera, calculated as:

$$\begin{cases} m = LP_{\text{min,width}} + LP_{\text{max,width}} \\ n = LP_{\text{min,height}} + LP_{\text{max,height}} \end{cases}$$

where $LP_{\text{min,width}}$ and $LP_{\text{max,width}}$ represent the minimum and maximum license plate widths, while $LP_{\text{min,height}}$ and $LP_{\text{max,height}}$ represent the minimum and maximum heights. Local adaptive thresholding may cause connections between plate and non-plate regions; morphological opening resolves this issue.

2 Experimental Results and Analysis

The experimental dataset comprises 2,232 real-world photographs captured by commercial cameras in various scenarios, including highways, automatic gates, daytime and nighttime conditions, and different weather conditions. Some images contain multiple license plates. Sample images from the dataset are shown in [Figure 5: see original paper].

The proposed method is implemented using C++ and OpenCV 3.2, with local histogram equalization and adaptive morphological closing operations accelerated on GPU using OpenCL. Detection rate and detection time are used to evaluate effectiveness. Detection rate is defined as the number of completely detected license plates—plates with all features, not just partial components like grilles or bumpers. Detection time measures the total duration from reading the image from disk to displaying results, not merely computation time.

[Figure 6: see original paper] shows license plates extracted from sample images in [Figure 5: see original paper] using the proposed method. The average extraction time is 20.77 ms (20.53 ms for image 1, 21.01 ms for image 4), demonstrating suitability for real-time detection.

Comparative experiments are conducted against existing methods: Empirical Mode Decomposition (EMD) [14], Binarization (BIN) [12], Fuzzified Gabor Filter (FGF) [15], Discrete Wavelet Transform (DWT) [14], Vertical Edge Detection Algorithm (VEDA) [16], LOG Edge Detection Algorithm (LOGEDA) [16], Harris Corner Detection [14], and Intensity Variance & Edge Density (IV&ED) [12].

[Figure 7: see original paper] and [Figure 8: see original paper] compare detection rates and processing times. The proposed method achieves a detection rate exceeding 99.3%, higher than all compared methods. This improvement stems from three factors: (1) adaptive morphological closing enhances contrast adaptively for different conditions, (2) rectangular windows in adaptive thresholding detect more pixels than square windows, and (3) morphological opening separates connected regions for smoother detection boundaries.

The proposed method also exhibits the lowest detection time, averaging only 20.01 ms, enabling real-time performance. The rectangular window approach contains more pixels than square windows, reducing computation time.

To further validate effectiveness, the algorithm is tested on 18,625 images from highway toll stations under diverse conditions (night, day, cloudy, rainy, complete and incomplete plates). The average detection rate is 99.32% with an average extraction time of 21.05 ms, confirming the algorithm’ s practical viability.

3 Conclusion

This paper proposes an improved license plate detection algorithm based on adaptive morphological closing operations to enhance detection rates and reduce processing time. The algorithm comprises four stages: (1) preprocessing via local histogram equalization, (2) adaptive morphological closing for contrast enhancement under varying conditions, (3) local adaptive thresholding using rectangular windows to capture more pixels while reducing computation, and (4) morphological opening to separate connected regions between plates and other vehicle parts. Experimental results on real-world datasets under diverse conditions demonstrate that the method achieves rapid license plate detection with an average detection rate of 99.3% and processing time of only 20.01 ms, outperforming existing methods in both accuracy and speed.

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Note: Figure translations are in progress. See original paper for figures.