A new license plate extraction framework based on fast Mean Shift

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ABSTRACT

License plate extraction is considered to be the most crucial step of Automatic license plate recognition (ALPR) system. In this paper, a region-based license plate hybrid detection method is proposed to solve practical problems under complex background in which existing large quantity of disturbing information. In this method, coarse license plate location is carried out firstly to get the head part of a vehicle. Then a new Fast Mean Shift method based on random sampling of Kernel Density Estimate (KDE) is adopted to segment the color vehicle images, in order to get candidate license plate regions. The remarkable speed-up it brings makes Mean Shift segmentation more suitable for this application. Feature extraction and classification is used to accurately separate license plate from other candidate regions. At last, tilted license plate regulation is used for future recognition steps.

Keyword list：License plate extraction, Fast Mean Shift, color image segmentation, compact KDE, feature selection, convex hull, Mahalanobis distance, affine transformation

1. INTRODUCTION

In recent years, Intelligent Transportation Systems (ITS) has been a priority and hotspot issue in the research field . Use the image processing technology to analyze the vehicles is an important part in the ITS. The most effective way to identify the vehicles is to tell the license plates apart. It mainly includes three techniques: Plate Location, Character Extraction, Character Recognition. Vehicle license plate detection is one of the most important part in vehicle recognition. The accuracy and speed of the location will directly affect the performance of the overall system.

Recently, worldwide researchers have done lots of studies on the license plate location algorithm, created a number of relatively mature methods, such as edge detection and mathematical morphology, fuzzy clustering segmentation, neural network, wavelet transform methods, the regional texture segmentation method that based on the color and texture feature. These methods are used in a wide range of applications in some specific areas, but their versatility and practicality still remains to be further improved. And a perfect license plate recognition system should still possess strong applicability and stability in some poor conditions, such as poor image quality of the vehicle or background interference or various lighting conditions, fractured plate, or image distortion, rotation, scale changes or multi-plate cases [1].

Most researchers tend to use the hybrid detection method with a variety of characteristic information. This method is just what we used in this text. But what distinguished us with the former methods is that begin with the rough plate location in the complex background, then adopt a new Fast Mean shift color segmentation by compact density representation, which brings a considerable speed improvement, to segment the roughly located main region into several candidate regions, and finally use the feature extraction and classification method to separate license plates from other candidate regions.

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The rest of the paper is organized as follows: Section 2 presents a rough plate location method in complex background. Section 3 introduces color vehicle image segmentation based on Fast Mean Shift. Section 4 describes the process of the feature extraction, classification and experimental results. Then tilted license plate regulation is introduced in Section 5. In the end, we demonstrate the present research and conclusions.

2. ROUGH LOCATION OF VEHICLE BODY

In practice, vehicle images are captured under complex backgrounds, and vehicle body is only a part of the whole image. This situation brings many difficulties for license location at the same time make the calculation more complex. Therefore, it is necessary to run rough vehicle location before license plate detection to filter certain interfering information and zoom out candidate region. This operation is meaningful for speed-up especially for the following Mean Shift algorithm.

The rough vehicle location method is based on the fact that the head of vehicle exists comparatively rich texture and high gray pixel variance is concentrated in vehicle regions. At first, execute binarization to the images and then use Gaussian Filter to smooth the images. The location of license plate centralizes in the middling or lower region in an image. So we limit the location region begin at upper quarter and end at lower quarter. Then we define a template sized 20×80 to traverse the limited region, and count the number of horizontal gray value jump in each template region. By experiment, we use an empirically count threshold range 10~20 times, and pick out regions satisfy the threshold. Then we define the region sized 400×360 which contains the most satisfied template regions as the vehicle's location. The result of rough location is shown in Fig.1.

Fig.1 Rough vehicle location result (600×480)

3．FAST MEAN SHIFT SEGMENTATION

3.1 Standard Mean Shift

Mean Shift method is a well established clustering technique that is widely used in feature space analysis, imaging applications such as image and video segmentation, object tracking, texture classification, and others. Implement Mean Shift to segment the automobile image, we would get several color license plate candidate regions. We review the ordinary standard Mean Shift[2] algorithm at first. Given n data points x_i in a d-dimension space R^d , the Kernel Density Estimator(KDE) of these data with a kernel K(x) and a symmetric positive definite d×d bandwidth matrix H is taken as

$$f(x) = \frac{1}{n}\sum_{i=1}^{n} K_H(x - x_i) \qquad (1)$$

Where $K_H(x_i - x) = |H|^{-1/2} K\left(H^{-1/2}\left(x_i - x\right)\right)$, and the function *f(x)* itself is an estimate of the probability density underlying the data points. Normally Mean Shift can be seen as a procedure of climbing hill, starting at point *x* and then brings *x* up along the hill of KDE, finally reach local maximum of KDE. Usually a special kernels of $K(x)=ck(||x|^2|)$ is useful, with the property of radially symmetric. The function *k(x)* is the profile of the kernel which makes *K(X)* integrates to one, and c is the constant normalization. Let *g* donates *-k'*, H is chosen as proportional to the identity matrix $H=h^2I$, the expression of the iteration process of Mean Shift is shown as

$$M(x) \equiv \frac{\sum_{i=1}^{n} x_i g(\| \frac{x - x_i}{h} \|^2)}{\sum_{i=1}^{n} g(\| \frac{x - x_i}{h} \|^2)} \to x \qquad (2)$$

Practically, the iteration procedure of Mean Shift tends to converge in a very few steps, typically about 5. However, the number of data points *n* is usually very large in practice, the Mean Shift has relatively high time complexity which is super-linear in the number of data points *n*. Considering this problem, if we use standard Mean Shift method directly to segment automobile images to get candidate license plate regions, we hardly receive acceptable efficiency, let alone real-time detection, especially when the image size is large. So we adopt a state-of-the-art Fast Mean Shift method proposed by Daniel Freedman and Pavel Kisilev[4].

3.2 Fast Mean Shift image segmentation

One major reason that influences the speed of Mean Shift is the description complexity of the KDE. The proposed method[4] is mainly focus on finding a compact KDE which uses fewer points to generate and still be able to be close to *f(x)*. Freedman's solution is to choose the samples $\hat{x}_i$ by sampling from the distribution given by $f(\cdot)$. They have proven that $\hat{f}$ is close to f when m is large enough.

Theorem 1: For each j=1,...,m, $\hat{x}_i$ is constructed as follows:

1. choose a random integer $r_j \in \{1,\ldots,n\}$;
2. choose a random sample δ_j from $K(\cdot)$;
3. set $\hat{x}_i = x_{r_j} + H^{1/2}\delta_j$.

Then $\hat{x}_i$ is a proper sample of f.

The more compact KDE can be incorporated into Mean Shift as the following steps:

1. Sample: Select m samples from the density f then yield $\{\hat{x}_j\}_{j=1}^{m}$. For the new density $\hat{f} = \sum_{j=1}^{m} K_{\hat{h}}(x, \hat{x}_j)$;
2. MeanShift: Perform MeanShift on each of the m samples: use $\hat{f}$ instead of f, then $\hat{x}_j \to \hat{M}^{\infty}(\hat{x}_j)$.
3. Map backwards: For each points x_i, find the closest new sample $\hat{x}_j^{*}$. Then $x_i \to \hat{M}^{\infty}(\hat{x}_j)$.

The real speed up occurs in Step.2, by using *m* samples rather original *n* points. In practice, we use a weighted form of Step.3 as $x_i \to \sum_{j=1}^{m} w_{ij} \hat{M}^{\infty}(\hat{x}_j)$, where weight $\sum_{j=1}^{m} w_{ij} = 1$. The optimal bandwidth is provided as $\hat{h} = (n/m)^{h/d+1}$. Varying sample factor *n/m* will receive different speed, and we can get a range of proper sub-sampling rate that could satisfy the efficiency at the same time the performance with the experiment. Fig.2 demonstrate the result by using fast Mean Shift segmentation with n/m=1,024. Time complexity is reduced considerably compare with standard Mean Shift method.

Fig.2 The performance of fast Mean Shift segmentation (n/m=1,024)

As we can see in Fig.2, even in the case that license plate region has quite similar color with the vehicle body, it still can be distinctly separated from the rest regions. Thus, Mean Shift could avoid drawbacks of traditional color region-based segmentation such as histogram method. These regions obtained will be acted as candidate region of license plate, used for subsequent region feature extraction. The information generated during the procedure of Mean Shift segmentation, like region boundaries and pixel numbers, are also useful for our next work.

4．FEATURE EXTRACTION

Before starting the feature extraction process, we can remove some regions that are oversized or undersized, based on the statistics of license plate region area in the vehicle image library. In the experiment, candidate regions over 4000 pixels or less than 1000 pixels are neglected. Then features of each region would be extracted in order to separate the license plate region from others. There are many feature extraction methods can be used for this purpose. However, certain features are only valid in specific environment. Three features are demonstrated as below, although they are not suitable for all situations, they would be effective and insensitive to most environment variance.

4.1 Convex hull area matching

In an automobile image, license plate region has relatively rich texture after we filter certain complex backgrounds, because there are characters and license plate frame. These textures can be used as features of license plate region. We select candidate regions that contain high density of corner points, which are widely used in feature extraction. However, these corner points won't be used directly as features, instead, we calculate the convex hull area of corner points sets in each candidate region, based on Graham's scanning algorithm. Then calculate the ratio between the area of convex hull and the area of the candidate region. Considering the fact that most license plate regions are comparatively regular parallelograms, its area ratio would be highly matched. So we can use this ratio as a matching feature and eliminate most non-parallelogram regions. Fig.3 shows the performance of this method, it is an obvious that license regions have higher matching degree with the convex hull of corner points.

Fig.3 Convex hull area of regions' corner point sets

4.2 Aspect ratio

Different view angle will cause shape distortion of the license plate, and may impact on the matching degree between the convex hull and license region, as shown in the right picture in Fig.3. In order to minimize the influence and guarantee area matching degree, aspect ratio is applicable in this situation. Normal definition of aspect ratio is the ratio of the width to the height of the region's MER (Minimum Enclosing Rectangle). Although the MER can be got by seeing the object region as a rigid body and the dimension of the MET can be taken as the width and height of the region, its calculation procedure still include finding out a horizontally oriented enclosing rectangle which is fit to the boundary by rotating the region step by step. We propose to use a special convex hull, minimum enclosing rectangle of each regions' corner point sets (Rectangle Convex Hull, RCH) in place of MER and define the aspect ratio as the ratio width to the height of the region's RCH. And then use Ratio=Weight/Height as another region feature, and it would result in higher efficiencies with a similar performance as MER.

Fig.4 Rectangle convex hull of regions' corner point sets

4.3 Edge density

After execution of the two feature extraction methods stated above, most disturbing non-license regions can be filter off. However, it is possible that there exists some region may have similar features as the license plate. License plate region has relatively high local pixel variance ratio because of characters, and this fact can be utilized as another important feature. Local pixel variance can be denoted by edge density response. In a region R with N_R pixels, edge density is the average value of each pixel in an edge magnitude image, and an edge magnitude image can be obtained by applying Sobel operator[5]. In a vehicle body image, there exits many horizontal edges but fewer vertical edges, so use vertical Sobel operator only could reduce calculation. After execution of Sobel operator, then use threshold methods as below to generate the edge response of an image.

$$E_{i,j} = \begin{cases} 1, & if\ D_{i,j} \geq T \\ 0, & otherwise \end{cases} , \quad 1 \leq i \leq Width, 1 \leq j \leq Height \tag{3}$$

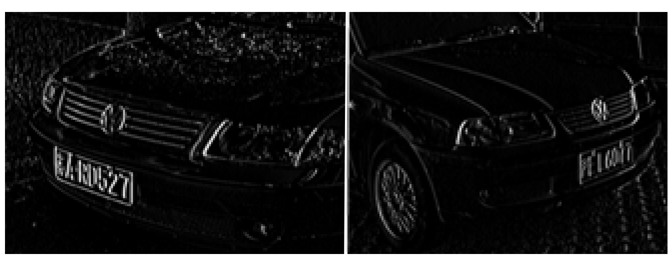
where， $D_{i,j}$ is vertical edge intensity function of the input image at pixel (i, j), while $E_{i,j}$ denotes the corresponding binary vertical edge image. In Eq.(4), T is a threshold, and defined as

$$T = \begin{cases} T_D & if\ T_D > T_0 \\ T_0 & otherwise \end{cases} , \quad T_D = D_m + D_\sigma \tag{4}$$

where， D_m and D_σ is the mean and standard deviation of $D_{i,j}$. T_0 (experimental value) is the lower threshold. As we can see in Fig.5(c)，small regions are removed in edge response images after threshold, and the edges of vehicle are intensified. Base on these calculations, the edge density response is defined as

$$D_R = \frac{1}{N_R} \sum_{i,j \in R} E_{i,j} \tag{5}$$

(a) Gray image after Gaussian filtered



(b) Vertical edge response images

(c) Edge density response images

Fig.5 Edge density response images

4.4 Feature classification

Three region features extracted above are constituted as a 3-dimension feature vector X, and there are many methods could be used to region classification. This paper uses a dynamic clustering method, k-Means, to divide the 3 dimension feature space, by using the Mahalanobis distance as the distance measure, with the minimum distance classifier as the decision-maker. With k-Means method, training images' feature data is divided into three categories, defined as three types of areas, Plate1, Plate2, Non-plate, representing the two different plate regions and non-vehicle license plate regions caused by the distance and angle distributions. Calculate the Mahalanobis distance between feature vector X of the identification sample and the center of each class model, and then classify X to the category with the minimum distance.

Table 1 The statistical mean data of the three features for three classes of regions

Classes	Convex Hull Area ratio	Aspect Ration	Edge density
Plate-1	0.954	3.12	22.46
Plate-2	0.93	3.05	15.37
Non-plate	0.712	3.73	0.157

Though training image samples, we obtain the mean vectors m_k, k = 1,2,3 of each class's feature vectors and the covariance matrix C_k ,k = 1,2,3,. In the experiment, we randomly selected 60% of sample images as the training sample set, and the rest used as test samples. During the test, we calculate the Mahalanobis distance (6) between the classified feature vector X and the mean vector m_k, and then X will be classified to the nearest region's category.

$$d_k^2 = \| X - m_k \|^2 = (X - m_k)^T C_k^{-1} (X - m_k) \quad , k = 1,2,3 \qquad (6)$$

In the experiment, the region is classified as a license plate as long as $d_1 < d_3$ or $d_2 < d_3$.

5. TILTED LICENSE PLATE REGION'S REGULATION

Due to diverse camera angle, some detected license plate regions may have different degrees of tilted angle. In order to facilitate following works such as character recognition, we need to regulate the extracted region to get an approximate horizontal rectangular area, while reducing as much tilted characters as possible. Common used geometric transformation methods are Radon transformation, affine transformation and perspective transformation.

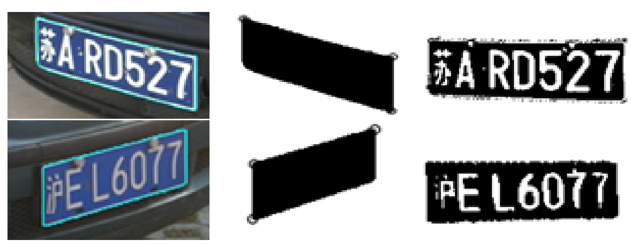
Using Radon transformation, the tilted region can be transformed to horizontal rectangular region, but characters are rotated too. Affine transformation has advantage of few parameters, which can simplify the calculation. It is not adequate for all geometric distortions. However, for the license plate recognition system usually with small angle distortion, affine transformation could be qualified.

5.1 Affine transform

Using affine transformation (AT), a transformation matrix between the object's coordinates of before and after affine transformation is needed. According to affine transformation principle, three non-collinear points determine the only affine transformation. In affine coordinate, affine transformation would not change the ratio of parallel segments.

The shape of license plate segmented after Mean Shift is regular enough that it could be approximately seen as a parallelogram. Therefore, we just need to know three vertices of the region and other three expected vertices and then the only affine transformation can be determined. By the relation between the transformed vertices, affine transformation matrix could be calculated. After that, we can apply the transformation matrix to each pixel of the plate region.

In order to obtain a rapid way to get vertices coordinate, we use the corner detection method again: applying threshold to tell apart the pixels inside and outside the plate region's boundary, which is stored during the Mean Shift procedure. Then the maximum number of corners is limited to 3, in the binary image, the detected three corners are the region's three vertices. If we wish the shape after transformation is a horizontal rectangle, three expected vertices can be defined as (0 , 0), (0 , H-1),(W-1 , 0), where H is the height and W is the weight. H and W can be determined by referring the specific ratio of standard size (W: H=440:140 in Chinese GB).



(a) (b) (c)

Fig.6 (a) Leaning license region before AT; (b) Three vertexes of parallelogram;
(c) Threshold license region after AT

The results are shown in Fig.6, the two license plate region is tilted about 30 degrees horizontally, and we get an ideal result after affine transformation.

6. CONCLUSION

Complex backgrounds and various scenes bring lots of difficulties to ALPR researches. Considering this situation, this paper presents a region-based method based on the new Fast Mean Shift algorithm. Compare with standard Mean Shift's calculation complexity, this accelerated method make color image segmentation more suitable for this application which has a strict speed requirement. In the experiment image library, there are about 400 images, size about 640×480, including various conditions, such as strong lighting, degrading of license plate, different view of shooting. The result demonstrates our method works well under these interferences, and the accuracy of detection is 92.6%. This is because the candidate regions are divided directly from color images rather than generated from features as most edge-based methods do. Our future works will focus on improving precision of the location algorithm and further optimization of the program for better efficiency.

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