Mean Shift for Accurate Number Plate Detection

Wenjing Jia, Huaifeng Zhang and Xiangjian He
Department of Computer Systems
Faculty of Information Technology
University of Technology, Sydney
{wejia, hfzhang, sean}@it.uts.edu.au

Abstract

This paper presents a robust method for number plate detection, where mean shift segmentation is used to segment color vehicle images into candidate regions. Three features are extracted in order to decide whether a candidate region contains a number plate, namely, rectangularity, aspect ratio, and edge density. Then, the Mahalanobis classifier is used with respect to the above three features to detect number plate regions accurately. The experimental results show that our algorithm produces high robustness and accuracy.

1. Introduction

Number plate detection, also called number plate localization or extraction, is used to correctly detect number plates from background vehicle images. This task is considered the most crucial step in the automatic number plate recognition (ANPR) system. Since there are problems such as poor image quality due to various ambient lighting conditions, image perspective distortion, interference characters, etc., number plates are often difficult to be detected accurately and efficiently in real applications.

Many methods have been proposed to detect number plates from vehicle images. Most researchers prefer a hybrid detection algorithm in order to make the algorithm more robust and accurate. People usually manage to get some candidate regions based on the features that appear uniquely in number plate regions. Then, combined with some priori knowledge of number plates, non-number plate regions are removed and real number plate regions are left, which means number plates are successfully detected.

In order to detect possible number plate regions (candidate regions), local variance of the vertical gradient [1][2] and vertical edge density [3][4] of input images are calculated. The resulted images are then binarized to get binary images, on which morphological operations can be implemented to obtain candidate regions. In [6][7], color-based methods are presented, where the color types and their sequence in the scanning cross-section of number plate areas are utilized to detect number plates. While how to decide the color of a certain pixel is a difficult problem. Neural network classifier is usually used to classify colors at each pixel.

This paper proposes a region-based number plate detection algorithm. Mean shift segmentation [9] is employed to segment a vehicle image into several candidate regions. Then, features are extracted according to statistical analysis in order to correctly classify each region into a corresponding class. Finally, minimum-distance linear classifier is used to make the final decision where different contributions of each feature to the final decision are considered by utilizing Mahalanobis distance metric.

Unlike the methods in [1-4], the proposed algorithm is a real region-based number plate detection method. We employ the color information in order to segment the input vehicle images into several candidate regions. In our method, the candidate regions that contain number plates are obtained more directly and accurately than previous methods, where the candidate regions are actually generated from some features, such as local variance [1][2] and edge density [3][4], within the real number plates, where an accurate number plate region can not be assured. Another point is that, unlike other color-based methods, our method does not need to decide the exact color at each pixel in order to do segmentation. This can reduce the computational complexity and improve the robustness of the algorithm.

The remaining parts of the paper are organized in the following order. The proposed algorithm is described firstly, where mean shift segmentation is introduced in Section 2, feature extraction in Section 3, and Mahalanobis classification in Section 4. Experimental results are shown and evaluated in Section 5. Section 6 is the conclusion part and also shows the future research work.

2. Mean shift image segmentation

2.1. Mean shift

Mean shift algorithm is a nonparametric statistical method for seeking the main mode of a point sample distribution [8][9].

Given n points data set $\{x_i\}_{i=1\cdots n}$ in the d-dimensional space R^d, the *multivariate kernel density estimator* with kernel $K(x)$ and window radius (bandwidth) h is given by

$$\hat{f}(x) = \frac{1}{nh^d}\sum_{i=1}^{n} K(\frac{x-x_i}{h}) \tag{1}$$

The *modes* of this density, where density $f(x)$ takes local maxima, are located among the zeros of the gradient $\nabla f(x) = 0$.

We denote

$$g(x) = -k'(x) \tag{2}$$

where $k(x)$ is the profile of the kernel function $K(x)$. If $g(x)$ is some profile of a kernel function $G(x)$, G is called the *shadow* of kernel K [8].

It can be deducted that searching the modes of the density can be done by searching the convergent points of the mean shift without estimating the density [9],

$$m_{h,G}(x) = \frac{\sum_{i=1}^{n} x_i g(\left\|\frac{x-x_i}{h}\right\|^2)}{\sum_{i=1}^{n} g(\left\|\frac{x-x_i}{h}\right\|^2)} - x \tag{3}$$

i.e., finding the points where the difference between the sample mean, using the kernel G, and x, the centre of the kernel (window), converges to zero.

We denote the sequence of successive locations of the sample mean with shadow kernel G as $\{y_j\}_{j=1,2,\cdots}$, where

$$y_{j+1} = \frac{\sum_{i=1}^{n} x_i g(\left\|\frac{x-x_i}{h}\right\|^2)}{\sum_{i=1}^{n} g(\left\|\frac{x-x_i}{h}\right\|^2)} \quad j = 1,2,\cdots \tag{4}$$

is the weighted mean at $x = y_j$ computed with kernel G and y_1 is the centre of the initial position of the kernel.

In this paper, the mean shift procedure is applied for the data points in the joint spatial-range domain. Each data point becomes associated to a point of convergence which represents the local mode of the density in the d-dimensional space. The process takes into account simultaneously both the spatial and range information. The output of the mean shift filter for an image pixel is defined as the range information carried by the point of convergence. This process achieves a high quality, discontinuity preserving spatial filtering [9]. For the segmentation task, the convergence points sufficiently close in the joint domain are fused to obtain the homogeneous regions in the image.

2.2. Mean shift segmentation

An image is typically represented as a 2-dimensional lattice of r-dimensional vectors (pixels), where r is 1 in the grey-level case, 3 for color images. The space of the lattice is known as the *spatial domain* while the grey level or the color is represented in the *range domain*. However, after a proper normalization with h_s and h_r, global parameters in the spatial and range domains, the location and range vectors can be concatenated to obtain a spatial-range domain of dimension $d = r + 2$.

The mean shift segmentation in the spatial-range domain is implemented on the mean shift filtered images. Assume the input original image is normalized with uniform kernel function, where the bandwidth in spatial domain and range domain are h_s and h_r respectively. Let $\{x_j\}_{j=1\cdots n}$ be the original image points, $\{z_j\}_{j=1\cdots n}$ be the points of convergence, and $\{L_j\}_{j=1\cdots n}$ be a set of labels for different regions.

1. For each $j = 1\cdots n$, run the mean shift filtering procedure for x_j and store the convergence point in z_j, as:
   a) Initialize $k = 1$ and $y_k = x_j$.
   b) Compute y_{k+1} according to (4) and let $k \leftarrow k+1$ until convergence.
   c) Assign $z_j = (x_j^s, y_{conv}^r)$ to specify that the filtered data at the spatial location of x_j will have the range components of the point of convergence y_{conv}.

2. Delineate in the joint domain the clusters $\{C_p\}_{p=1\cdots m}$ by grouping together all z_j which are closer than h_s in the spatial domain and h_r in the range domain, i.e., concatenate the basins of attraction of the corresponding convergence points.
3. For each $j=1\cdots n$, assign $L_j=\{p \mid z_j \in C_p\}$.
4. Optional: eliminate spatial regions smaller than M pixels.

The superscripts s and r denote the spatial and range components of a vector respectively.

3. Feature extraction

After the candidate regions are obtained by applying mean shift segmentation, features of number plates are to be extracted in order to correctly differentiate the license plate regions from others.

According to statistical analysis, compared with other non-number plate regions, number plate regions take some unique features, such as they have rectangle shape, they have determined aspect ratio, and they have evenly distributed higher color variance. In this experiment, three features are defined in order to detect the number plate area from segmented candidate areas.

3.1. Rectangularity

Number plates are rectangle shape with a certain aspect ratio. This is the most important shape feature of number plates. Rectangularity is a measurement that represents how well an object fits its minimum enclosing rectangle (MER). It is defined as [10]

$$R=\frac{A_O}{A_{MER}} \tag{5}$$

where A_O is the area of the object and A_{MER} is the area of the object's MER.

One quick and straightforward method is to rotate the object as a rigid body to get its MER. With this method, the object is rotated as a rigid body through a range in steps of $\Delta\theta$. After each incremental rotation, a horizontally oriented MER is fit to the boundary. The rotating angle at which the MER goes through the minimum value is picked out. The size and dimension of the MER at this angle can be taken to be the A_{MER} and the dimension of the region.

In this project, considering that the tilted angles of vehicles caused by uneven or curvy road surface vary in a very limited range, the range of rotating angle is set as $[-15°,15°]$ with $\Delta\theta=1°$.

3.2. Aspect ratio

The aspect ratio is defined as the ratio of the width to the height (or length) of the region's MER,

$$R=\frac{W}{H} \tag{6}$$

Sine the MER of the object region can be easily computed via rotating the region within a certain range, the dimension of the object's MER can be taken as the width and the height of the region.

3.3. Edge density

Applying the above two features to filter the segmented regions, we can remove lots of non-number plate regions. However, there are still many candidate areas which take similar rectangularity and aspect ratio features as the number plate areas do, such as often the head lights. Considering that the number plate areas take unique texture feature, an important approach to region description is to quantify its texture content.

Although no formal definition of texture exists, plate regions tend to have a high density of edges.

The edge density is measured in a local block by firstly summing all edge pixels within this window. The edge density is normalized by the number of pixels involved while the feature is obtained.

It is observed that most of the vehicles usually have more horizontal lines than vertical lines [11]. In order to reduce the complexity of algorithm, the vertical edges are detected. In this paper, edge information is acquired by applying a 3×3 Sobel edge detector.

4. Mahalanobis classification

Before the feature extraction procedure, segmented regions are firstly filtered roughly using the number of pixels in each region, where too small or too big regions are removed in order to reduce the unnecessary computational complexity. The resulted regions are called region of interest (ROI) in this paper. For each ROI, three features described above are extracted, i.e., rectangularity, aspect ratio, and edge density to compose the feature vector $\mathbf{x}$ as,

$$\mathbf{x}=\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}=\begin{bmatrix} rectangularity \\ aspect\_ratio \\ edge\_density \end{bmatrix} \tag{7}$$

In the project, according to observation, there exist two classes of number plates, which suffer a distinct difference in their aspect ratios. So, totally three classes of regions are defined, i.e., *plates-1, plates-2*, and *non- plates*. The statistics data for three classes of regions are shown in Table 1.

Table 1.The statistical data of three classes of regions

Classes \ Features		Rectangularity		Aspect Ratio		Edge Density	
		m	σ^2	m	σ^2	m	σ^2
Class1	Plates-1	0.93	0.04	2.63	0.2199	159.46	59.1178
Class2	Plates-2	0.93	0.04	3.78	0.4165	212.13	46.8551
Class3	Non-plates	0.72	0.11	3.42	1.2996	24.28	20.2080

In this table, in order to reduce the unnecessary computation, regions:

1) which are too small or too big;
2) of which rectangularity is less than 0.5; or
3) of which aspect ratio does not fall in the range of $[1,5]$.

are removed firstly from target candidates.

In order to correctly classify the regions, feature vector's covariance matrix of three classes regions have been computed using a training data set. In our experiments, 10% of sampled data are used for training to compute the mean vector $\{m_k\}_{k=1,2,3}$ and covariance matrix $\{C_k\}_{k=1,2,3}$ of three classes of regions. The others are used for testing.

During testing, we measure the Mahalanobis distance [12] from the feature vector $\mathbf{x}$ to the modes $\{\mathbf{w}_k\}_{k=1,2,3}$ and assign $\mathbf{x}$ to the class of the nearest mode.

$$d_k^2 = \|\mathbf{x} - \mathbf{m}_k\|^2 = (\mathbf{x} - \mathbf{m}_k)'\mathbf{C}_k^{-1}(\mathbf{x} - \mathbf{m}_k)$$
$$k = 1,2,3 \qquad (8)$$

where as long as $d_1 < d_3$ or $d_2 < d_3$, the region is decided as a number plate region.

5. Experiments

5.1. Experiments set-up

The proposed algorithm has been tested in various car images captured from a highway intersection. The target vehicle images are 324×243 color images. In order to do the classification, we employed mean shift segmentation algorithm with $(h_s, h_r, M) = (5,6.5,400)$ to segment input vehicle images first. Figure 1b and Figure 1c give show mean shift segmentation results when applied to vehicle images, where different regions are represented with different colors.

Segmented regions are then filtered roughly using the number of pixels of the region in order to remove too small and too big regions. For the remained regions (ROIs), three features are extracted to compose the feature vector. Feature vectors of each ROIs are then inputted the Mahalanobis-distance classifier to make the final decision.

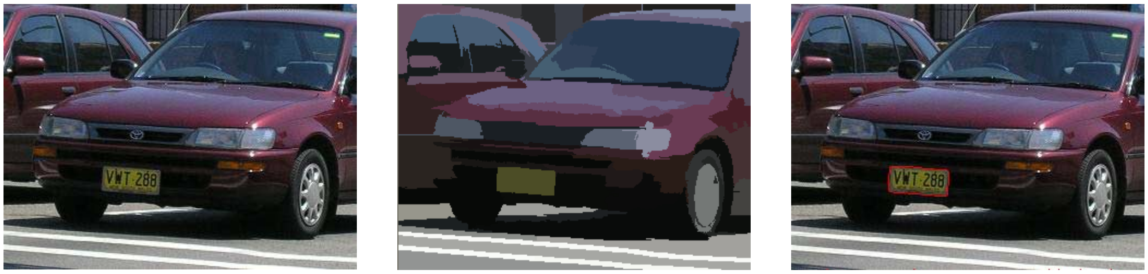
Figure 1c and Figure 2c show detected number plates where the contours have been highlighted with red circles.

5.2. Performance evaluation

In order to evaluate the performance of the proposed algorithm, we applied it to various vehicle images captured in a highway intersection.

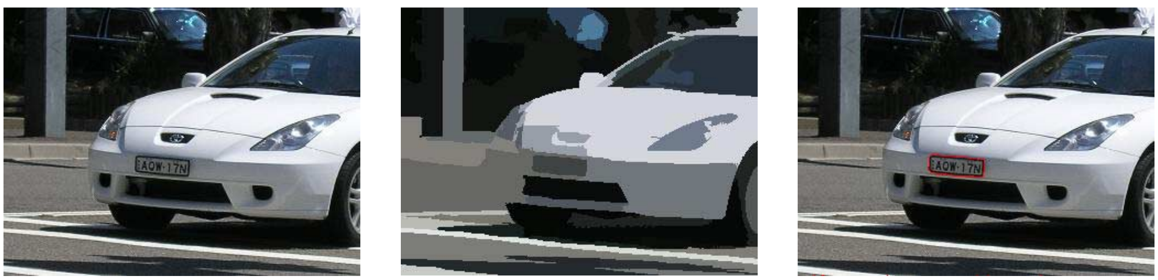
From experiments, the proposed algorithm shows great robustness and accuracy for those vehicle images where the color of number plate is different from that of the vehicle where the number plate is adhered to. Compared with some existing color-based number plate detection algorithms which only process limited number of color combinations, the proposed algorithm can process various color combinations between number plates and vehicles as long as the two colors where the number plates are sticked are different. This advantage also exists in correct detection in unevenly distributed illumination condition under which the image is captured. This is mainly because, unlike other color-based detection algorithms, our algorithm does not rely on the exact color information at each pixel to segment the number plate area from vehicle body.

The proposed algorithm also shows its great insensitiveness to interference characters. Figure 3a shows one situation where there are interference characters ("ISUZU" at the top part of the picture) in the vehicle body. Figure 3b shows another case where there are pretty interfering characters (two green letter P's) next to the number plates (the letter "P" stands for "provisional", which is used to indicate a stage of driver licenses). The detected results are shown in Figure 4a and Figure 4b respectively. Compared with those texture-based detection algorithms, it can be seen



(a) (b) (c)

Figure 1. Testing sample 1. (a) Original image. (b) Segmented image. (c) Detected result.



(a) (b) (c)

Figure 2. Testing sample 2. (a) Original image. (b) Segmented image. (c) Detected result.

from the results that the proposed algorithm has no difficulty at all when dealing with this situation thanks to mean shift segmenting.

6. Conclusion

A robust and effective color number plate detection algorithm has been proposed. This algorithm employs mean shift segmentation and linear classification. Feature vectors are extracted from the segmented regions. A Mahalanobis distance linear classifier is applied in order to correctly classify each ROI into correct modes. The proposed algorithm shows great robustness when detecting the color number plates from vehicles which have a different color with that of number plate where the number plates are adhered to. The proposed algorithm is proved to be robust when dealing with cases where interference characters exist on vehicle body. More effective use of the gradient variance information will be one part of future work to improve our method.

7. References

[1] S.-Z. Wang and H.-J. Lee, "Detection and recognition of license plate characters with different appearances," *Intelligent Transportation Systems, 2003. Proceedings. 2003 IEEE*, vol. 2, pp. 979-984, 2003.

[2] S. Kim, D. Kim, Y. Ryu, and G. Kim, "A robust license-plate extraction method under complex image conditions," *Pattern Recognition, 2002. Proceedings. 16th International Conference on*, vol. 3, pp. 216-219 vol.3, 2002.

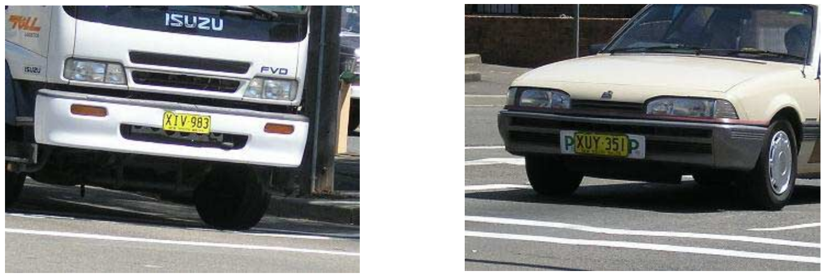
[3] H. Bai, J. Zhu, and C. Liu, "A fast license plate extraction method on complex background," *Intelligent Transportation Systems, Proceedings. 2003 IEEE*, vol. 2, pp. 985-987, 2003.

[4] H. Bai and C. Liu, "A hybrid license plate extraction method based on edge statistics and morphology," *Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on*, vol. 2, pp. 831-834, 2004.

[5] Y. Yanamura, M. Goto, D. Nishiyama, M. Soga, H. Nakatani, and H. Saji, "Extraction and tracking of the license plate using Hough transform and voted block matching," *Intelligent Vehicles Symposium, 2003. Proceedings. IEEE*, pp. 243-246, 2003.

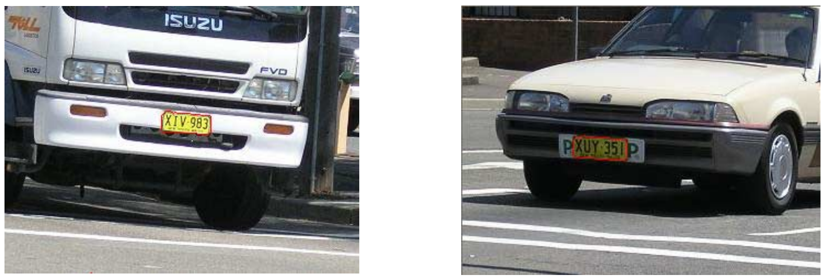
[6] W. Wei, M. Wang, and Z. Huang, "An automatic method of location for number-plate using color features," *Image Processing, 2001. Proceedings. 2001 International Conference on*, vol. 1, pp. 782-785 vol.1, 2001.

[7] K. I. Kim, K. Jung, and J. H. Kim, "Color Texture-Based Object Detection: An Application to Number plate Localization," *Proceedings of the First International Workshop on Pattern Recognition with Support Vector Machines*, pp. 293-309, 2002.



(a) (b)

Figure 3. Two cases where interference characters exist.



(a) (b)

Figure 4. Detected number plates when interference characters exist.

[8] Y. Cheng, “Mean shift, mode seeking, and clustering,” *Pattern Analysis and Machine Intelligence, IEEE Transactions on* ,vol. 17, pp. 790 – 799, 1995.

[9] D. Comaniciu and P. Meer, "Mean shift: a robust approach toward feature space analysis," *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, vol. 24, pp. 603-619, 2002.

[10] K. R. Castleman, Digital Image Processing. Toronto: Prentice Hall, 1996.

[11] M. Yu and Y. D. Kim, "An approach to Korean license plate recognition based on vertical edge matching," *Systems, Man, and Cybernetics, 2000 IEEE International Conference on*, vol. 4, pp. 2975-2980 vol.4, 2000.

[12] J.P. Marques de Sá., Pattern recognition: concepts, methods, and applications. New York: Springer, 2001.