Image and Vision Computing 27 (2009) 1134–1142

Contents lists available at ScienceDirect

Image and Vision Computing

journal homepage: www.elsevier.com/locate/imavis

An edge-based color-aided method for license plate detection

Vahid Abolghasemi *, Alireza Ahmadyfard

Faculty of Electrical Engineering and Robotic, Shahrood University of Technology, Shahrood, Iran

ARTICLE INFO

Article history:
Received 15 October 2007
Received in revised form 28 September 2008
Accepted 23 October 2008

Keywords:
License plate recognition
Edge analysis
Morphological processing
Color analysis

ABSTRACT

In this paper, the problem of license plate detection is considered. Low quality images due to severe illumination conditions, vehicle motion, viewpoint and distance changes, complex background, etc. are some of popular problems which have to be considered. In order to alleviate these problems, two different image enhancement methods (using intensity variance and edge density) are proposed. The aim is to increase contrast of plate-like regions to avoid missing plate location especially in poor quality images. Furthermore, a novel match filter is designed to detect candidate regions as plate. This filter models the vertical edge density of plate region regarding its neighborhood. As the filtering procedure is simple, this approach can be used for real-time applications. In the proposed method, we also use colored texture in the plate as a cue for plate detection. This feature is preserved under viewpoint change. In order to characterize the color information in plate, the MNS (multimodal neighborhood signature) method is used. A well-organized database, consisting of car images with different known distances and viewing angels have been prepared to verify the performance of plate detection algorithm. This database can be used to establish a precise evaluation of the proposed method and any other related work. The results of experiments on different type of car images in complex scenes confirm the robustness of proposed method against severe imaging conditions.

1. Introduction

Intelligent transportation systems (ITSs) have been developed as a major tool for analyzing and also handling the moving vehicles in cities and roads [1]. These systems attempt to facilitate the problem of identification of cars, via various techniques which mainly rely on automated (rather than manual) algorithms. Image processing is one of these techniques which deal with images and/or video sequences taken from vehicles. One unique property that can be taken into account for identifying all vehicles is their license plate number. Security control of restricted areas, traffic law enforcements, surveillance systems, toll collection and parking management systems are some applications for a license plate recognition system. Although human observation seems the easiest way to read car license plate, the reading error due to tiredness is main drawback for manual systems. This is the main motivation for research in area of automatic license plate recognition. An adequate system for this purpose must deal with severe imaging conditions such as high/low lighting, complex background, plate deficiencies (damaged or dirty) and a range of distances and viewpoints by which car is imaged.

A license plate recognition (LPR) system mainly consists of three major parts; license plate detection (LPD), character segmentation and character recognition. Due to diversity of parameters involved in car images, the first step, i.e. license plate detection is the most crucial task among these steps. We briefly review the major works in this area which reported in computer vision literature. Then our proposed method for detecting the license plates is introduced in details.

The proposed method is consisting of two major parts. In the first part, we propose an algorithm to stretch image contrast in plate-like regions. In this part we attempt to enhance plate image adaptively using two features: local intensity variance and local vertical edge density. In the second part a novel fast method is proposed to filter out non-plate regions. In this algorithm, we provide a model of edge densities at license plate image as a matched filter to detect candidates for license plate.

The paper is organized as follows. First, a review of previous works is presented. In Section 3, the proposed method is described. The experimental results and evaluation of the algorithms are given in Section 4. Finally, the paper is concluded in Section 5.

2. Previous works

In this section, we review some previous works proposed for license plate detection relevant to our method. From the earlier attempts which license plate recognition has been considered, methods based on edge analysis combined with morphology operations achieved promising results [1,2]. Presence of dark characters

* Corresponding author. Tel.: +44 0 7529343857, +989123730069.
E-mail address: abolghasemiv@cardiff.ac.uk (V. Abolghasemi).

0262-8856/$ - see front matter © 2008 Elsevier B.V. All rights reserved.
doi:10.1016/j.imavis.2008.10.012

on the light background at license plate provides strong edges which can be used as a cue to detect the license plate. Unfortunately, solely using edge information, fails the algorithm in complex scenes. Hence, combining edge information with other cues improves the detection rate.

Hough transform is another technique which attempts to find the rectangular shapes. It can be useful in finding the boundary box of a license plate regardless of characters. This method is not suitable for conditions in which plate borders are not clear due to damages or dirt. This method is only suited for closed shut images of cars. Computational complexity is another disadvantage of this method [3].

Techniques based on train and test such as Adaboost [4] are also used in this area. In this method, first it needs to train the planned classifier using a set of plate and non-plate images. After training step, a car test image located in a natural scene is feed to the system. The system detects the location of plate in the test image. This is principle function of classifier-based algorithms. Simplicity and speed are the attractive features for Adaboost learning with respect to other classifiers. However, in compare to edge-based methods Adaboost is slow. Adaboost method fails to detect license plate when the range of variations for distance or viewing angle increases.

Neural network is widely used for plate detection and also recognition [5–7]. PCNN, TDNN and DTCNN are some of those applied networks. Adding new license plate features in designing neural networks will improve the detection rate; it increases the computational time, though. Mainly, there is always a trade-off between the number of features used in the system and the computational time. Combination of other types of networks can also be used for this application [1]. Therefore, designing novel networks is to be considered as the future work for researchers.

Color is a distinctive feature which can be used for license plate detection [8,9]. Based on human perception this feature is very powerful for object recognition. However, the sensitivity of this feature to the parameters such as color of car, illumination condition and the quality of imaging system has been restricted its usage. Representation of color in an invariant manner is of main objectives for color-based object recognition system.

In order to perform the plate detection job, combination of cues can provide better detection rate. For instance, a promising result for combination of color and texture has been reported [1,10].

Gabor is one of the strongest tools for texture analysis which is used for license plate detection [11]. The arrangement of characters on license plate produces a specific texture pattern which can be considered as a plate feature. Using Gabor filters, promising results has been reported [11]. The computational complexity of applying Gabor filter on car image is considerably high. This is due to multiple direction and scale in this analysis.

Wavelet analysis is another approach for texture analysis. Due to special property of license plates (dark characters on the light background), it inherits considerable contrast information. This information can be extracted for car image using wavelet analysis. The multi-scale property of wavelet enables detection of plates in different scales [12,13].

The reviewed algorithms are mainly devoted for first step, i.e. LPD of a LPR system. There exist other methods designed for two other steps, i.e. character segmentation and character recognition which is beyond the scope of this paper.

3. The proposed method

3.1. Pre-processing

As mentioned earlier, a major cause of failure for a plate detection system is low quality of car image. In order to improve the quality of plate image, we propose a pre-processing algorithm which increases the image contrast at locations where might be a license plate. In the following subsections, we introduce two different methods for image enhancement.

3.1.1. Image enhancement using intensity variance

The proposed method is a modified version of Zheng et al. [14] algorithm. The modification is suggested to improve the image enhancement in [14]. Zheng et al. used the variance of pixel intensities at the local neighborhood of a pixel to improve image contrast at plate-like regions. In [14], it is stated that the variance of intensity for constituting pixels of the license plate has a limited range and does not change dynamically. Based on this idea they propose an enhancement function. This function increases image contrast at regions where local variance of intensity is around 20.

Through the experiments, we noticed that this enhancement method does not work well under severe illumination change. We modified Zheng et al. method [14] to overcome the addressed problem. We first review the Zheng et al. method.

Consider I, I' denote the input grayscale and the enhanced images, respectively. The size of input image is $m \times n$. Let I_{ij}, I'_{ij} be intensity levels at pixel P_{ij} in I, I', respectively. In order to enhance the input image, an enhancement function is defined as follows [14]:

$$I'_{ij} = f(\sigma_{W_{ij}})(I_{ij} - \bar{I}_{W_{ij}}) + \bar{I}_{W_{ij}}, \tag{1}$$

where σ_{wij} and $\bar{I}_{wij}$ are local standard deviation and average intensity value, regarding window W centred at pixel P_{ij}, respectively. The enhancement coefficient f is defined as follows [14]:

$$f(\sigma_{W_{i,j}}) = \begin{cases} \frac{3}{\frac{2}{400}(\sigma_{W_{i,j}}-20)^2+1} & \text{if } 0 \leqslant \sigma_{W_{i,j}} < 20, \\ \frac{3}{\frac{2}{1600}(\sigma_{W_{i,j}}-20)^2+1} & \text{if } 20 \leqslant \sigma_{W_{i,j}} < 60, \\ 1 & \text{if } \sigma_{W_{i,j}} \geqslant 60. \end{cases} \tag{2}$$

As can be seen from Fig. 1, the intensity of pixels with local intensity variance between 0 and 60 are enhanced. Based on our experiments the local intensity variance for a plate region can be out of considered range 0–60.

In order to improve the algorithm presented in [14], we adapt the enhancement coefficient $f(\sigma_{wij})$ using local intensity variance. So, we define this coefficient as $f(\sigma_{wij}, \sigma_0)$, which is a function of variables σ_{wij}, σ_0. Variable σ_0 measures dominant variance of near-by pixels of P_{ij} and is defined as follows:

$$\sigma_0 = \frac{\sum_{k=(-p/2)}^{p/2} \sum_{1=(-q/2)}^{q/2} \sigma_{w_{i+k,j+1}}}{p \cdot q}, \tag{3}$$

where p and q represent the height and width of rectangular area around pixel P_{ij}, respectively.

The modification of Zheng's algorithm makes it robust to illumination variations. It is worth mentioning that the complexity for computing $\sigma_{wij}, \bar{I}_{wij}$ using the proposed algorithm in [14] is rela-

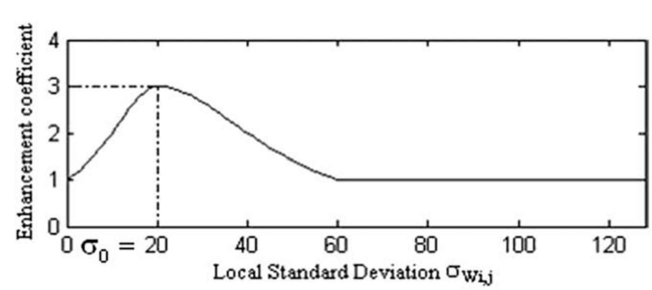

Fig. 1. The enhancement coefficients $f(\sigma_{W_{ij}})$.

tively low. This is due to using bilinear interpolation for computing these values. As can be seen from Fig. 2, which is a high illuminated image, the license plate has been considerably enhanced after applying the proposed method (Fig. 2(b)), while applying the Zheng's method does not improve the quality very considerably (Fig. 2(c)).

Although the modified method of [14] enhances the plate image, it also enhances other parts of image. This is a drawback for this enhancement method.

3.1.2. Image enhancement using edge density

In order to increase image contrast only at plate-like regions of image, we use the density of vertical edges as a criterion to detect candidates for plate regions. In fact, the density of vertical edges has been suggested (instead of the variance of intensity) as criterion for local enhancement of car image.

(a) *Edge density estimation*

Measuring the edge density at a local neighborhood is a robust criterion for enhancing the car image at candidate regions for plate. The motivation is based on existing strong vertical edges on within license plate region. The details of the proposed enhancement are as follows.

In order to estimate density of vertical edges in the image, we first compute the gradient image. A simple and proper candidate filter for this purpose is Sobel operator, Eq. (4). Then by comparing the gradient image against a predefined threshold, the edge image is obtained (Fig. 3(b)). It is worth noting that in order to avoid missing weak edges across the plate region, the threshold is set to a low value.

$$h = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}. \tag{4}$$

In the next step, we estimate edge density using a 2D Gaussian filter (Fig. 4(a)). The size of estimator has been selected from average size of license plates in the database which is 30×80.

After convolving the binary edge map with this Gaussian kernel, an estimation for edge density is yielded. The result has been shown in Fig. 4(b).

In order to reduce the effect of other factors in enhancement, we normalize the edge density map to the range 0 to 1.

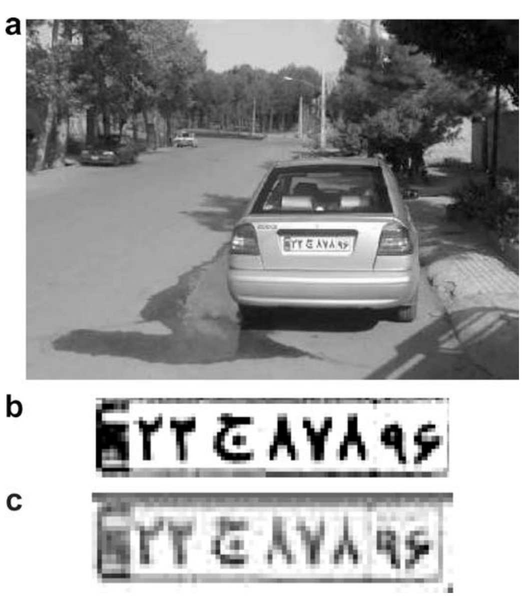

Fig. 2. (a) Input car image. Result of (b) the proposed method. (c) Zheng's method.

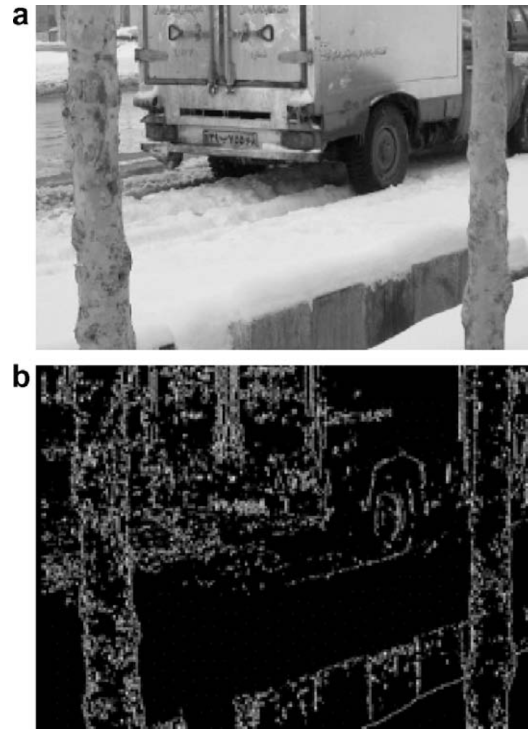

Fig. 3. (a) Sample car image. (b) Vertical edge map.

(b) *Enhancement stage*

We aim to increase image contrast in plate-like regions using the local density of edges in the image (Fig. 4(b)). For this purpose, we replace the variance of image intensity with the density of vertical edges in the enhancement function [14]. The new formula for image enhancement based on edge density is suggested as follows:

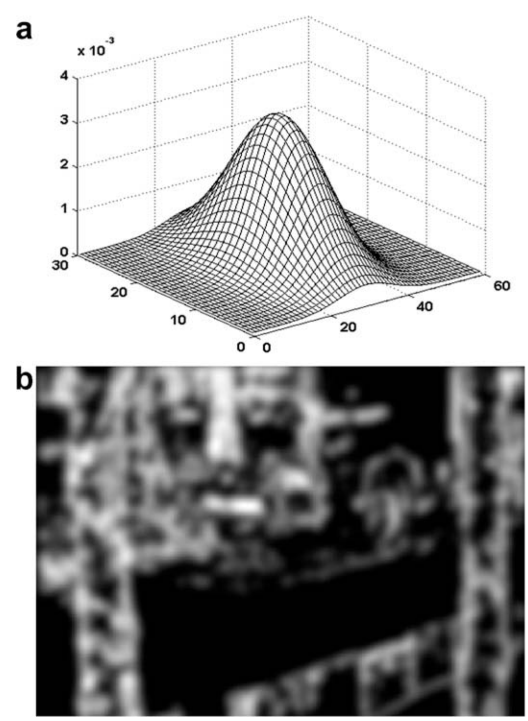

Fig. 4. (a) The 2D Gaussian kernel W_g. (b) Result after convolving Fig. 2(b) and Fig. 3(a).

$$I'_{ij} = f(\rho W_{g_{ij}}(I_{ij} - \bar{I}_{W_{ij}}) + \bar{I}_{W_{ij}}. \quad (5)$$

$f(\rho W_{g_{ij}})$ is the weighting function which assigns appropriate weights for pixels intensity, with respect to the Gaussian kernel shown in Fig. 4(a). This function is depicted in Fig. 5.

As can be seen from Fig. 5 locations in image with approximate edge density 0.15–0.45 are considerably affected by enhancement scheme. These regions are likely to be candidates for license plate. The intensity of pixels with edge density of more than 0.5 remains unchanged. This range for parameter ρ has been achieved, empirically.

We defined the weighting function f in enhancement formula as follows:

$$f(\rho W_{g_{ij}}) = \begin{cases} \frac{3}{\frac{2}{(0.15)^2}(\rho_{W_{g_{i,j}}} - 0.15)^2 + 1} & \text{if } 0 \leqslant \rho_{W_{g_{i,j}}} < 0.15, \\ \frac{3}{\frac{2}{(0.5-0.15)^2}(\rho_{W_{g_{i,j}}} - 0.15)^2 + 1} & \text{if } 0.15 \leqslant \rho_{W_{g_{i,j}}} < 1, \\ 1 & \text{if } \rho_{W_{g_{i,j}}} \geqslant 1. \end{cases} \quad (6)$$

We used the bilinear interpolation algorithm in [5] to reduce the computational complexity for enhancement. Fig. 6 shows the result of image enhancement using the proposed method. As seen from this figure the image contrast at the plate region has been considerably improved.

3.2. License plate detection

By observing different types of license plate in images we noticed that density of vertical edges at the license plate area is considerably higher than its neighborhood (Fig. 7(b) and (c)). Moreover, this special feature does not occur in other regions. This unique property and also low complexity of edge-based methods motivated us to use edge information for the car plate detection.

After enhancing the car image using edge density criterion we indicate the locations with significant density of vertical edges as plate candidates. Then using the above criterion, we filter out false candidates. For this purpose, we designed a matched filter which gives a strong response at plate-like regions. This filtering is performed on the edge density image. As the most of clutter part in image is removed from the region of interest at the first stage, computational time for this filtering is low.

3.2.1. Vertical edge density estimation

Edge density estimation is similar to what previously applied in Section 3.1.2(a), but here in order to avoid missing plate edges especially in bad lighting condition, we use a low threshold for edge detection (Fig. 7(b)). The final result after smoothing is shown in Fig. 8.

3.2.2. Designing a matched filter

According to the discussed idea for plate detection, we simply model the edge density at plate region using a mixture of Gaussian

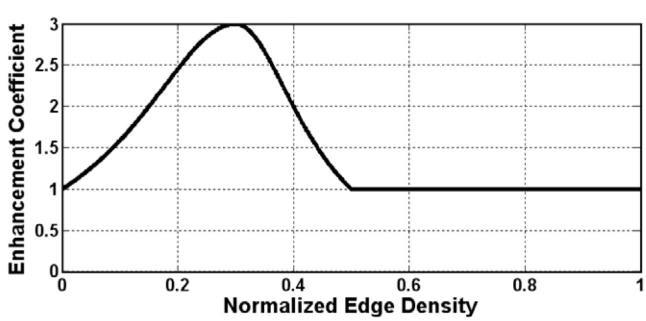

Fig. 5. The enhancement coefficients $f(\rho_{W_{ij}})$.

Fig. 6. (a) Input car image. The plate (b) before and (c) after image enhancement algorithm.

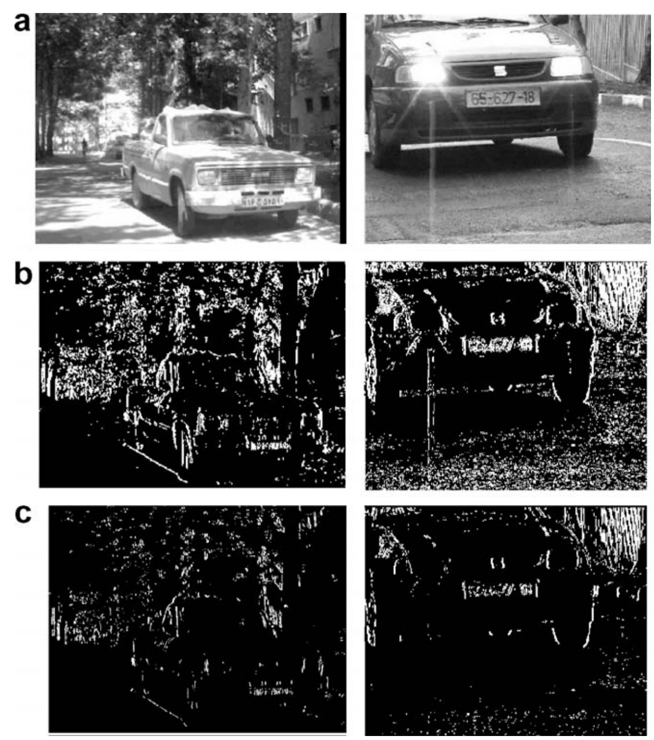

Fig. 7. (a) A car image in a complex scene. The vertical edges extracted from the gradient image using (b) low and (c) high threshold values.

functions as a surface Fig. 9(a). This model emphasizes the constancy of intensity values within plate region, along horizontal direction. On the other hand, expected edge density along vertical direction at the middle of region are maxima and it decreases when approaching to plate borders (Fig. 8). This function properly models the low edge densities above and below of the car plate. The mathematical equation of this mixture model is

$$h(x,y) = \begin{cases} A.\exp\left(-x^2/0.2\sigma_x^2\right) & \text{for } 0 \leqslant x < \frac{m}{3} \text{ or } \frac{2m}{3} < x \leqslant m,\ 0 \leqslant y < n, \\ B.\exp\left(-x^2/0.2\sigma_x^2\right) & \text{for } 0 \leqslant x < \frac{m}{3} \text{ or } \frac{2m}{3} < x \leqslant m,\ 0 \leqslant y < n. \end{cases} \quad (7)$$

The function represents a rectangular $m \times n$ mask. As can be seen from Fig. 9, the filter varies only in vertical, i.e. x direction. Thus, the symbolis variance of the main lobe toward x direction. We select the value of this parameter based on approximate plate height in car image. It should be noted that the variance of two side

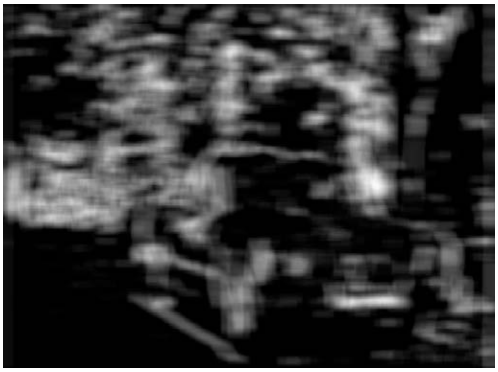

Fig. 8. Result of applying Gaussian kernel on edge image in Fig. 7(b) (left).

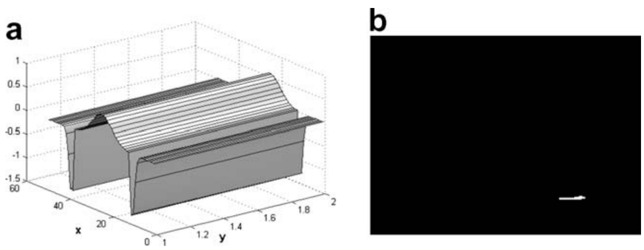

Fig. 9. (a) A 3D plot of the plate model filter. (b) The result of filtering and thresholding in Fig. 7(b) (left).

lobes are one tenth of that for the main lobe. These parameters are set empirically. The parameters A, B ($A < 0, B > 0$) adjust the average of matched filter to be zero.

The designed matched filter is convolved with estimation of the edge density for finding instance(s) of license plate. It is expected that this filtering process provides a strong response at plate-like regions, while no considerable response provides elsewhere. The zero mean value for the filter results no response at constant edge density such as asphalt, walls, sky, etc.

The result of this filtering on edge image is compared against a predefined threshold to find candidates for license plate. Note that as the filtering response in plate-like regions is considerably strong, the plate detection process is not sensitive to the level of threshold. We set the threshold value equal 80% of maximum intensity value in the filtering result image. Fig. 9(b) shows the result of plate detection on the image Fig. 7(a) (left). The detected regions are processed during next stage in order to find the boundary of plates.

3.2.3. Region extension procedure

The extracted regions from the previous stage have irregular shape. To extract the license plate from these candidates, we extend all candidate regions twice as the biggest default license plate size. Fig. 10a–c depict the candidate region respect to corresponding license plate.

3.2.4. License plate extraction using morphological processing

Morphology is a branch in image processing which is used for shape analysis. The value of each pixel at output of a morphological filter is determined based on the value of corresponding pixel and a specified neighborhood of it in input image. Based on the size and shape of the considered neighborhood, one can define a morphological operation which is sensitive to specific shapes [15].

The result of previous stage is a few numbers of detected candidates as the license plate. We have to find the genuine one(s) as true license plate(s).

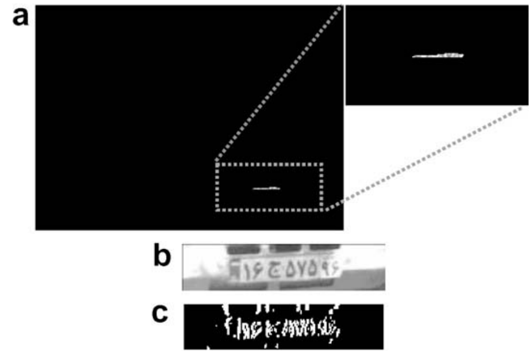

Fig. 10. (a) Description of license plate location. (b) Result of extending procedure and (c) its corresponding edges.

Since a car plate consists of a number of characters in a regular arrange the vertical edges in the image of license plate are considerably dense compared to clutter parts. By applying morphological closing on edge image at the neighborhood of each candidate region (Fig. 10(c)) we construct a connected component which specifies the license plate (Fig. 11(a)). In this operation, a rectangular structuring element (SE) is used. The height and width of SE is set to 3 pixels and the maximum number of pixels between two characters, respectively. A post-processing stage using morphological opening is required to remove produced small regions. The SE for this step is set to a rectangular somewhat smaller than a character size. As seen from Fig. 11(b) the opening process reshapes the previous region to plate frame.

Although morphological operation is reported to be slow in the literature, since in the proposed algorithm the regions of interest on which the morphological filtering is applied, is limited only to the candidate regions the process is not time consuming.

To detect genuine region from the modified candidates we use simple geometrical features such as shape, aspect ratio and size of region to detect license plate(s). Fig. 12 shows the final result for detecting the license plate in car image Fig. 7(a) (left). It should be noted that as the number of candidate regions are few, only these simple geometrical criteria are enough to find genuine license plate.

3.3. Color analysis of candidate license plate

The result of experiments shows that the employed features in some complex images are not sufficient to properly filter the candidate regions for license plate. In order to increase the accuracy of license plate detection we use color information on plate. Almost all license plates in worldwide countries consist of a logo such as country flag. Some sample images are shown in Fig. 13. These colored logos can be considered as multimodal color neighborhoods with unique modes. The most important advantage of color object analysis in license plate detection is the robustness to viewpoint changes which increases the detection rate.

National flag is a part of Iranian license plates which consists of three color bars; green, white and red (Fig 13(c)).

There are a wide range of approaches proposed for color object detection. In some approaches simply a color object is represented using its color histogram regardless of the shape and geometrical relation between color patterns. Many efforts have been reported

Fig. 11. (a) Closed edge image shown in Fig. 10(c). (b) Result of opening in Fig. 6(a).

Fig. 12. (a) Final defined region and (b) its corresponding gray scale image.

Fig. 13. Some sample plate with logos.

for modeling of a color object in such a way that not being too complex as in appearance based methods but more descriptive than a histogram based method. The multimodal neighborhood signature method (MNS) [16] is one of such approaches which describes an object using color of adjacent regions in the image. MNS finds color modes of each local neighborhood in a RGB image. The mode of each neighborhood may be unimodal, bimodal or generally multimodal. The method description is as follows.

The input RGB image is first divided into blocks. Then using mean shift algorithm, the color modes for each block is computed [16]. A simple signature matching technique is applied to compute the dissimilarity between two MNS image signatures[1] [16]. The dissimilarity criterion is the distance between each feature (color pairs) [16]. The algorithm attempts to find a match for all query features, assuming that the query signature contains only information about the object of interest. Fig. 14 demonstrates the scheme for computing this distance in the case of bimodal features.

We applied MNS algorithm on the candidate regions. Then, based on the modality and signature matching result, one region declared as the license plate. The results for some sample regions of interests accompany with their results in the plate area are shown in Fig. 16. The detected modes are shown with circles in Fig. 16(c) and (d) in RGB space. The signatures which we use as the model features are shown in Fig. 15.

4. Experimental results

In order to evaluate the proposed method in different conditions, we collected two different car image sets. SET I consists of the images taken from cars freely in different scenes, with different lighting condition and from different distance. Some sample images of this dataset are shown Fig. 17. On the other hand, the images in SET II are taken in controlled condition, almost with the same illumination condition and at specified distances (1, 2, 3, 4, 5 and 6 m) and angles (10°, 20°, 30°, 40°). Some samples are given in Fig. 18. Both databases totally include more than 700 images with the size of 640*480. Our experiments have been tested on Iranian license plates involving Persian digits and characters, but we observed the algorithm can also overcome in other similar plate types.

As mentioned, Zheng's method fails in detection license plates in very low/high illuminated images. We first improved this method using intensity variance. The result shows that even in severe illumination conditions the plate location is enhanced. The drawback is that clutter parts in the image are also enhanced. In order to alleviate this problem, we used edge density instead of the intensity variance for image plate enhancement. As can be seen from Table 1, the latter approach yields better results. As can be seen from this table, edge-based enhancement is more reliable and fast in compare to two other methods.

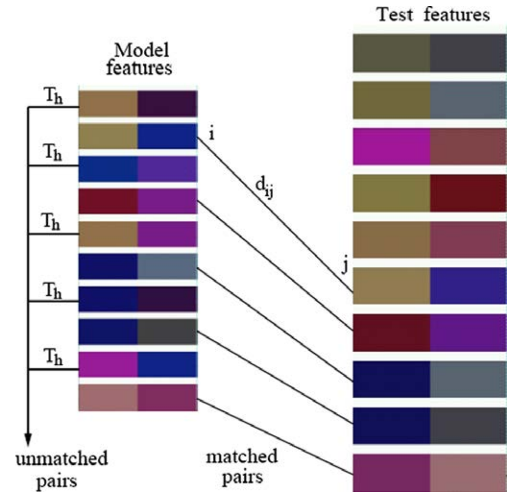

Fig. 14. The MNS signature matching.

By applying the proposed matched filter on the above databases, a promising result for detecting the candidate regions was achieved. The filter rejects most of clutter parts in car image with low computational complexity. Because of simplicity of the algorithm, it can be used for real-time applications. Moreover, the filtering is very robust to illumination change. Fig. 19 shows some sample images and the result of plate detection.

In order to evaluate robustness of the proposed method against viewpoint and distance changes, another experiment using images of SET II was conducted. We observed that the algorithm does not work properly for images with extreme viewing angle and also far distances. The results are given in. The results show that when angle between camera and plate increases, the detection system fails. Furthermore, once the distance between camera and car plate increases the detection algorithm is less sensitive to viewpoint. However, while the shutting distance increases the performance will decrease. It shows that the proposed filter can work well in a limited distances between camera and plate. In order to improve result even in very close or far shots we can apply the algorithm for images in different scales (multi-scale analysis). Of course the computation time would increase in a multi-scale analysis.

Another consideration is the threshold value selected in Section 3.2 which affects the performance. Choosing a low threshold, achieves a promising result while it requires high computational time. A large threshold value decreases both computational time and total performance. Hence, there is always a tradeoff for choosing the threshold value. In this paper we selected the value 0.6 empirically after evaluation of different results for various car images with different imaging conditions. Fig. 20 plots the missing rate and computational time as two functions verses the threshold value. It can be seen that 0.6 is the optimum value for this parameter.

When the MNS method was applied to detect the location of true license plate, the performance of system was improved. The results are shown in Table 2. As seen from the table even in images with severe changes in camera angle the result is acceptable. This is due to invariability nature of color against changes in viewing

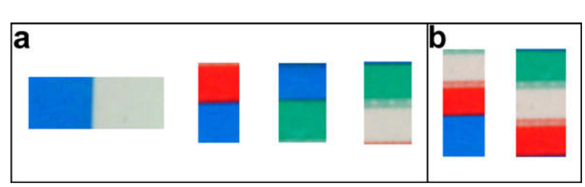

Fig. 15. Some model features for (a) bimodal and (b) trimodal case.

[1] Each block is regarded as a MNS signature

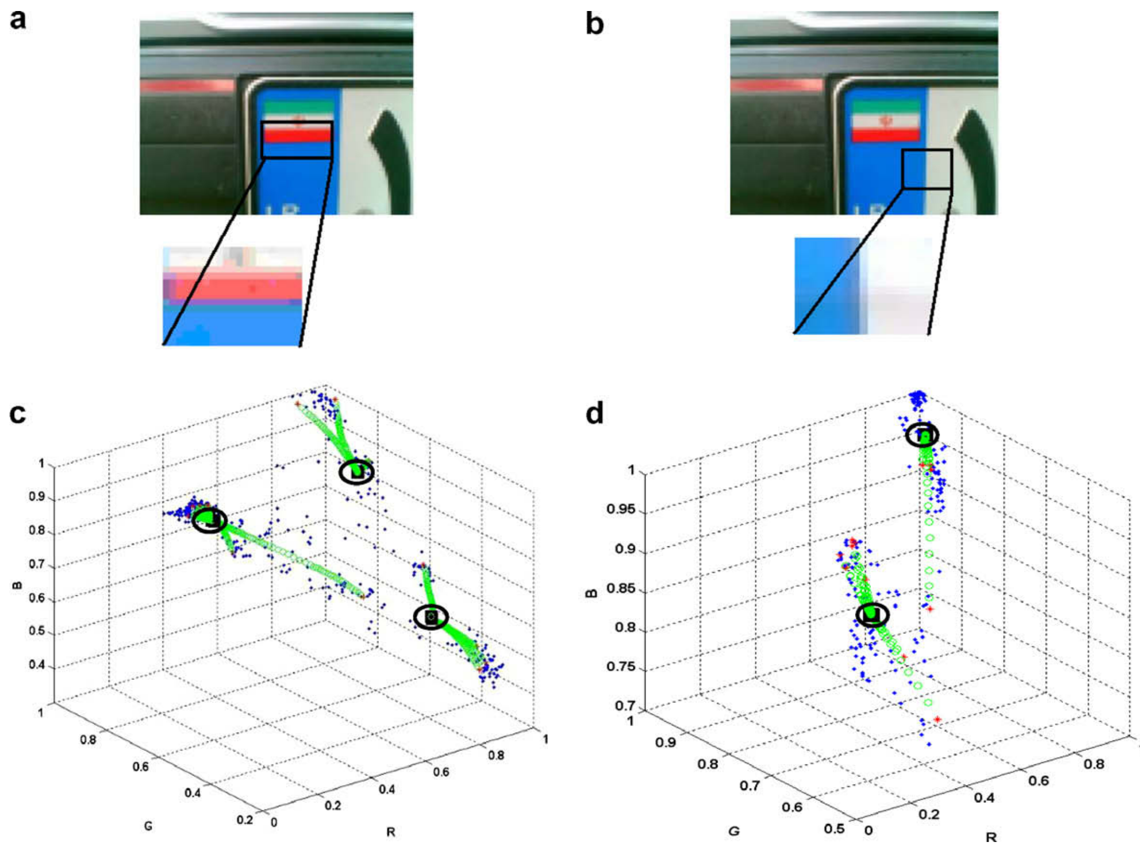

Fig. 16. (a, b) Regions of interest. (c, d) The color modes estimated by mean shift method.

angle. The table shows that final stage (MNS) improves the recognition rate. Figs. 21 and 22 show the results of bio-mode detection using MNS method. As seen from the figures, MNS method could successfully detect at least one bio-mode in the plate area even in severe geometric or illumination conditions. It also shows that we can apply this method for other kind of plates in other countries. Moreover, despite other existing methods such as [9] and [18] which deal with color of plate background, we take the advantage of color modes in the plate region which is unique and can be a better descriptor for plate location.

In spite of the achieved gain when MNS method is used for plate detection, the computational complexity is a drawback which makes it unsuitable for real time applications. Moreover, the algorithm fails when the plate is imaged from far distance (more than 5 m). This is

Fig. 17. Some sample images in SET I.

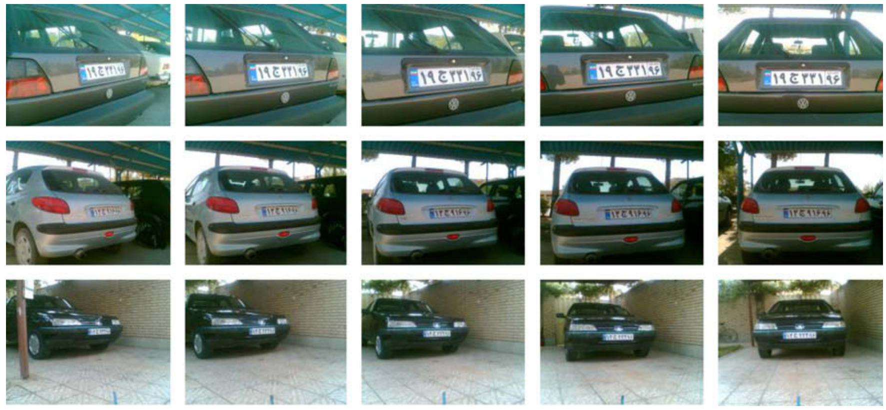

Fig. 18. Some sample images in SET II.

because the size of colour logo on plate becomes so small. The estimation of colour modes in this situation is imperfect (Fig. 23).

5. Conclusion

In this paper two different methods for enhancing the plate-like regions in gray scale images were proposed. The performance of these methods was evaluated. Based on our observation edge-based enhancement is more robust than intensity-based enhancement against severe illumination conditions.

In second part, a novel matched filter was suggested to detect plate candidates. This filter models the density of vertical edge at the neighborhood of plate area. The filter is defined as a mixture of Gaussian functions. It does not impose much complexity to the system and hence is fast. Therefore, it can be used for real time applications. In addition, experimental results confirmed the strength of filter in detection plate like regions. Then morphological operators used for identifying the most probable candidate as license plate. Using morphology, we can extract the bounding box of plate.

Table 1
A comparison of three enhancement methods, system used: MATLAB 6.0, P IV 3.0 GHz.

Method	Time (s)	No. of images with enhanced plate out of total 300
Zheng et al.	~1.2	200
Improved Zheng	~1.6	257
Edge density-based	~1.1	290

Fig. 19. Some result after applying match filter: column (a) car image, (b) detected regions, (c) detected plates.

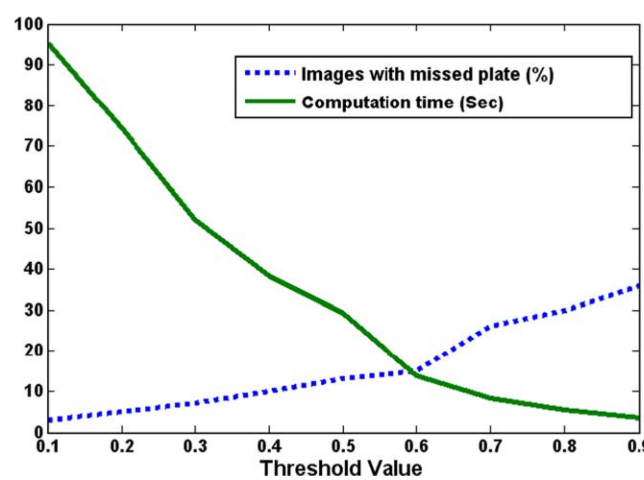

Fig. 20. Line graph of computation time and missed plate as a function of threshold value.

Table 2
Result plate detection on SET II.

False positives after MNS	MNS filtering		Match filter		Distance (m)	Angle
	Detected bio-modes		False positives	Missed plates		
	Blue–white	Blue–red				
1%	85%	91%	10%	2%	**1–2**	0°–10°
1%	84%	79%	11%	3%	**2–4**	
3%	64%	53%	15%	5%	**4–6**	
2%	87%	90%	13%	5%	**1–2**	30°–40°
4%	82%	79%	18%	5%	**2–4**	
8%	60%	48%	21%	6%	**4–6**	

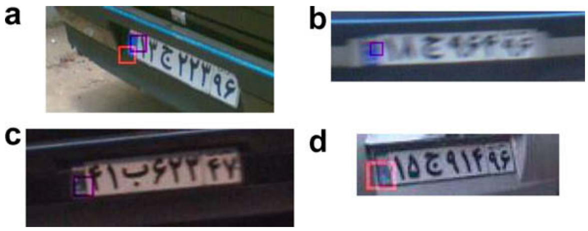

Fig. 21. MNS result for (a) extreme viewpoint, (b) blurred plate, (c) low illumination, (d) low resolution.

Fig. 22. MNS result for other types of plates.

Fig. 23. Two failed MNS result.

As a perceptual and invariable feature, color was considered. We used MNS algorithm to characterize colour logos on plate (color modes) and improved the accuracy of detection. This technique assigns labels for local neighborhood similar to the desired colored object. The drawback is high complexity of this method which makes system undesirable for real time applications. As future work we aim to decrease the computation time of colour analysis by modifying MNS method.

References

[1] Christos Nikolaos E. Anagnostopoulos, Ioannis E. Anagnostopoulos, Vassili Loumos, Eleftherios Kayafas, A license plate-recognition algorithm for intelligent transportation system applications, IEEE Transactions on Intelligent Transportation Systems 7 (3) (2006).
[2] S.Z. Wang, H.M. Lee, Detection and recognition of license plate characters with different appearences, in: Proc. Conf. Intell. Transp. Syst., vol. 2, 2003, pp. 979–984.
[3] T.D. Duan, T.L. Hong Du, T.V. Phuoc, N.V. Hoang, Building an automatic vehicle license plate recognition system, in: Proc. Int. Conf. Comput. Sci. RIVF, 2005, pp. 59–63.
[4] L. Dlagnekovin, Video-based car surveillance: license plate, make, and model recognition, M.Sc Thesis, Comput. Sci. Eng. Dept., Univ. California San Diego, La Jolla, March 2004.
[5] S. Draghici, A neural network based artificial vision system for license plate recognition, International Journal Neural Systems 8 (1997) 113–126.
[6] R. Parisi, E.D. Di Claudio, G. Lucarelli, G. Orlandi, Car plate recognition y neural networks and image processing, IEEE International Symposium on Circuits and Systems 3 (1998) 195–198.
[7] Gang Li, Ruili Zeng, Ling Lin, Research on vehicle license plate location based on neural networks, in: First International Conference on Innovative Computing, Information and Control, 2006.
[8] X. Shi, W. Zhao, Y. Shen, Automatic license plate recognition system based on color image processing, in: O. Gervasi et al. (Eds.), Lecture Notes on Computer Science, vol. 3483, Springer, New York, 2005, pp. 1159–1168.
[9] E.R. Lee, P.K. Kim, H.J. Kim, Automatic recognition of a car license plate using color image processing, in: IEEE International Conference on Image Processing, Austin, Texas, 1994, pp. 301–305.
[10] K.I. Kim, K. Jung, J.H. Kim, Color texture-based object detection: an application to license plate localization, in: S.-W. Lee, A. Verri (Eds.), Lecture Notes on Computer Science, vol. 2388, Springer, New York, 2002, pp. 293–309.
[11] F. Kahraman, B. Kurt, M. Gökmen, License plate character segmentation based on the Gabor transform and vector quantization, in: A. Yazici, C. Sener (Eds.), Lecture Notes on Computer Science, vol. 2869, Springer, New York, 2003, pp. 381–388.
[12] C.-T. Hsieh, Y.-S. Juan, K.-M. Hung, Multiple license plate detection for complex background, in: Proc. Int. Conf. AINA, vol. 2, 2005, pp. 389–392.
[13] Sunil Kumar, Nitin Khanna, Santanu Chaudhury, Shiv Dutt Joshi, Locating text in images using matched wavelets, in: Proc. of the 8th International Conference on Document Analysis and Recognition, 2005.
[14] Danian Zheng, Yannan Zhao, Jiaxin Wang, An efficient method of license plate location, Pattern Recognition Letters 26 (2005) 2431–2438.
[15] Hamid Mahini, Shohreh Kasaei, Faezeh Dorri, Fatemeh Dorri, An efficient features-based license plate localization method, in: Proc. of 18th International Conference on Pattern Recognition, ICPR, vol. 2, 2006, pp. 841–844.
[16] D. Koubaroulis, J. Matas, J. Kittler, MNS: a novel method for colour-based object recognition and image retrieval, Technical Report VSSP-TR-6/99, University of Surrey, December 1999.
[18] Shyang Lih Chang, Li Shien Chen, Yun Chung Chung, Sei Wan Chen, Automatic License Plate Recognition, IEEE Transactions on intelligent transportation systems 5 (1) (2004).