Degraded Number Plate Image Recognition for CCTV Surveillance

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Abstract: - ANPR(Automatic Number Plate Recognition) is now very popular in suspected vehicle search for CCTV surveillance on the road. When capturing vehicle images by using CCTV camera, there are two types of image degrading such as motion blur or out-of-focus blur. Number plate character segmentation and recognition processes are not simple in the degraded car images. In this paper we present efficient simple algorithm of sharpness estimation and image enhancement with selective de-blurring for number plate recognition. After number plate location, de-blurring process is selectively performed depend on whether the value of sharpness estimation is lower than predefined threshold. Selective de-blurring process is followed by image enhancement, layout analysis, character segmentation and character recognition processes of number plate images. The proposed algorithm outperforms the indiscriminative de-blurring for all plate images as well as the direct number plate recognition without de-blurring.

Key-Words: - Number Plate Recognition, Degraded Plate Image, De-blurring Plate Image

1 Introduction

CCTV surveillance is widely used for searching vehicles reported stolen, pay parking violation and pay tax violation as well as involved in criminal [4-8]. Government officers are increasingly adopting ANPR technologies in CCTV surveillance, which function to automatically capture an image of vehicle's image, identify number plate location, recognize license plate number, compare the plate number to the database of vehicles of interest, and alert the officer when a vehicle of interest has been observed in real-time processing. Commercial ANPR algorithms are very powerful in the area of vehicle access control of parking lot since the vehicle images are very clean which are captured in the environment of low speed and close distance by using trigger signal at the specific entrance points[1].

However the vehicle image quality is sometimes poor which are captured by CCTV camera on the road due to blurring effects. When capturing vehicle images by CCTV camera, there are different causes of blur such as the blur due to the motion of camera and the out-of-focus. The degraded vehicle images by blurring effects decrease the accuracy of number plate recognition. In order to increase the recognition accuracy in CCTV surveillance, the de-blurring process is selectively performed depend on whether the vehicle images are severely blurred or not.

In this paper, we present efficient simple algorithm of sharpness estimation and selective de-blurring process for number plate recognition. After number plate location from a vehicle image, image enhancement with de-blurring process which is selectively performed depend on whether the value of sharpness estimation is lower than predefined threshold as shown in Fig. 1. The overall flow of the proposed license number plate recognition consists of number plate location, sharpness estimation, image enhancement with selective de-blurring, layout analysis, character segmentation and character recognition.

The proposed algorithm is experimented for the 5,230 vehicle images captured by using CCTV camera during day and night time on a load of Korea. The experimental result and analysis results are also mentioned

Fig. 1. Example of plate image enhancement with de-blurring process.

2 Algorithm Overview

The sharpness estimation and selective image de-blurring processes are added to normal automatic number plate recognition procedures for CCTV surveillance as shown in Fig. 2. Plate region location can be derived by the connected components analysis of the dominant character string depend on plate types in binarized vehicle image. After plate region location, a sharpness value can be estimated by analyzing character stroke sharpness then both the skew-correction and size-normalization of plate image can be performed. If sharpness value is greater than predefined threshold, the plate image de-blurring process is selectively performed, otherwise image de-blurring process is skipped.

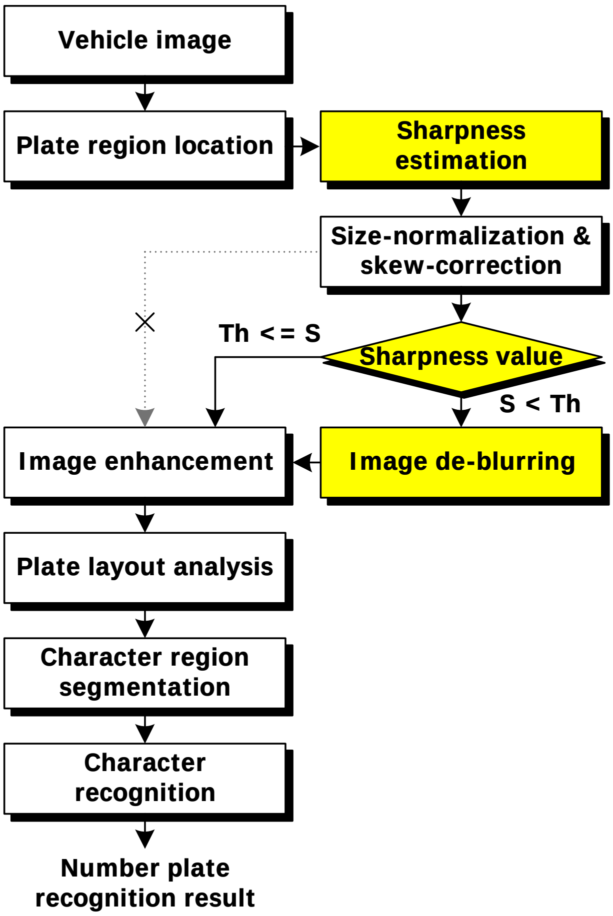

Fig. 2. A flow of plate recognition algorithm.

After image enhancement, plate layout is analyzed for identifying a plate type among 6 Korean plate types. Each character region can be segmented and normalized according to typical plate type. The segmented and normalized plate characters are recognized by using neural networks. In this paper, the sharpness estimation and image de-blurring processes are mainly explained on details.

3 Automatic Number Plate Recognition

Overall ANPR processes such as plate region extraction, sharpness estimation and de-blurring, image enhancement, and character segmentation and recognition, are explained. To increase the accuracy of ANPR in CCTV surveillance, the selective de-blurring process is introduced in his paper.

3.1 Plate region extraction

The quality of vehicle images which are captured by CCTV camera on the road, is sometimes poor due to motion blur or out-of-focus blur. In order to derive binarized strokes in plate of poor quality vehicle image, stroke accumulating algorithm of horizontal edge lines in DoG(Difference of Gaussian) filtering result was introduced [1]. Connected components of strokes are analyzed to find a dominant character string in plate region. Finally plate location can be estimated using dominant character location. A plate image is cropped based on the estimated plate location, skew-corrected and size-normalized.

3.1.1 Plate location

Binarized stroke edge images are derived including surrounding edges as shown in Fig. 4 from a blurred vehicle image captured by CCTV surveillance camera on the road as shown in Fig. 3. .

Fig. 3. A blurred vehicle image captured by using CCTV surveillance camera on a road.

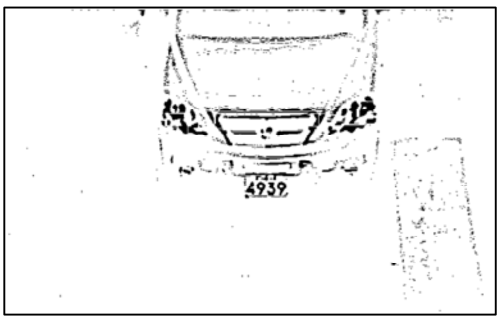

Fig. 4. A binarized vehicle image by the stroke accumulating algorithm of horizontal edge lines of DoG filtering results.

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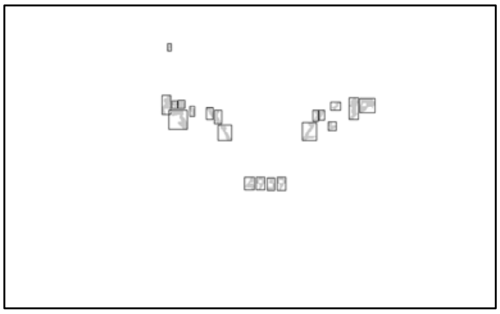

Fig. 5. Connected component analysis for extracting dominant character string in a plate region.

Fig. 6. Estimated plate location which is derived by connected component analysis.

Connected components of a binarized vehicle image are derived and non-character components are removed using predefined character size range as shown in Fig. 5. In all kinds of Korean plates, 4 big numbers are equally used as dominant characters. By extracting 4-dominant connected components, plate location can be estimated as show in Fig. 6.

3.1.2 Skew correction and size normalization

Typical plate region for 6 plate types of Korea can be estimated based on the 4-dominant numbers. The estimated plate image is transformed to create size normalized rectangle plate image by using simple transforming rules as shown in Fig. 7. This size of W and H in TARGET image are defined as 240 and 120 respectively.

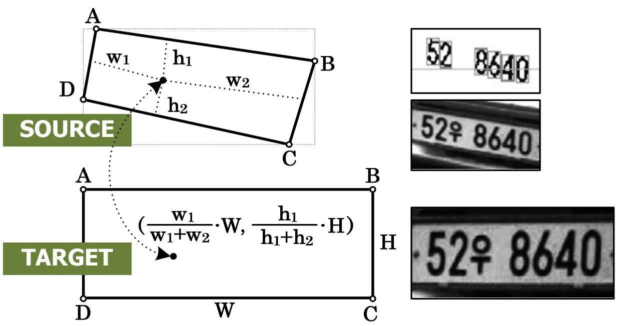

Fig. 7. Skew correction and size normalization of plate image.

3.2 Sharpness estimation and de-blurring

Sharpness can be calculated based on the edge of 4-dominant numbers which are extracted from connected component analysis. If sharpness value is lower than predefined threshold, this plate image is regarded as a severely blurred image. The blurred image is de-blurred by using simple un-sharp masking method.

3.2.1 Sharpness estimation

We derive a measure that captures whether the slope changes quickly, a characteristic of sharp edges. The slope changes are derived from edge pixels of 4-dominant numbers of plate image as shown in Fig. 8. We use difference of differences in grayscale values of a median-filtered image (ΔDoM) as an indicator of edge sharpness as defined in Kumar[2].

Fig. 8. Edge pixels of 4-dominant numbers in calculating sharpness (plotted the magnified image of Fig. 3).

Median filtering is used to smooth gray level variations due to noise while preserving edges. We compute ΔDoM separately for horizontal and vertical directions. In the x direction, ΔDoM is:

$$\Delta\mathrm{DoM}_x = [I_m(i+2,j) - I_m(i,j)] - [I_m(i,j) - I_m(i-2,j)] \qquad (1)$$

To relate the difference of differences to edge-width, we note that edge-width is inversely proportional to slope. The change in slope, ΔDoM, is a discrete version of the second derivative. By integrating the second derivative, summing 4DoM over a window of size 2w+1 is defined as D.

$$\Delta\mathrm{DoM}_x = \sum_{i-w\le k\le i+w} \left|\Delta\mathrm{DoM}_x(k,j)\right| \qquad (2)$$

Since the width of noticeable blur decreases as contrast increases[2], we need to normalize the quantities by the contrast at the edge. The contrast is estimated using the same window of size 2w+1 as used for ΔDoM, around each identified edge at pixel (i,j):

$$C = \sum_{i-w \le k \le i+w} \left| I(k,j) - I(k-1,j) \right| \quad (3)$$

where $I(k,j)$ is the value of a pixel located at (k,j) in the image. The normalized estimate at each edge-pixel is computed, and the pixel is classified as sharp if it is greater than a predefined threshold, T_S. The sharpness $S_x(i,j)$ in the x-direction at a pixel located at (i,j) in an image is computed as

$$S_x(i,j) = \frac{\sum_{i-w \le k \le i+w} \left| \Delta \mathrm{DoM}_x(k,j) \right|}{\sum_{i-w \le k \le i+w} \left| I(k,j) - I(k-1,j) \right|} \quad (4)$$

In order to compute the sharpness of an image, the sharpness estimates at each edge-pixel need to be combined. The sharpness in x for a plate region is computed as:

$$R_x = \frac{\#sharpPixels_x}{\#edgePixels_x} \quad (5)$$

In order to analysis the feasibility of sharpness estimation, we generate 5 different blurred vehicle images by using Gaussian filter of Adobe Photoshop image edit tool. Sharpness estimation results of each blurred images with sharp pixel threshold, $T_S = 2.0$, are shown in Fig. 9.

① Original image S = 0.72
② Blur − 1pixel S = 0.62
③ Blur − 2pixels S = 0.60
④ Blur − 3pixels S = 0.54
⑤ Blur − 4pixels S = 0.39
⑥ Blur − 5pixels S = 0.25

Fig. 9. Sharpness estimation of various Gaussian blurred vehicle images (Only plate regions are cropped from vehicle images for showing).

3.2.2 Plate image de-blurring and enhancement

Plate image are selectively de-blurring process according to sharpness estimation result. In this paper, we defined sharpness value S=0.5 in Eq. (5) as a threshold for severely blurred image. The severely blurred images are corrected by de-blurring process[3-4].

General method for out-of-focus blur removal is unsharp masking. It consists of subtracting a smoothed version of the image from the image itself, then adding the obtained result (the unsharp mask) to the original image.

$$f_{\mathrm{sharp}}(x,y) = f(x,y) + k \times g(x,y)$$
$$where,\ g(x,y) = f(x,y) - f_{\mathrm{smooth}}(x,y) \quad (6)$$

$f_{\mathrm{sharp}}(x,y)$ represents the final, sharpened image, $f(x,y)$ is the original image, $f_{\mathrm{smooth}}(x,y)$ denotes a smoothed version of the original image, $g(x,y)$ is the unsharp mask and k is a constant scalar value, controlling the amount of sharpening in Eq. (6). Normally, the smoothed version of the original image is obtained by applying a low-pass Gaussian filter, whereas the value of k is defined as 0.4 in this paper.

Plate image contrast enhancement is performed by logistic sigmoid transform of histogram as shown in Fig. 10. We can derive parameter values based on the range of the sigmoid function according to histogram [9].

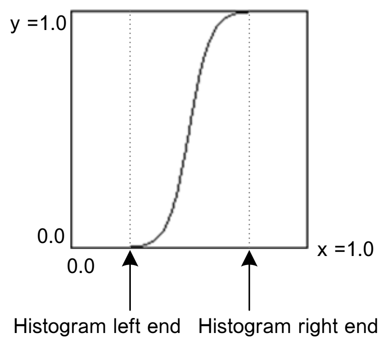

Fig. 10. Logistic sigmoid transfer function for contrast enhancement.

The sigmoid transfer function can be calculated with slope regulate parameter a as follow:

$$y = \frac{\dfrac{1}{\left(1+e^{-2a(x-0.5)}\right)} - \dfrac{1}{\left(1+e^{a}\right)}}{\dfrac{1}{\left(1+e^{-a}\right)} - \dfrac{1}{\left(1+e^{a}\right)}} \quad (7)$$

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3.4 Character segmentation and recognition by layout analysis

The contrast enhanced gray plate image is converted to binary image by using Sauvola[10] adaptive binarization rule as follow:

$$t(x,y) = m(x,y)\left(1 + k\left(\frac{s(x,y)}{R} - 1\right)\right) \quad (8)$$

An identical plate layout among 6 different layouts can decided according to the 4 big dominant numbers in Korea. Character segmentation is performed depend on a typical plate layout types. Character segmentation and normalization examples are shown in Fig. 11 from contrast enhancement with selective de-blurring process.

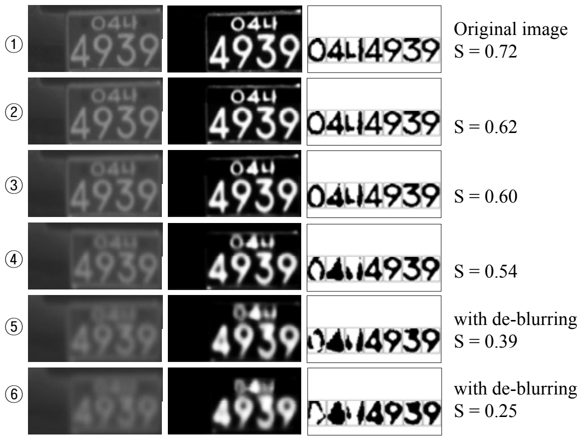

Fig. 11. Neural network architecture for Korean number plate recognition (with selective de-blurring for S < 0.5).

Segmented plate characters are recognized Back-propagation neural networks which are modeled for Korean and numeral recognition as shown in Fig. 12.

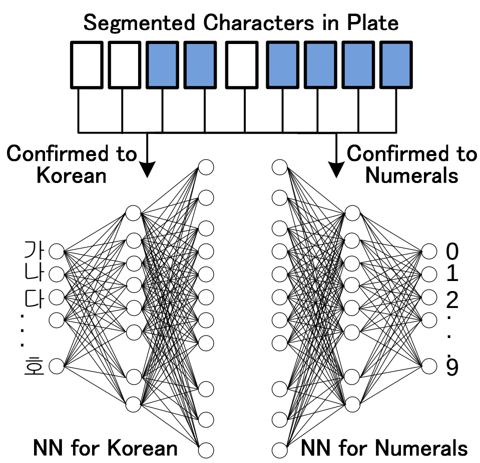

Fig. 12. Neural network architecture for Korean and number recognition.

4 Experimental Results

The proposed ANPR for CCTV surveillance is experimented for 5,230 vehicle image database captured on a road by using CCTV camera during day and night in Korea as shown in Fig. 13. Vehicle image database consist of 4,123 white background and 1,107 black background. Image size of with and height is 1,296 and 964 pixels respectively.

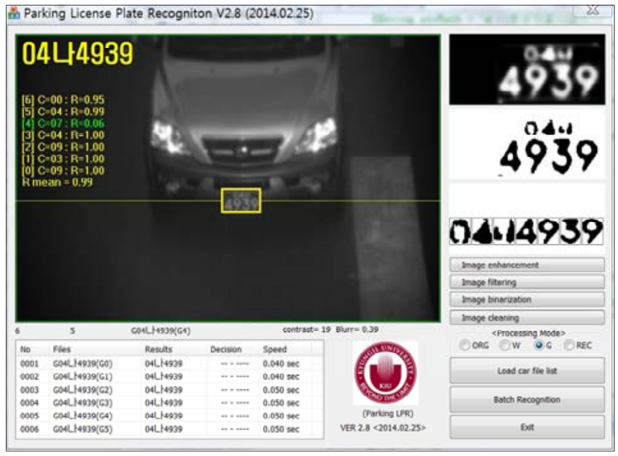

Fig. 13. Simulation user interface of ANPR for CCTV surveillance.

The accuracy of plate localization and recognition results whether the selective de-blurring is used or not, is shown in Table 1.

Table 1. Recognition accuracy of proposed ANPR for CCTV surveillance.

Algorithm	Plates	Success	Accuracy
Original	5,230	4,890	93.5%
Complete de-blurring	5,230	4,864	93.0%
Selective de-blurring	5,230	5,036	96.3%

In Table 1, “Success” is the number of plates that all characters in a plate are segmented and recognized completely. Recognition accuracy of selective de-blurring process in ANPR was 96.3%. Our new method leads to 2.8% improvement in number plate recognition accuracy. According to simulation result of “Complete de-blurring”, if de-blurring is performed to all plate images than the recognition accuracy is rather decreased due to over sharpening for un-blurred plate images.

In the experimental database, the difficult vehicle images for plate localization and recognition are shown in Fig. 14. These vehicle images are too severely blurred for recognition even though they are success in localization. The Gaussian blur or motion blur level is too high to blur correction that are proposed in this paper.

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(a) (b) (c)

Fig. 13. Samples of character recognition error with enhanced images (a), binarized images (b) and segmented images (c).

In order to blur correction for severely blurred vehicle images, other sophisticated methods in frequency domain such as Wiener filtering are required in spite of time consuming algorithms.

5 Conclusion

An efficient simple algorithm of sharpness estimation and selective de-blurring process in ANPR for CCTV surveillance is introduced. After number plate location from a vehicle image, image enhancement with de-blurring process which is selectively performed depend on whether the value of sharpness estimation is lower than predefined threshold. The proposed method is experimented for 5,230 vehicle image database captured on a road by using CCTV camera during day and night in Korea. Recognition accuracy of selective de-blurring process in ANPR was 96.3%. Our method leads to 2.8% improvement in number plate recognition accuracy.

However new frequency domain sophisticated de-blurring algorithms are required for severely blurred vehicle image recognition.

References:

[1] J. Kim, Automatic Malaysian Vehicle License Plate Recognition, International Conf. on Machine Vision, Berlin, Germany, May, 2013.

[2] J. Kumar, F. Chen and D. DoerMann, Sharpness Estimation for Document and Scene Images, International Conf. on Pattern Recognition, Tsukuba, Japan, Nov. 2013.

[3] J. Fan, Robust Document Image Enhancement with Watershed Segmentation, International Workshop on Camera-Based Document Analysis and Recognition, Curitiba, Brazil, Sept., 2007.

[4] I. Konya, Adaptive Methods for Robust Document Image Understanding, University of Bonn, Germany, Ph. D Dissertation, 2012

[5] S. Saha, S. Basu, M. Nasipuri and D. Basu, "License plate localization from vehicle images: an edge based multi-stage approach", International Journal of Recent Trends in Engineering, Vol. 1, No. 1, pp.284-289, May 2009.

[6] K. Nakao, M. Saitoh, K. Sugimoto and T. Okazaki, "Development of a License Plate Number Recognition System Incorporating Low-Resolution Cameras," Mitsubishi Heavy Industries, Ltd. Technical Review Vol. 45 No. 3, 2008.

[7] I. Tsai, J. Wu, J. Hsieh and Y. Chen, "Recognition of Vehicle License Plates from a Video Sequence," IAENG International Journal of Computer Science, 2009

[8] D. Wazalwar, E. Oruklu and,J. Saniie,"A Design Flow for Robust License Plate Localization and Recognition in Complex Scenes," in Journal of Transportation Technologies, 2012, pp. 13-21

[9] R. C. Gonzalez and R. E. Woods, "Digital Image Processing," 3rd Edition, Prentice Hall, Saddle River, 2008.

[10] F. Shafait, D. Keysers and T. Breuel, Efficient Implementation of Local Adaptive Thresholding Techniques Using Integral Image, SPIE DRR 2008, San Jose, USA, Jan, 2008.