Image Processing-based Validation of Unrecognizable Numbers in Severely Distorted License Plate Images

Sangsik Jang[1], Inhye Yoon[1], Dongmin Kim[1,2] and Joonki Paik[1]

Abstract – This paper presents an image processing-based validation method for unrecognizable numbers in severely distorted license plate images which have been degraded by various factors including low-resolution, low light-level, geometric distortion, and periodic noise. Existing vehicle license plate recognition (LPR) methods assume that most of the image degradation factors have been removed before performing the recognition of printed numbers and letters. If this is not the case, conventional LPR becomes impossible. The proposed method adopts a novel approach where a set of reference number images are intentionally degraded using the same factors estimated from the input image. After a series of image processing steps, including geometric transformation, super-resolution, and filtering, a comparison using cross-correlation between the intentionally degraded reference and the input images can provide a successful identification of the visually unrecognizable numbers. The proposed method makes it possible to validate numbers in a license plate image taken under low light-level conditions. In the experiment, using an extended set of test images that are unrecognizable to human vision, the proposed method provides a successful recognition rate of over 95%, whereas most existing LPR methods fail due to the severe distortion.

Keywords: License plate recognition, Image enhancement, Image processing, Super resolution

1. Introduction

As the deployment of video surveillance systems rapidly grows, the acquisition of criminal evidence through the extraction of meaningful information from the recorded images attracts increasing attention. Since the entire environment of interest cannot be continuously monitored by a human watchman, recorded video from closed circuit television (CCTV) cameras plays an important role in providing evidence of a crime. Although an excessive amount of image information is recorded by the CCTVs, the validation of criminal evidence often fails due to a number of degradation factors: i) insufficient resolution, ii) non-ideal illumination, iii) random or periodic noise, and iv) geometric distortion [1]. In particular, the recognition of crime-related vehicle license plate numbers is not successful in many cases, because the plate image is very small, dark, noisy, and distorted.

Super-resolution (SR) and noise removal are traditional tools used in the attempt to overcome the image restoration problem. Estimation of the original image from the observed, degraded version is a well-known inverse problem, which cannot be solved without the *a priori* information of the original image. For this reason, the recognition of numbers from a degraded license plate image is generally impossible.

Under the assumption that license plate images are generally good enough to be recognized by human vision, a typical license plate recognition algorithm consists of three steps: i) the detection of the license plate region, ii) the detection of the sub-region containing the numbers and characters, and iii) the recognition of the numbers in the sub-region. Shen-Zheng has proposed a license plate recognition algorithm using the gradient feature to detect the license plate region [3]. Hongliang has proposed a license plate detection algorithm using morphology and edge statistics [4]. Luo has proposed a license plate recognition algorithm using the Sobel operator in the HSV color space [5]. Ahmadyfard has proposed a method using texture and color information [6]. Chang has proposed a license plate recognition algorithm using color edges and fuzzy sets [7]. The above mentioned methods can successfully recognize license plates only if the input image has sufficiently high resolution under well-lighted conditions.

The proposed algorithm analyzes the factors that degrade the input image and decomposes them into removable and un-removable classes. Geometric distortion and periodic noise can be removed by inverse geometric transforms and suitable notch filters, respectively. On the other hand, low-resolution degradation and low light-level noise cannot be easily restored. For this reason we synthetically add the same degradation factors to the reference images and attempt to recognize the input degraded image by computing the similarities between the degraded reference images and the original image. Although both input de-

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graded and synthetically degraded reference image are not recognizable to human vision, the similarity comparison of the underlying information makes recognition possible.

The rest of the paper is organized as follows: We present image enhancement methods for license plate images in Section 2. The proposed license plate recognition algorithm is discussed in Section 3. In Section 4 we present some of the experiment results in order to demonstrate the validity of the proposed work. Section 5 concludes the paper.

2. A Review of the Pre-processing Methods for License Plate Images

In this section, we briefly describe some of the pre-processing methods used for license plate images.

2.1 De-interlacing

Interlaced scanning is used in existing analog CCTVs, which alternately display even and odd rows [8]. This method uses the afterimage effect of the human visual system to save on bandwidth when transmitting signals at the cost of interlacing artifacts, as shown in Fig. 1(a).

Various de-interlacing methods have been developed to compensate for interlacing artifacts, and can be classified into the field extension and field combination methods [9]. We adopt one of field extension methods, namely the line-doubling process. The method repeats either the even or the odd lines. Fig. 1(b) shows the results of a progressively scanned version of Fig. 1(a) using the line doubling method.

(a)

(b)

Fig. 1. The interlaced and progressively scanned images: (a) a captured frame from a video with interlaced scanning and (b) the progressively scanned version of Fig. 1(a) using line doubling

2.2 Geometric Distortion Compensation

In general, CCTVs are placed at a sufficient elevation to avoid interfering with the passage of pedestrians or vehicles. License plate images captured under such conditions do not have a true right rectangular shape.

If the number region is skewed or geometrically distorted, recognition of the corresponding numbers becomes difficult. If an input image has a sufficiently high visual quality, geometric distortion compensation can increase the recognition rate. Fig. 2 shows an original rectangular license plate image and its corresponding distorted version.

(a)

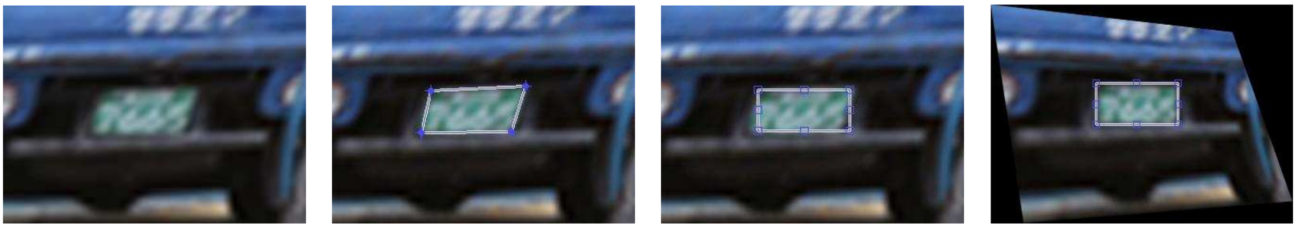
(b)

Fig. 2. A rectangular-shape license plate image and its geometrically distorted version: (a) the original image and (b) the distorted image

In order to eliminate the geometric distortion, the direct linear transformation algorithm (DLT) is a common choice [10]. It uses a number of arbitrary points in the homogeneous coordinates. More specifically, given a projection transformation matrix, the i-th coordinate $X_i = (x_i, y_i)$ of the input image is transferred to another output coordinate, $X_i' = (x_i', y_i')$, based on the following relationship:

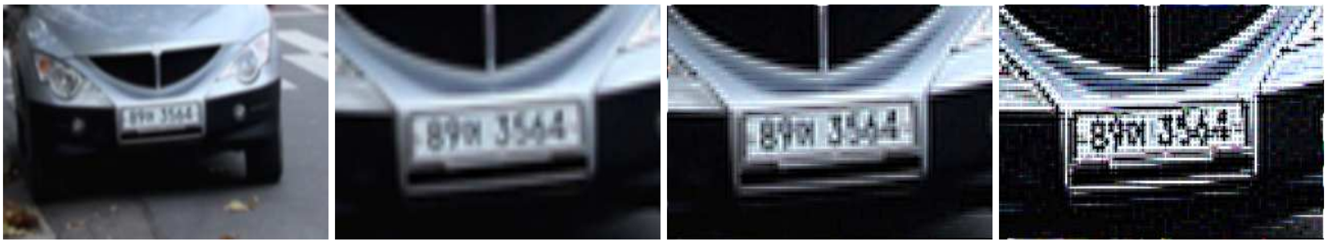
$$X_i' = HX_i. \tag{1}$$

The first step of the DLT algorithm is the estimation of the four sides of the geometrically distorted rectangular region, whose four vertices $X_i = (x_i, y_i)$ are shown in Fig. 3(b). We then interactively assign a new set of four vertices $X_i' = (x_i', y_i')$ of the desired right rectangle as shown in Fig. 3(c). Given four pairs of corresponding points, the transformation of the geometrically distorted input image into the right rectangular image is accomplished by solving (1). The resulting compensated image by the inverse geometric transformation is shown Fig. 3(d).



(a) (b) (c) (d)

Fig. 3. The compensation process for geometric distortion: (a) a distorted input image, (b) the four vertices of the distorted license plate region, (c) the set of four vertices for the right triangle superimposed on the input license plate region, and (d) the geometric compensated image by using DLT



(a) (b) (c) (d)

Fig. 4. The super-resolution method results: (a) the low-resolution input image, (b) the upsampled image using bilinear interpolation, (c) the visually optimized result of spatially adaptive super-resolution, and (d) the spatially adaptive super-resolution result used for license plate recognition

2.3 Super-resolution

The spatial resolution of a CCTV image is in general very low because the camera is set to capture as wide area as possible and an object-of-interest is not close enough in most situations. In particular, the acquisition of high-resolution license plate regions for moving vehicles is practically impossible [11]. Even if the current 640x480 D1 class camera is upgraded to a full high-definition (HD) camera with a 1920x1080 resolution, the fundamental limits in the spatial resolution still remain an open problem.

In order to obtain better spatial resolution from the recorded low resolution images, we can use either image interpolation or super-resolution techniques [12]. Image interpolation simply uses the adjacent pixels' intensity values to fill in the vacant pixel generated in the upsampling process. Since interpolation simply increases the size of the image it cannot restore lost information due to subsampling degradation. On the other hand, the super-resolution algorithm regards the low-resolution input image as a distorted version of the desired high resolution image. Utilizing the *a priori* information of an original image, the algorithm can effectively remove the degradation coming from the subsampling process, so that a good high-resolution image can be achieved. The super-resolution algorithm can be divided into a single frame-based approach or a multiple frame-based approach. Although the multiple frame-based approaches have the capability to obtain better high-resolution images than the single frame-based one, it is not suitable to the surveillance application because a sufficient number of well-correlated set of image frames are generally not provided. The well-known single-frame based super-resolution method is an example-based super-resolution and spatially adaptive regularization [13]. A spatially adaptive regularization method first perform a typical image interpolation, and then restores the high frequency components by using a regularized image restoration method that iteratively removes the subsampling degradation. The regularization parameter of the spatially adaptive super-resolution algorithm determines the relative weight of the *a priori* information of the original image, such as smoothness, and data fidelity. In this work we set the regularization parameter to be as small as possible to maximize the recognition rate of the license plate numbers in spite of losing visual quality. Figs. 4(a) and 4(b) respectively show a low-resolution input and its upsampled version by bilinear interpolation. Fig. 4(c) shows the result of the spatially-adaptive super-resolution method run for the optimum visual quality, whereas Fig. 4(d) shows the result used for the optimum recognition rate of license plate numbers.

3. The Identification of Numbers in Unrecognizable License Plate Images

In this section we present the proposed license plate number recognition method, which consists of: i) the detection of a sub-region containing numbers, ii) the resizing and filtering of the sub-region for comparison with the reference numbers, and iii) the recognition of numbers by selecting the highest correlated number.

3.1 The Detection of Sub-Regions Containing Numbers in a License Plate Image

Fig. 5 shows a preprocessed license plate region as a result of geometric compensation, filtering, and super-resolution.

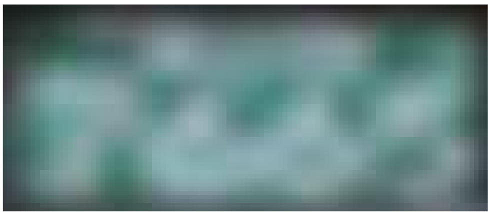
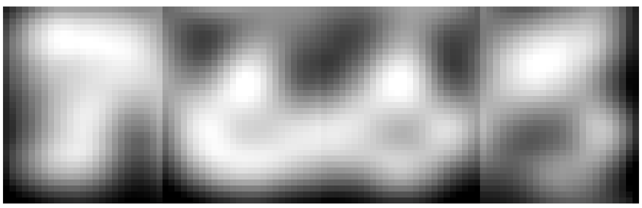


Fig. 5. The preprocessed license plate region

Because a license plate region contains several different sets of numbers and characters, we need to segment the sub-region of main numbers. Each country has its own regulations regarding the style and size of the numbers in a license plate. In South Korea two types of license plate are currently in use. The old style plates consist of a two-digit number representing the vehicle type, a single Korean character indicating the vehicle use, and a four-digit unique identification number, as shown in Fig. 6.

Fig. 6. An old-style South Korean license plate. The two-digit number in the upper left rectangle represents the vehicle type, the single character in the upper right rectangular region indicates the vehicle use, and the four-digital number in the lower rectangular region identify the vehicle.

If a user interactively specifies the four-digit number region, as shown in the bottom rectangle of Fig. 6, four sub-regions are automatically detected by using separable horizontal and vertical projections, as shown in Fig. 7.



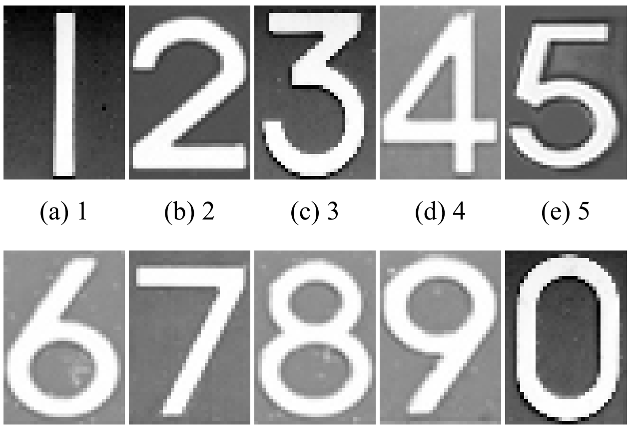
1st number 2nd number 3rd number 4th number

Fig. 7. The four sub-regions corresponding to the identification numbers

Each of the four numbers is compared with the ten high-quality reference numbers shown in Fig. 8. Amongst the ten reference numbers, the one with the highest correlation is considered to be the recognized number of the corresponding sub-region.

3.2 Resizing and Filtering

Because a CCTV image has a very low resolution and various levels of degradation, as shown in Fig. 3, super-resolution followed by the set of preprocessing steps cannot restore a sufficient amount of information for visual recognition, as shown in Fig. 7. Because of the nominal difference between the processed image shown in Fig. 7 and the reference set of images shown in Fig. 8, a direct comparison using a correlation measure is also unrealistic. Therefore, to make an effective comparison, we reduce the reference number images to the same low-resolution found for the input images and then resize it back to the original resolution using the same super-resolution algorithm. Although the processed reference images seem to lose visual information, they keep the same frequency components as the corresponding low-resolution input images, making it possible to recognize the number using the correlation between the low-resolution input image and the set of processed reference images.

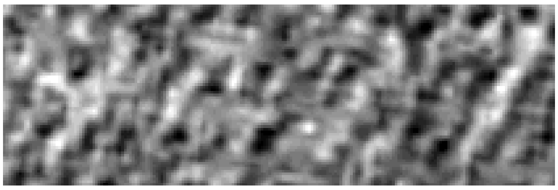


(a) 1 (b) 2 (c) 3 (d) 4 (e) 5

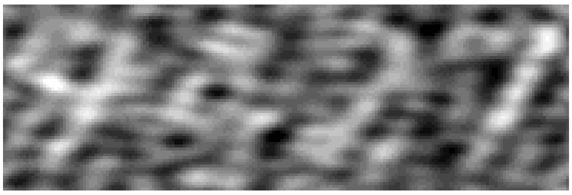
(f) 6 (g) 7 (h) 8 (i) 9 (j) 0

Fig. 8. The sub-region unique identification numbers

In addition to resizing, CCTV images are corrupted by several types of noise. In particular, periodic noise is a major degradation factor which harms the recognition performance. Notch filters are known to be effective in the elimination of periodic noise [14]. Fig. 9 shows the result of notch filtering removing periodic noise. The set of reference images are also filtered by the same notch filter to compensate for the lost frequency components in the low-resolution input image.



(a)



(b)

Fig. 9. Periodic noise removal using a notch filter: (a) an image with periodic noise and (b) the periodic noise removed

Because CCTV images are acquired under various illumination conditions, they usually have different average brightness, or DC value; noise is especially prevalent under low illumination conditions. To resolve this problem, we perform two-dimensional (2D) bandpass filtering, as shown in Fig. 10, which removes the DC values and high-frequency components due to noise amplification.

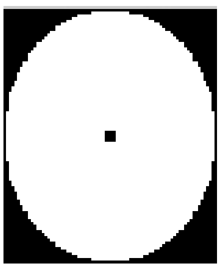
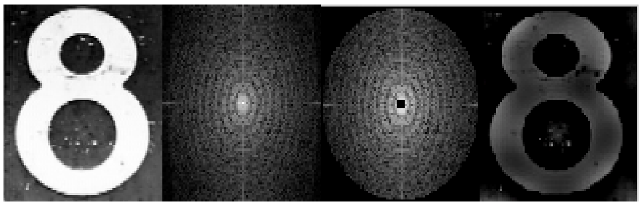


Fig. 10. The 2D frequency response of the proposed bandpass filter with the Fourier transform coefficients at zero in the black region and one in the white region

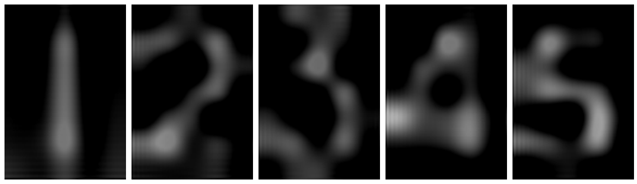
As a result of bandpass filtering both the input and reference images, they have the same zero average brightness level and at the same time the low light-level noise is removed from the input image. Fig. 11 shows the results of the proposed filtering. Fig. 11(a) shows a number sub-region in the set of ten reference images, Fig. 11(b) shows the Fourier transform of Fig. 11(a), Fig. 11(c) shows the superimposed black regions to be removed from the Fourier transform, and Fig. 11(d) the result of the bandpass filtering.

Fig. 12 shows the ten reference images processed by resizing and filtering.



(a) (b) (c) (d)

Fig. 11. The result of using the proposed donut-shape filter: (a) the original image, (b) the Fourier transform coefficients, (c) the filtered Fourier transform coefficients, and (d) the resulting image by the inverse Fourier transform



(a) 1 (b) 2 (c) 3 (d) 4 (e) 5

(f) 6 (g) 7 (h) 8 (i) 9 (j) 0

Fig. 12. The ten reference images processed by resizing and filtering

3.3 Number Recognition

A number of different methods have been examined for number recognition in the sub-regions, such as separable projection with binarization, the use of morphological templates, and principal component analysis (PCA). However, a direct comparison using the correlation between the resized, filtered versions of the input and reference images shows the best recognition results in most cases. This result can be justified because the undesired noise and different brightness levels are completely removed in the filtering process and only the necessary frequency components remain during the resizing process. In this paper, we determine the cross-correlation between the input image and ten reference images using:

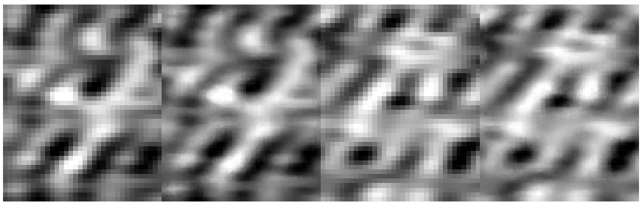
$$C_{fg} = \frac{\sum\sum(f-\bar{f})(g-\bar{g})}{\sqrt{\sum\sum(f-\bar{f})^2(g-\bar{g})^2}}, \qquad (2)$$

where f represents one of the ten filtered, resized reference images, and g the filtered, resized input image. After computing ten cross-correlation values according to the ten reference numbers, the result with the highest cross-correlation value is determined to be the recognized number.

3.4 Example-Based Super Resolution

In this paper, spatially-adaptive super-resolution was performed. In our future research we will consider example-based super resolution. In the case of simple interpolation, the image size is increased; however the high-frequency components are not restored. To solve this problem, the high-frequency components are reconstructed from the *a priori* high-resolution training images. By restoring the high frequency components from the high resolution training set, the detailed shapes of image can be successfully reconstructed under the assumption that the low-resolution images are degraded versions of the high- resolution images [15, 16].

Example-based super resolution consists of a patch learning process and an image restoration process. In the learning process, high-resolution images are divided into high frequency and low frequency components for each component patch. Each high-frequency patch and its corresponding low-frequency counterpart is stored in the patch dictionary. In the restoration process, the missing high frequency components of the low-resolution input images are restored using the information from the high-resolution components patch. Fig. 13 shows the results of example-based super resolution. Although Fig. 13 does not make a significant visual enhancement, it provides acceptable recognition results using the proposed algorithm.



(a) (b) (c) (d)

Fig. 13. Four number images processed using the proposed method and example-based super resolution: (a) the proposed method, (b) the example-based super resolution, (c) of the proposed method, and (d) the example-based super resolution

4. The Experiment Results

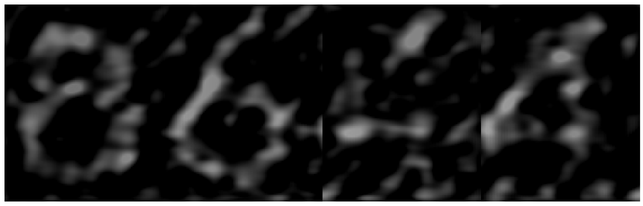
In this section, we demonstrate the feasibility of the proposed license plate recognition method using various sets of test images taken by CCTV cameras.

4.1 The Recognition of an Old-style Korean License Plate taken under a Low Light-level Condition

Fig. 14 shows an old-style Korean license plate image with geometric distortion, periodic noise, and low light-level noise.

Fig. 14. An old-style Korean license plate image taken in a low light-level condition

Fig. 15 shows the four sub-regions processed by the geometric compensation, super-resolution, noise filtering, and segmentation processes.



1st number 2nd number 3rd number 4th number

Fig. 15. The four number images processed using the proposed image process algorithm

Each number in Fig. 15 is compared to the 10 reference images, which are also processed using the same set of image processing algorithms, as shown in Fig. 12. The corresponding four sets of cross correlation values are shown in Fig. 16. In each case, the reference number with the highest cross correlation is recognized as the result. In this experiment the four-digit number is recognized as 8644, based on the cross-correlation values shown in Fig. 16.

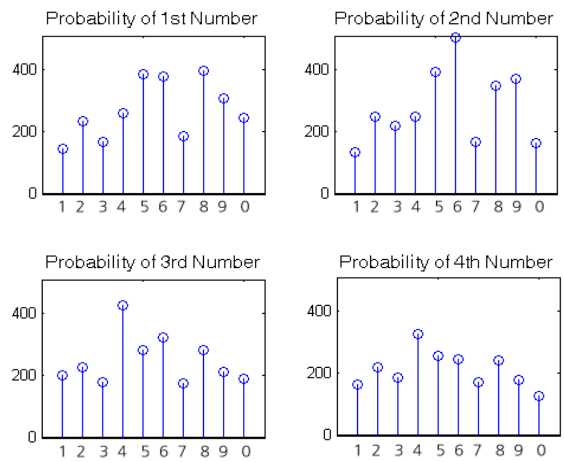


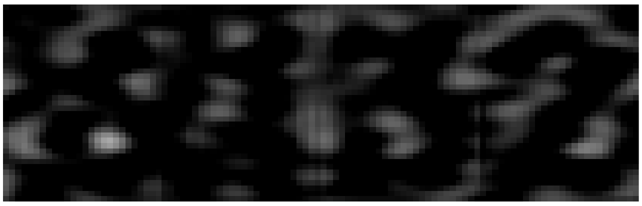
Fig. 16. The distribution of the cross-correlation values for each number sub-region

4.2 The Recognition of a New-style Korean License Plate taken under a Low Light-level Condition

Fig. 17 shows a new-style Korean license plate image with geometric distortion, periodic noise, and low light-level noise.

Fig. 17. A new-style Korean license plate image taken in a low light-level condition

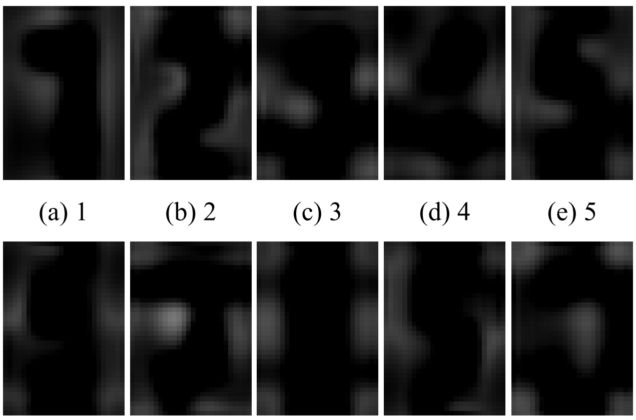
Fig. 18 shows the four sub-regions processed by geometric compensation, super-resolution, noise filtering, and segmentation.



1st number 2nd number 3rd number 4th number

Fig. 18. The four number sub-regions processed by the set of proposed image processing algorithms

The set of reference images for the new-style license plate are shown in Fig. 19, which is degraded by the same processing used in Fig. 15.



(a) 1 (b) 2 (c) 3 (d) 4 (e) 5

(f) 6 (g) 7 (h) 8 (i) 9 (j) 0

Fig. 19. The ten reference images processed by the proposed image processing algorithms

Each number in Fig. 18 is compared to the 10 reference images, which are also processed by the same set of image processing algorithms, as shown in Fig. 19. The corresponding four sets of cross correlation values are shown in Fig. 20. In each case, the reference number with the highest cross correlation is recognized as the result. In this experiment, the four-digit number is recognized as 6132, based on the cross-correlation values shown Fig. 20.

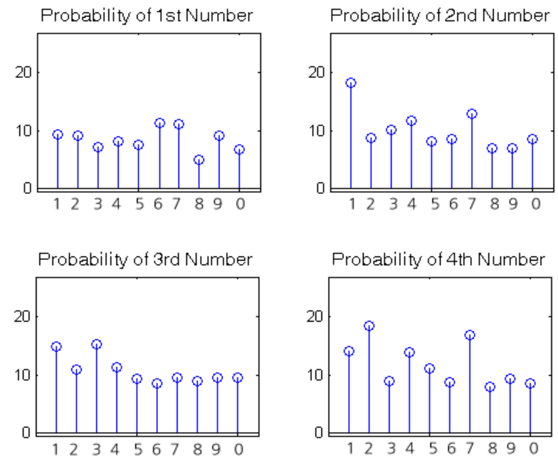


Fig. 20. The distribution of the cross-correlation values for each number sub-region

4.3 A Summary of the Recognition Results from Additional Experiments

In this subsection we discuss the recognition results from twenty license plate images using the proposed method. Fig. 21 shows the accumulated numbers of correctly recognized and ground truth license plate numbers.

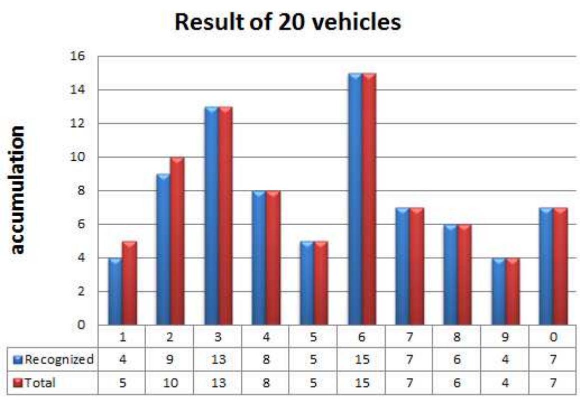
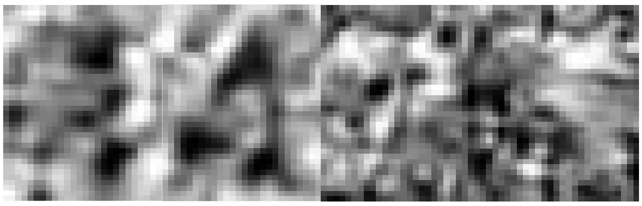


Fig. 21. The accumulated numbers of correctly recognized (left, blue) and ground truth (right, red) license plate numbers

Since Korea uses a four-digit vehicle identification number, twenty license plate images give 80 numbers. Most numbers were correctly recognized except for two cases where the input images were severely degraded, as shown in Fig. 21. More specifically the “1” was recognized as a “4”, and the “2” was recognized as a “3”, as shown in Figs. 22(a) and 21(c), respectively. Fig. 22(b) and Fig. 22(d) respectively show the real “4” and “3”.



(a) (b) (c) (d)

Fig. 22. The incorrectly recognized numbers: (a) 1 incorrectly recognized as 4, (b) 4 in the same condition, (c) 2 incorrectly recognized as 3, and (d) 3 in the same condition

Fig. 23 shows the cross correlation results. The blue columns show the correlation coefficient regarding each reference number and Fig. 13(a). The red columns show the correlation coefficient regarding each reference number and Fig. 13(b).

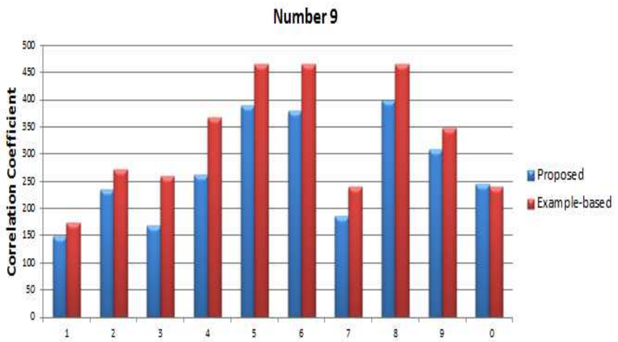


Fig. 23. The correlation coefficients from Fig. 13(a) and Fig. 13(b)

Fig. 24 shows more cross correlation results. The blue columns show the correlation coefficient from each reference number and Fig. 13(c). The red columns show the correlation coefficient from each reference number and Fig. 13(d).

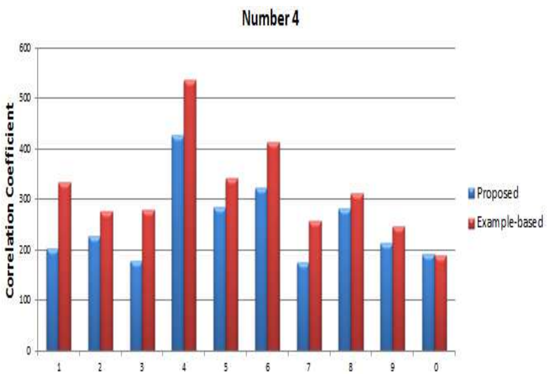


Fig. 24. The correlation coefficients from Fig. 13(c) and Fig. 13(d)

As shown in Fig. 23 and Fig. 24, the correlation coefficient increased when using the example-based super-resolution. Referring to the above figures, we can conclude that by using example-based super-resolution, the recognition results are not changed but the total image information is increased.

5. Conclusion

An image processing-based validation method for unrecognizable numbers in severely distorted license plate images has been presented, where the various severe distortions include low-resolution, low light-level, geometric distortion, and periodic noise. The major contribution of this work is in that the proposed method can recognize numbers in severely distorted license plate images, whereas most existing LPR methods fail in recognizing numbers under these conditions. The proposed method adopts a novel approach: a set of reference number images are intentionally degraded using the same factors estimated from the input image. After a series of image processing steps including geometric transformation, super-resolution, and filtering, comparisons using the cross-correlation between the intentionally degraded reference and input images can provide successful identification of numbers, even though they are visually unrecognizable. As a result, the proposed method can successfully validate numbers in license plate images taken from a distance under low light-level conditions. In the experiment using an extended set of test images that are unrecognizably distorted for human vision, the proposed method provided successful recognition rate of over 97%, whereas most existing LPR methods would fail.

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