Image Enhancement Technology for Improved Object Recognition in Car Black Box Night

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** Short Paper*

***Abstract*:** Videos recorded on surveillance cameras or by car black boxes at night have distorted images due to illumination variation. Therefore, it is difficult to analyze morphological characteristics of objects, and it is limiting to use such distorted images as evidence in traffic accidents. Image restoration is performed by amplifying the brightness of nighttime images using linearized gamma correction to increase their contrast (which destroys visual information) and by minimizing degradation factors caused by irregular traveling.

***Keywords*:** Image processing, Gamma correction, Night images, Degraded image restoration, Noise removal

1. Introduction

According to National Police Agency data, the number of traffic accidents in 2014 in Korea was 223,552, with 4,762 deaths and 337,497 injuries, including 101,280 nighttime accidents causing 2,446 deaths and 153,432 injuries, plus 8,771 hit-and-runs resulting in 207 deaths and 13,622 injuries. In these kinds of accidents, automobile video recorders play a key role, as they provide important evidence about what happened on the road.

Advanced countries are enacting laws requiring the installation of so-called black boxes, focusing on commercial vehicles; the installation of automobile data recorders (including visual recording aids) has been mandatory for commercial vehicles in Korea since 2013 under the Traffic Safety Acts, and domestic sales of black boxes for automobiles in 2014 was more than three million, with continued growth expected.

Recently, image processing technologies for vehicle cameras have been studied in various related fields. The cameras installed in vehicles often have characteristics of radical illumination variation [1-4]. Therefore, image sensor technology for cameras was developed to deal with cases of two or more light sources in one scene, or with sudden illumination changes [5-9]. However, there is a disadvantage in that the additional improvement in image sensor performance brings huge development costs and time scales.

For that reason, research into digital image processing–based gamma correction and high-dynamic-range imaging is receiving a lot of attention.

To improve image quality under illumination variation, an evaluation of images for brightness and contrast must be done in advance.

Quality evaluation of images was studied by Oakley and Bu [10]. However, because their evaluation interpreted the distribution of the histogram subjectively, it is difficult to use their work for objective evaluation. In 2008, the word descriptor was introduced by Restrepo and Ramponi [11]. It symbolizes distribution charts as “a, A, b, B, c, C, d, D” after dividing a distribution of the histogram for brightness and contrast and re-distributing them into four sections. However, this method had little objectivity, and was under-utilized because it also used classifications such as "very bright, very high contrast ratio."

In this study, a restoration method for degraded images recorded in a vehicle black box is suggested to acquire clearer images of accidents on a dark road at night. First, contrast improvement by gamma correction is performed in order to recognize objects, such as cars or pedestrians, in low light–level images recorded at night.

Secondly, image restoration–enhancing sharpness is applied with a median filter to the improved images through gamma correction.

The structure of this paper is as follows. In Section 2, the basics of gamma correction are explained, and the suggested algorithms for noise removal and sharpness enhancement are elucidated in Section 3. In Section 4, the

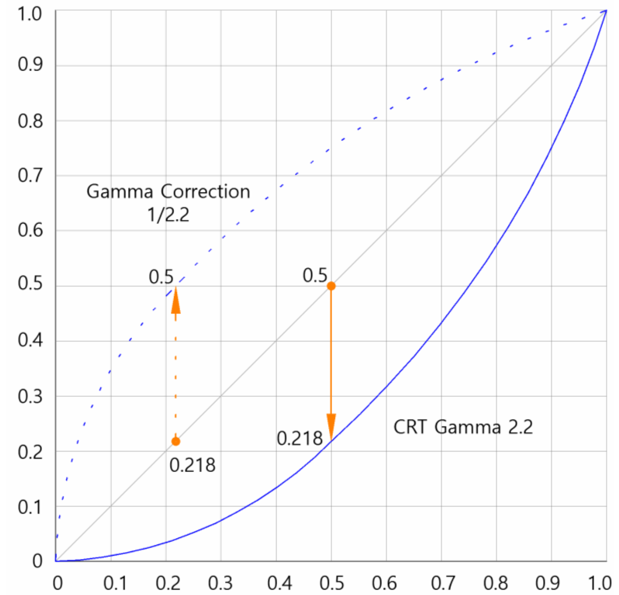


Fig. 1. Brightness gamma graph of the input image.

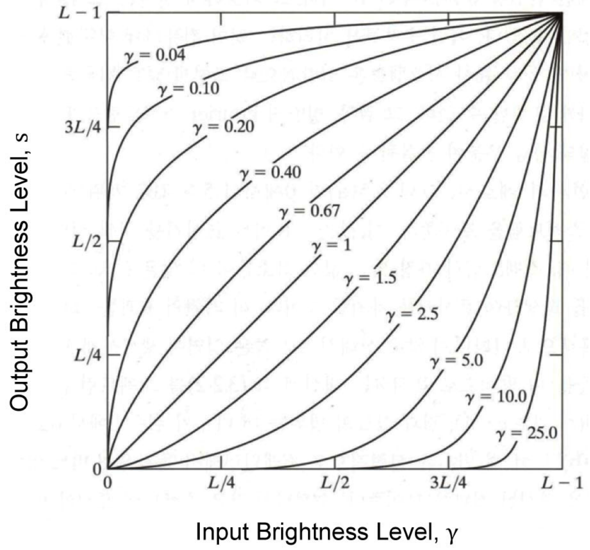


Fig. 2. Input and output brightness change by gamma values.

results of the suggested experiment are described, and this paper is concluded in Section 5.

2. Related Work

2.1 Gamma Correction Algorithm

Gamma correction was introduced to compensate for differences, because the brightness of images displayed on a monitor is different from the input information of those images.

Because the relation of brightness displayed on monitors to the input signal is non-linear, it is processed such that the output values for the input values are compensated inversely.

When non-linear reactions of output devices are revised with gamma correction, the exponential law is used.

Generally, the exponential law can be represented in the form of $y = T(x)(c,x)^{\gamma}$, where c and γ are positive constants, and c represents linear change, but γ is determined by the degree of nonlinearity: for $\gamma = 1$, it is linear, and for $\gamma < 1$ or $\gamma > 1$, it becomes non-linear, as seen in Fig. 2.

Display response is a nearly exponential curve that is downward-convex, as seen in Fig. 1, and this index is called gamma. The yellow downward arrow indicates that 0.218, the pixel value at 50% intensity, releases at lower than 25% compared to 1.0, the pixel value at 100% intensity.

Gamma is pre-distorted to express accurate color for display output, and therefore, a linear red-green-blue (RGB) property is acquired on display.

Gamma correction is the technology that uses a non-linear mapping function to revise nonlinearity in image data, and it can be processed via software before correction.

Inverse gamma transformation is used to compensate for the non-linear property occurring in the display device. If gamma correction is not used, the bright part of a screen image is more expanded, and the dark part is compressed and becomes darker. Gamma correction is needed to accurately represent the brightness values of the original images on output devices, such as a monitor, and it can be used in the image processing field.

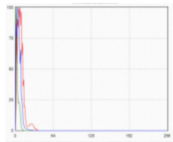
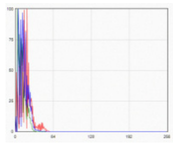
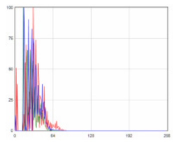
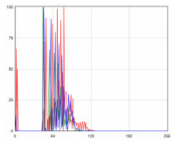
Gamma Value	Image	Histogram
$\gamma = 1.0$		
$\gamma = 0.7$		
$\gamma = 0.5$		
$\gamma = 0.3$		

Fig. 3. Results by gamma value.

Fig. 3 represents images and histograms by gamma values, where $\gamma = 1.0$ is the original image recorded in a vehicle black box at night.

As the gamma value decreases, the image gets dark, and a histogram of the distribution of pixel values is concentrated on the left side; as the gamma value increases, the image gets bright, the distribution of pixel values moves to the right side, and the distribution of the

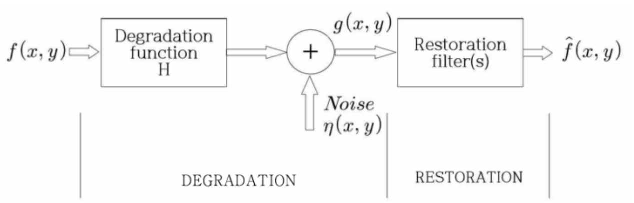


Fig. 4. Restoration model of a degraded image.

histogram is widened.

2.2 Restoration Model of Degraded Images

Degraded images can be represented as follows:

$$g(x,y)=H\left[f(x,y)\right]+\eta(x,y) \tag{1}$$

When partial information of degradation function H is given, i.e., the energy of additional noise $\eta(x,y)$, the process to acquire an estimation of original image $\hat{f}(x,y)$ is the image restoration. If the information about H and $\eta(x,y)$ is used, $\hat{f}(x,y)$ will be closer to $f(x,y)$ If H is linear in the spatially invariant process, a degraded image can be shown as follows (using two-dimensional convolution):

$$g(x,y)=h(x,y)*f(x,y)+\eta(x,y) \tag{2}$$

Here, $h(x,y)$ is the spatial expression of the degradation function, and the asterisk indicates the convolution.

The convolution in the spatial domain becomes multiplication of Fourier transform pairs in the frequency domain, so the equivalent frequency domain model is as follows:

$$G(u,v)=H(u,v)F(u,v)+N(u,v) \tag{3}$$

Each capital letter signal is a Fourier transform, and $H(u,v)$ is the optical transfer function.

In Fig. 5, the center column shows the original images according to the gamma values, and the right column shows noise-removed images from applying a median filter.

The median filter changes the pixel values into the median values of the neighboring pixels' brightness values. A median filter has superior performance in removal of specific noise types, and provides the advantage of preservation of image edges, compared to a linear mean filter of similar size. Substituting the pixel values with the median values of the neighboring pixels' brightness values is represented by Eq. (4):

$$\hat{f}(x,y)=\underset{(s,y)\in S_{xy}}{median}\left\{g(s,t)\right\} \tag{4}$$

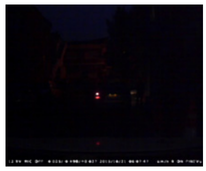
Gamma Value	Gamma Correction	Restoration Image
$\gamma=1.0$		
$\gamma=0.7$		
$\gamma=0.5$		
$\gamma=0.3$		

Fig. 5. Result of image restoration from applying a median filter.

The set of coordinates for the quadrangular window (neighbors), which is centered on (x,y) and sized $m\times n$, is represented as S_{xy}, and the pixel values of (x,y) are included in the median value calculation.

3. Image Processing using an Unsharp Mask

For sharpness enhancement of images, the process of removing unsharp versions from original images is performed. This process, the so-called unsharp mask, is comprised of three work stages. First, blur the original image. Second, eliminate the blurred image from the original (the result of this process is called the mask). Third, add the mask to the original image.

When the blurred image is expressed as $\hat{f}(x,y)$, the unsharp mask is represented by Eq. (5):

$$g_{mask}(x,y)=f(x,y)-\hat{f}(x,y) \tag{5}$$

Adding the weighted mask image to the original is represented by Eq. (6):

$$g(x,y)=f(x,y)+k*g_{mask}(x,y) \tag{6}$$

Here, the weighted value $k(k\geq 0)$ is included for generality, and it is an unsharp mask, as defined above, when $k=1$.

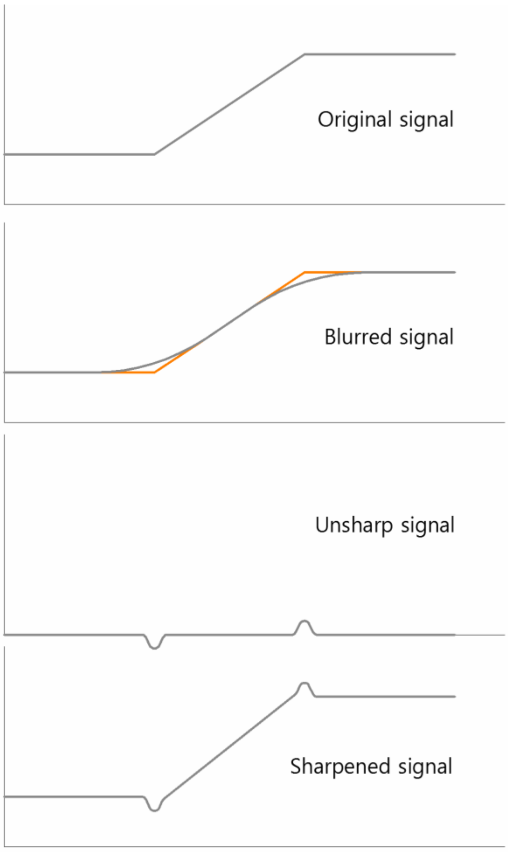


Fig. 6. Unsharp Mask principle.

Fig. 6 shows the principle of the unsharp mask, and in the first row, the cross-section of brightness is shown as a horizontal scan line crossing the vertical edge, which shifts from the dark region to the bright region in the image. The second row shows the smoothing result marked on the original signal (dotted line) for reference. The third row is the unsharp mask, and it is acquired by removing the blurred signal from the original. And the fourth row is the final result of sharpening.

The restoration images in Fig. 7 are the noise-removed ones using the median filter algorithm. The unsharp mask images are the result of applying 100% of the appointment level of the contrast application level, 10 pixels of the size of the contrast application range from the edge, and five of the threshold, which determines whether to raise the contrast on the edge, showing a considerable difference. And they represent more improved sharpness than the original images.

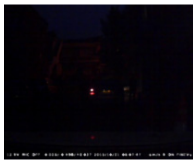
Gamma Value	Restoration Image	Unsharp Mask
$\gamma = 1.0$		
$\gamma = 0.7$		
$\gamma = 0.5$		
$\gamma = 0.3$		

Fig. 7. Results according to unsharp mask.

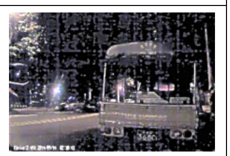
Gamma Value	Gamma Correction	Unsharp Mask
$\gamma = 1.0$		
$\gamma = 0.7$		
$\gamma = 0.5$		
$\gamma = 0.3$		

Fig. 8. Result I according to the proposed method.

4. Results

In this paper, the results of enhanced sharpness with removed noise after performing gamma correction for images at night are presented. In Fig. 8, $\gamma = 1.0$ is the original image from a black box recorded at night, and the illumination state of the vehicle's tail light is only distinguishable by examination with the naked eye. We can see that the objects, such as the body of the vehicle, the pedestrian, and the background are differentiated and identified by the gamma value.

From Fig. 9, $\gamma = 1.0$ is the original image, and it is too dark to distinguish the vehicle without headlights; however, it can be distinguished by using the proposed method.

In Fig. 10, $\gamma = 1.0$ is the original image from a black box recorded at night and is the result of object recognition enhancement of the accident vehicle. The driver and the victim, by applying the proposed method to the dark image

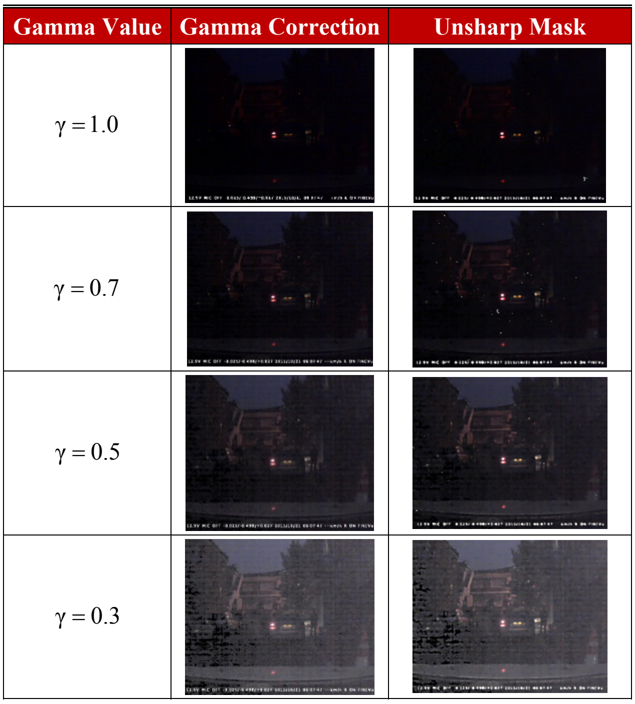


Fig. 9. Result II according to the proposed method.

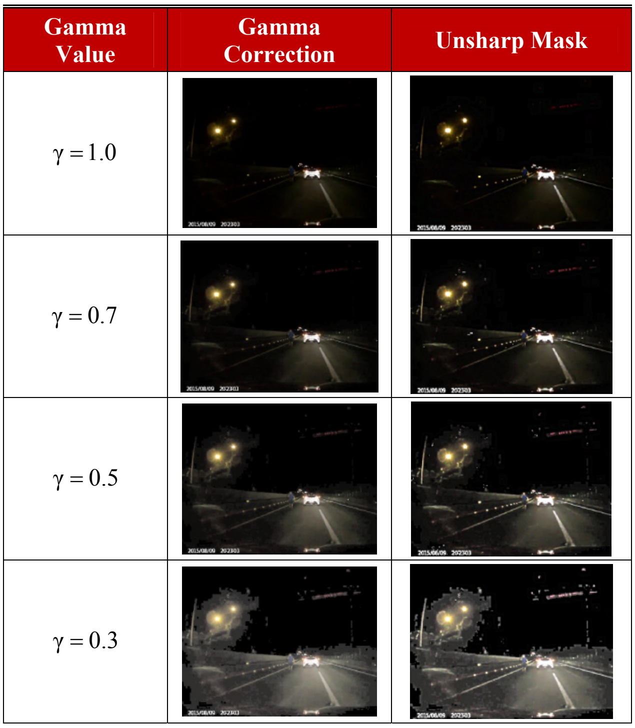


Fig. 10. Result III according to the proposed method.

of the accident, can be seen.

From Fig. 11, $\gamma = 1.0$ is the original image of a black box recorded at night, and we can see that it is a collision with a bike that crossed against the light. The vehicle is distinguished by applying the proposed method.

Figs. 8-11 show the results of sharpness enhancement of the images from a vehicle's black box recorded night by performing gamma correction, filtering them, and applying

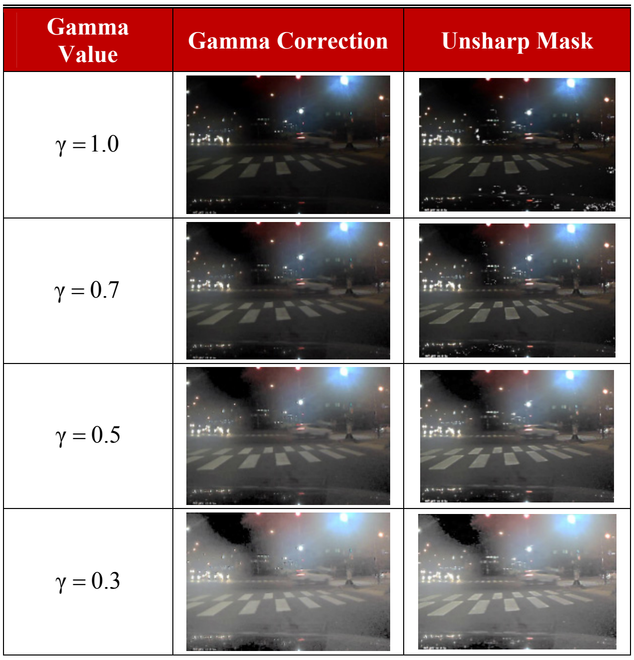


Fig. 11. Result IV from the proposed method.

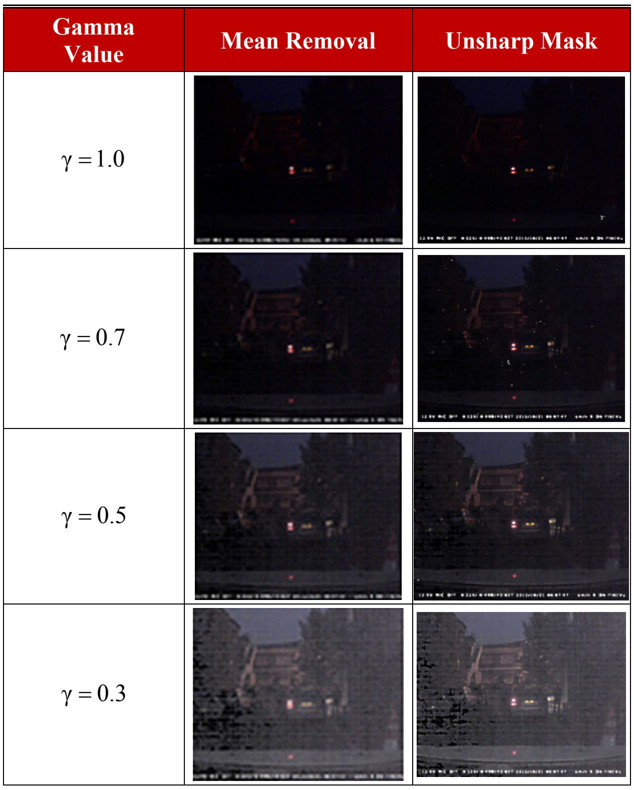


Fig. 12. Comparison of the proposed method and mean removal.

image processing under the proposed method.

As the gamma value decreases, it is easier to distinguish the objects. If the gamma value is greater than 0.7, there are some problems such that noise like cloud is seen, and the bright section becomes brighter.

However, based on the gamma value 0.5, enhancement of the image shows that objects are distinguishable with

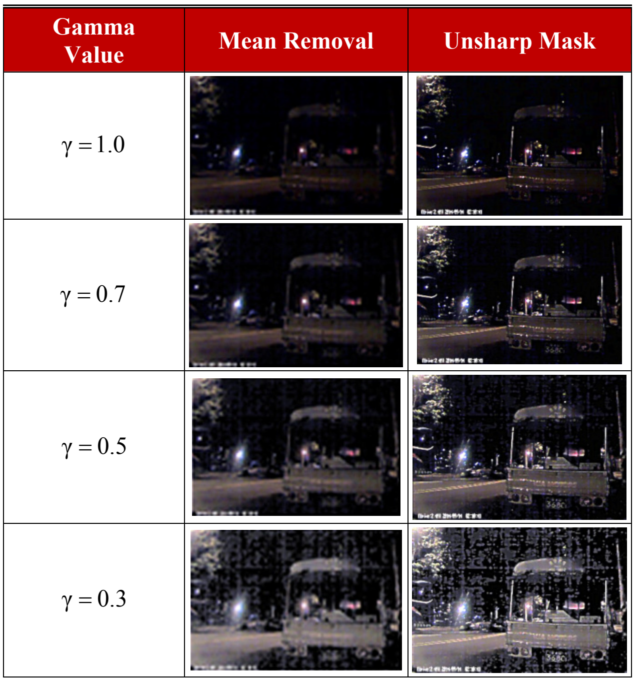


Fig. 13. Comparison of the proposed method and mean removal.

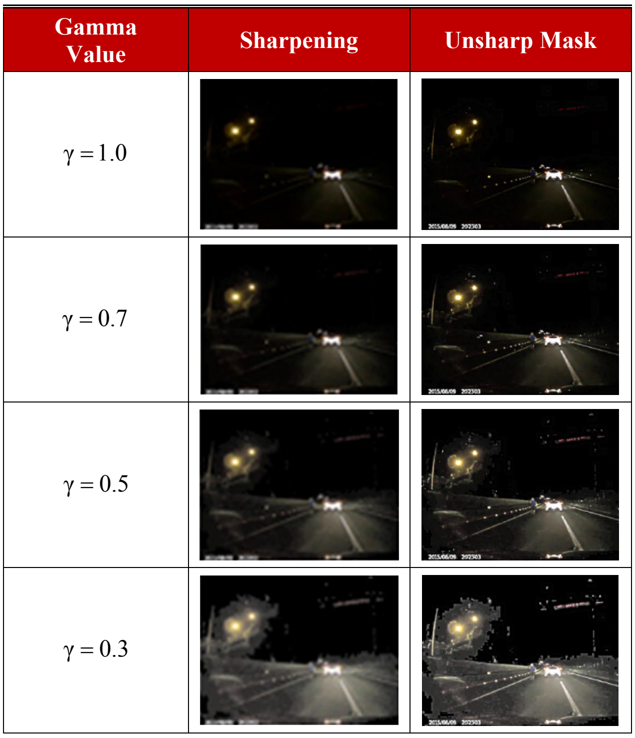


Fig. 14. Comparison of the proposed method and the result of sharpening.

the naked eye.

The images in Figs. 12 and 13 are enhanced in sharpness by applying mean removal and the unsharp mask to the corrected images where the gamma value was initially applied, and we can see that the results based on the proposed method show higher sharpness in the images.

The images in Figs. 14 and 15 are enhanced by

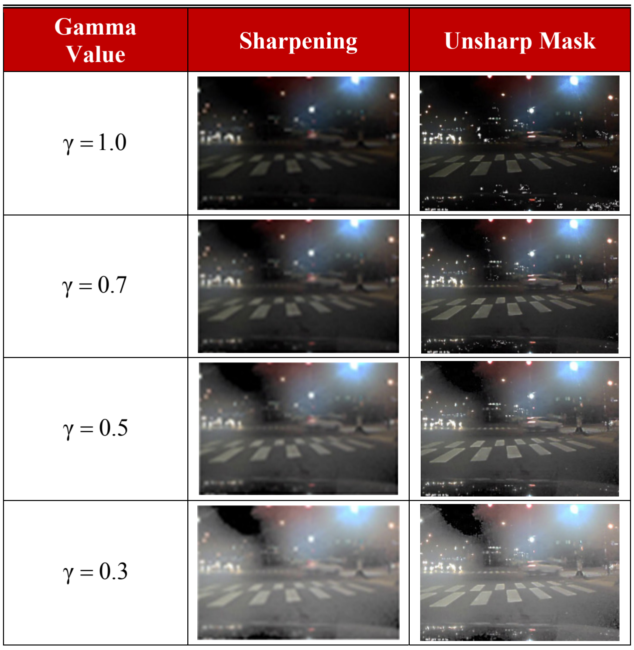


Fig. 15. Comparison of the proposed method and the result of sharpening.

sharpening the images initially corrected by the gamma value and with the unsharp mask, which sharpens the images by increasing the contrast between color boundaries. We can see that the results based on the proposed method show greater sharpness in the images.

5. Conclusion

There is a limitation in using a vehicle's black box images recorded at night as objective evidence for a traffic accident, since it is difficult to distinguish images with the naked eye.

In this paper, a method to enhance degraded images recorded at night is proposed to solve such problems.

The images acquired by the proposed method are significantly enhanced in object recognition of vehicles, pedestrians, and other bodies, compared to the original images. It is expected that the proposed method can contribute to interpreting accident images, to solving noise problems, such as the cloudiness mentioned above, and to improving contrast, noise removal, and sharpness. Parallel processing studies applying useful techniques for night image restoration should still be done.

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