Avoiding Glare by Controlling the Transmittance of Incident Light

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Abstract: In this paper, we introduce a new method for enhancing the visibility of human vision. In particular we propose a method for avoiding glare caused by strong incident light, such as sunlight and headlight of oncoming vehicles, in driving situations. Our method controls the transmittance of incident light pixel by pixel according to the power of the incident light. For computing the transmittance of light efficiently from camera images, we propose a leaning based method utilizing a generative adversarial network (GAN). By using our method, the visibility of drivers can be improved drastically, and objects in dark place become visible even under strong backlight, such as sunlight and headlight of oncoming vehicles.

1 INTRODUCTION

As shown in the statistics of traffic accidents in Fig. 1, serious accidents increase drastically when the relative angle between the sun and the driver's viewing direction becomes small (Hagita and Mori, 2013). This is because the dynamic range of the entire scene becomes very large under the existence of backlight as shown in Fig. 2, and the visibility of objects in dark place is greatly deteriorated because of the limited dynamic range of human vision. Furthermore, since the dark adaptation takes much more time than the bright adaptation in human vision, the strong backlight, such as sunlight and headlight of oncoming vehicles, causes invisibility for a long time in human vision. Therefore, it is very important to improve driver's visibility in such high contrast situations.

Thus, we in this paper introduce a new method for enhancing the visibility of human vision by directly controlling the incident light on human eyes. In particular, we propose a method for controlling the transmittance of glass pixel by pixel according to the power of incident light. For this objective, we capture the intensity of incident light by using a camera. However, the intensity of light observed by a camera is often saturated because of the high power incident light such as sunlight and headlight as shown in Fig. 2. Thus, for computing the transmittance of incident light efficiently from saturated camera images, we propose a leaning based method utilizing a generative adversarial network (GAN) (Goodfellow et al., 2014). GAN is a very successful neural network,

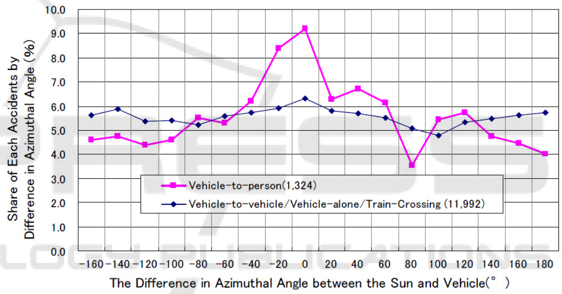

Figure 1: The relationship between the car accident rate and the relative angle between the sun and the viewing direction of driver (Hagita and Mori, 2013).

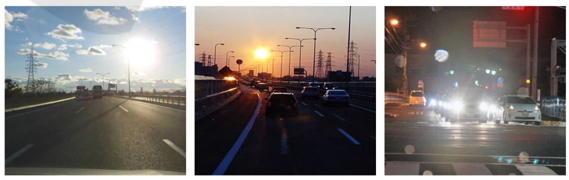

Figure 2: High contract scenes caused by the backlight of sunlight and headlight of oncoming vehicles.

and many variations have been proposed in recent years (Radford et al., 2016; Isola et al., 2017; Zhu et al., 2017). In this paper, we propose a conditional GAN for generating transmittance images efficiently from saturated camera images. Our conditional GAN learns ideal light intensity for driver's vision, and generates transmittance images for providing ideal light intensity to drivers.

By using our method, the visibility of drivers can be improved drastically, and objects such as pedestri-

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ans in dark place become visible, even if the incident light includes strong backlight, such as sunlight and headlight of oncoming vehicles.

2 RELATED WORK

In computer vision, many methods have been proposed for producing high dynamic range (HDR) images from low dynamic range (LDR) images (Mann and Picard, 1995; Debevec and Malik, 1997). These methods combine multiple static images taken under different exposure time. To extend these method for dynamic scenes, the optical flow estimation was also combined with HDR methods (Tomaszewska and Mantiuk, 2007; Kalantari and Ramamoorthi, 2017; Wu, et al., 2018). For obtaining HDR images from single shot imaging, coded exposure techniques have been proposed (Schedl et al., 2013). More recently, variable exposure imaging, which controls exposure time pixel by pixel, has also been proposed and used for generating HDR images from single shot imaging (Uda et al., 2016). These single shot methods provide us better HDR images under dynamic scenes.

Although these methods enable us to improve the quality of images taken by cameras, the generated HDR images are not directly visible for human observers, and these HDR images must be transformed to LDR images again by using some tone mapping functions before showing them to human observers (Reinhard et al., 2002). As a result, these information pipelines are not so efficient when we want to show high quality images to observers. Thus, we in this paper consider a direct improvement of light incident on the human observers. In particular, we consider a method for improving the visibility of human drivers on the road.

Some countermeasures have been taken for improving the visibility of vehicle drivers by directly controlling light. For example, at the entrance and the exit of tunnels, the light is strengthened for urging the bright adaptation and dark adaptation of drivers vision (CIE, 2004). Also on the vehicle side, automatic anti-glare mirrors (GENTEX) have been realized, which automatically adjust the amount of reflected light according to the magnitude of incident light. Recently, dimmable windows which block sunlight and heat have also been developed (SmaerGlass).

However, these anti-glare systems change the reflectance or transmittance of entire mirrors or windows uniformly. Therefore, if an intense light is incident on a part of the mirror or the window, the entire mirror or the entire window becomes dark, and dark objects in the scene become invisible. If it is a mirror, this is not a big problem, but in the case of windshields, it is very dangerous to darken all the windshield surface.

For shutting out specific incoming light selectively, the polarization is often used. For example, if we put polarized glass in front of an observer, and if we emit polarized light from the headlamp of the vehicle, whose polarization is rotated 90 degrees from the polarization of the observer, then the light from the headlamp can be shut out selectively in the observed light (Land, 1948). Although the polarization can eliminate specific light efficiently, it can be used only for artificial light or specific natural light such as reflected light, and it cannot control the intensity of arbitrary incident light with arbitrary amount.

Thus, in this paper, we propose a method for controlling the transmittance of light pixel by pixel, so that strong incident light such as sunlight and headlight of other vehicles is weaken, and weak incident light of dark place is transmitted as it is.

3 OPTICAL ADAPTATION IN HUMAN VISION

In general, when the human eye moves from a bright place to a dark place, the lowest observable brightness of vision decreases making proper observation possible even in dark places. This is called dark adaptation, and the human vision which completed the dark adaptation is called scotopic vision. On the other hand, when we move from a dark place to a bright place, the highest observable brightness of vision rises, and the lowest observable brightness also rises. As a result, bright scenery can be observed by the human vision. This process is called bright adaptation, and the human vision which completed the bright adaptation is called photopic vision.

In general, the bright adaptation finishes in 30 seconds, whereas the dark adaptation takes about 30 minutes. Therefore, once the human vision changes to the photopic vision from the scotopic vision by a strong incident light, it cannot return to the scotopic vision easily.

At dusk, the human vision is in an intermediate state between photopic vision and scotopic vision, which is called mesopic vision. When bright sunlight enters the human eyes in mesopic vision state, the light adaptation occurs, and the state changes from the mesopic vision to the photopic vision. Once the state is changed to the photopic vision, it cannot return to the mesopic vision easily, and the visibility of dark places is degraded for long time. As a result, the drivers cannot see pedestrians and obstacles at dusk,

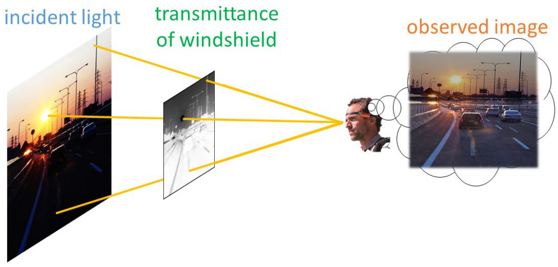


Figure 3: Controlling the transmittance of windshield pixel by pixel according to the incident light.

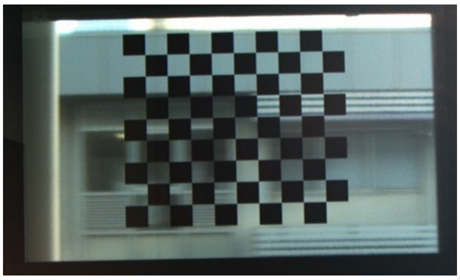


Figure 4: Controlling the transmittance of windshield pixel by pixel by using a LCD panel.

and the possibility of serious car accidents increases.

Thus, in this paper, we control the transmittance of windshield pixel by pixel, so that strong incident light such as sunlight and headlight of other vehicles is weaken, and weak incident light of dark place is transmitted as it is, as shown in Fig. 3. By controlling the transmittance of the windshield like this, the scotopic vision and the mesopic vision can be preserved at night and dusk, and the drivers can recognize pedestrians and obstacles even under strong backlight.

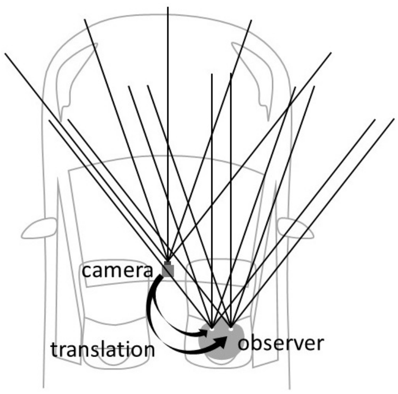


Figure 5: Incident light of camera and incident light of observer. Since the depth of background scene is very large comparing with the distance between the camera and the observer, we can assume that the incident light at the camera viewpoint and the incident light at the observer's viewpoint are parallel to each other.

4 CONTROLLABLE WINDSHIELD

Unfortunately, there is no glass material which can control its transmittance pixel by pixel. Thus, we in this research combine a liquid crystal display panel (LCD) with a glass, so that the transmittance of each pixel of the glass can be controlled.

Suppose an incident light with the magnitude of E_i goes though the i-th pixel of the LCD and comes into the eye of the observer. Then, the observed intensity I_i can be described as follows:

$$I_i = E_i \alpha_i \tag{1}$$

where, α_i is the transmittance of i-th pixel of the LCD.

Fig. 4 shows the observed intensity through an LCD when we set a transmittance image of checker pattern to the LCD. As we can see in this image, incident light rays at black pixels are blocked, and only background scene at white pixels is visible.

For controlling the transmittance of the windshield for an observer, we need the incident light image at the viewpoint of the observer, i.e. the intensity of incident light in all the orientation at the viewpoint. For obtaining the incident light image, we use a camera fixed near the observer as shown in Fig. 5. Although the viewpoints of the camera and the observer are different, we can generate the incident light image of the observer from that of the camera just by translating the image. This is because the depth of the background scene is very large comparing with the distance between the camera and the observer and we can assume that the incident light at the camera viewpoint and the incident light at the observer's viewpoint are parallel to each other as shown in Fig. 5. Thus, by using the camera image, we can compute the transmittance image at each viewpoint of the observer.

5 COMPUTING TRANSMITTANCE BY USING GENERATIVE ADVERSARIAL NETWORK

The naive method for controlling the transmittance of the windshield is to simply cut the high intensity part in the observed incident light image. However, this is not a good method for several reasons. Firstly, the high intensity part in the observed camera image is often saturated because of the high power of incident light, such as sunlight and headlight, and thus its actual intensity E_i cannot be obtained. Secondly, there seems to be a better way to control the transmittance

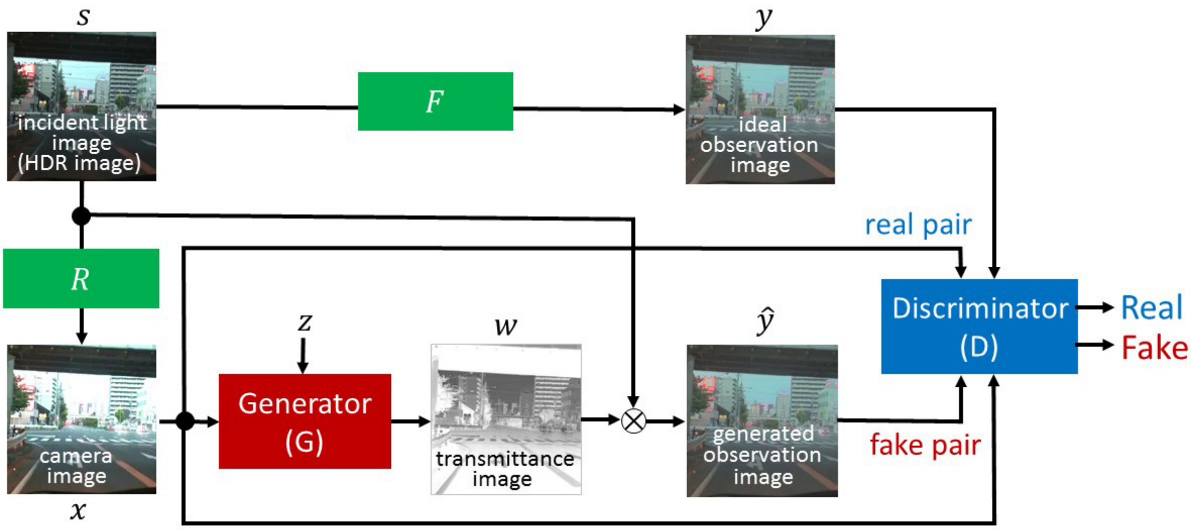


Figure 6: Generative adversarial network (GAN) for generating transmittance images. Generator, G, produces a transmittance image, w, from a camera image x. Then, it is multiplied with the incident light image, s, and produces an observation image, $\hat{y}$. The discriminator, D, trains so that it can distinguish real and fake pairs of camera image and observation image correctly. On the other hand, the generator, G, trains so that it minimizes correct answer of discriminator.

for enhancing the visibility of the scene. For example, it may be useful if we can enhance the visibility of pedestrians selectively.

Thus, we in this paper control the transmittance of LCD by using deep learning. In particular, we use Generative Adversarial Network (GAN) (Goodfellow et al., 2014) for generating visually pleasant intensity image after controlling the transmittance of incident light. In this research, we use conditional GAN (Isola et al., 2017), and generate transmittance images, i.e. LCD images, from input camera images which are saturated partially because of high power incident lights, such as sun and headlight.

The network structure of our conditional GAN is as shown in Fig. 6. The generator G is a 16-layer convolution-deconvolution network (U-Net) (Ronneberger et al., 2015) and the discriminator D is an 8-layer convolution network. We represent high power incident light by an HDR image s, and consider that a camera image x is generated from the HDR image s through a camera response function R as follows:

$$x = R(s) \tag{2}$$

Since the camera image x generated from the response function R is a low dynamic range image, the camera image x is saturated if we have strong incident light.

The generator generates a transmittance image w, i.e. LCD image, from the saturated camera image x as follows:

$$w = G(x, z) \tag{3}$$

where, z denotes a random noise vector.

Then, an observation image $\hat{y}$ is computed by multiplying the high dynamic incident light image s with the transmittance image w obtained from the generator as follows:

$$\begin{aligned} \hat{y} &= s \otimes w \\ &= s \otimes G(x, z) \end{aligned} \tag{4}$$

where, $\otimes$ denotes a pixel-wise multiplication.

We also compute ideal observation image y from the high dynamic incident light image s by using a tone mapping function F as follows:

$$y = F(s) \tag{5}$$

Then, a pair of saturated camera image and the observation image, $\{x, y\}$ or $\{x, \hat{y}\}$, is given to the discriminator, and the discriminator judges whether the pair is given from the ideal observation image y or the observation image $\hat{y}$ computed from the transmittance w generated by the generator.

The network is trained, so that the discriminator maximizes the rate of correct judgments and the generator minimizes it. Thus, the training of our conditional GAN can be described as follows:

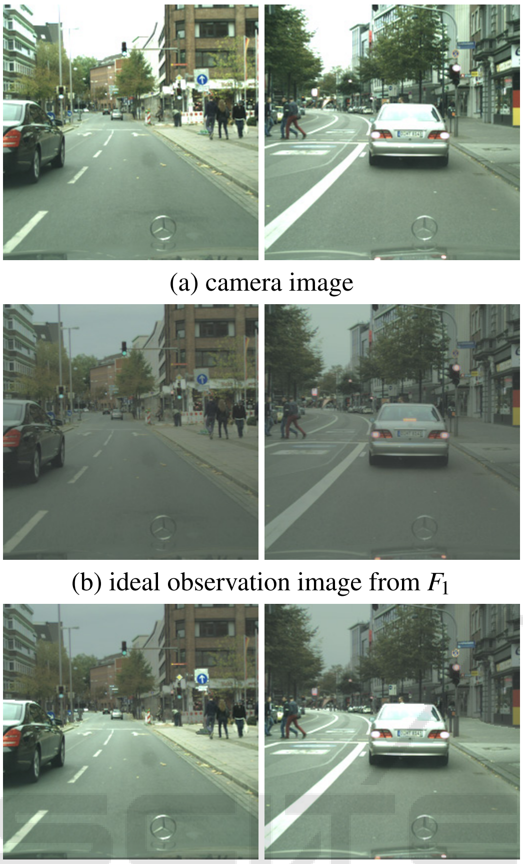
$$G^* = \arg\min_G \max_D \mathcal{L}_{cGAN}(G, D) + \lambda \mathcal{L}_{L1}(G) \tag{6}$$

where, $\mathcal{L}_{cGAN}$ is the following adversarial loss:

$$\begin{aligned} \mathcal{L}_{cGAN}(G, D) = {} & E_{x,y \sim p_{data}(x,y)}[\log D(x, y)] + \\ & E_{x \sim p_{data}(x), z \sim p_z(z)}[\log(1 - D(x, s \otimes G(x, z)))] \end{aligned} \tag{7}$$

and $\mathcal{L}_{L1}$ is an L_1 loss as follows:

$$\mathcal{L}_{L1}(G) = E_{x,y \sim p_{data}(x,y), z \sim p_z(z)}[\|y - s \otimes G(x, z)\|_1] \tag{8}$$



(a) camera image

(b) ideal observation image from F_1

(c) ideal observation image from F_2

Figure 7: Examples of camera images and ideal observation images generated by using F_1 and F_2 as tone mapping functions in our training data set. The camera images are saturated, while the ideal observation images are not saturated. However, the visibility of pedestrians, vehicles, road markers and road signs is degraded in ideal observation images generated from F_1, while the visibility of those in F_2 is preserved.

At the initial stage of the training, the discriminator can easily identify the fake observation images, but gradually it becomes difficult to identify the fake images, and at the final stage of the training the generator can generate transmittance images for generating visually pleasant observation images for observers.

The proposed method can generate ideal transmittance images for LCD control, even if the input camera images are partially saturated. Furthermore, the ideal observation image can be designed freely by modifying the tone mapping function F. For example we can emphasize vehicles and pedestrians in the ideal observation images by designing the tone mapping functions according to the objects in the scene. In the next section, we consider the design of tone mapping function F.

6 DESIGNING TONE MAPPING FUNCTIONS

In this research, we consider two different types of tone mapping functions.

The first one is a simple tone mapping function $F_1(s)$ proposed by Reinhard et al. (Reinhard et al., 2002), which is often used as a standard tone mapping function, where s denotes the intensity of incident light image.

The second one is a tone mapping function, which varies according to the object in the scene. For emphasizing pedestrians, vehicles, road and road signs in the scene, we define the following tone mapping function, $F_2(s)$:

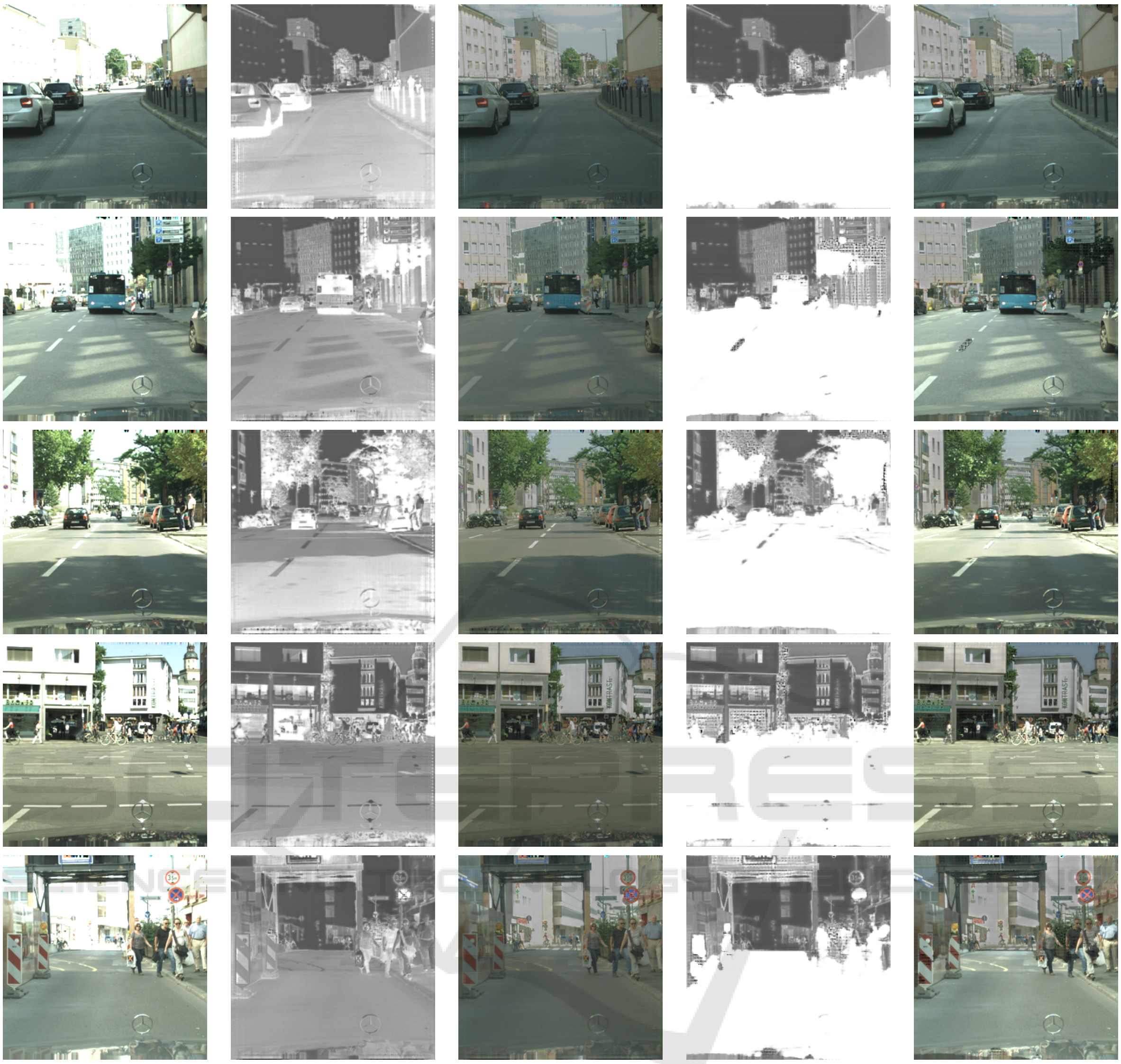
$$F_2(s) = \begin{cases} s : \text{pedestrians, vehicles, road, road signs} \\ F_1(s) : \text{others} \end{cases} \tag{9}$$

By using this function, we can preserve the intensity of pedestrians, vehicles, road and road signs, while the intensity of others decreases according to Reinhard's tone mapping function.

7 DATA SET AND TRAINING

For training our network, we need high dynamic incident light images, s, and their camera images, x, considering the camera response function, R. In this research, we generated camera images, x, by simply cropping the intensity of the high dynamic incident light images, s. We also generated ideal observation images, y, from high dynamic incident light images, s, by using tone mapping functions, F_1 and F_2, described in section 6. We made 2974 sets of training data from images in Cityscapes dataset (Cityscapes). The annotation in Cityscapes dataset was used in F_2 function.

Fig. 7 shows some examples of our training data. Fig. 7 (a) shows camera images, Fig. 7 (b) shows ideal observation images made by using F_1 as a tone mapping function, and Fig. 7 (c) shows those made by using F_2. As we can see in these images, the ideal observation images are not saturated, while the camera images are saturated at high intensity part, such as faraway buildings. However, the visibility of pedestrians, vehicles, road and road signs is degraded in ideal observation images generated from F_1. On the contrary, the visibility of those in F_2 is preserved. We trained our network by using these training data with 100 epochs.



(a) camera image (b) transmittance image of F_1 (c) observed image of F_1 (d) transmittance image of F_2 (e) observed image of F_2

Figure 8: Our results from test data. Column (a) shows input camera images, and column (b) shows transmittance images generated from our network trained by using F_1 as a tone mapping function. Column (c) shows images observed by using transmittance images in column (b). Column (d) and (e) show those obtained by using our network trained by using F_2 as a tone mapping function. As show in (c) and (e), both networks generated transmittance images properly, so that the observed images do not suffer from saturation unlike input camera images in (a). However, the visibility of pedestrians, road signs and vehicles is degraded in the observed images in (c), while the visibility of those objects is preserved in the observed images in (e).

8 EXPERIMENTS

We next show the experimental results obtained by using F_1 and F_2 as tone mapping functions.

The first column (a) in Fig. 8 shows input camera images which are not included in the training data sets. As we can see in these images the intensity of faraway buildings is saturated, and some buildings are not visible because of the heavy saturation.

The column (b) in Fig. 8 shows transmittance images obtained from the generator trained by using F_1 data set. As shown in these images, the transmittance was generated so that the incident light at high intensity part is suppressed and the incident light at low

camera image F_1 F_2

Figure 9: Comparison of the tone mapping functions, F_1 and F_2, used in the training step of our network. Both F_1 and F_2 enable us to see faraway buildings and their details, which are not visible in the original camera images. However, the visibility of pedestrians is degraded in F_1, while that is preserved in F_2.

intensity part is preserved. The column (c) in Fig. 8 shows observed images obtained after transmittance control based on Fig. 8 (b). As shown in these images, the observed images are not saturated unlike camera images in Fig. 8 (a), and the detail of faraway buildings is clearly visible. However, the intensity of all over the image is decreased in (c), and as a result, the visibility of important objects, such as pedestrians and road signs, is degraded in Fig. 8 (c).

Fig. 8 (d) shows transmittance obtained from our generator trained by using F_2 data set, and Fig. 8 (e) shows images observed after applying transmittance images in Fig. 8 (d). As shown in (e), our network trained by F_2 provides clear view of pedestrians, vehicles, road and road signs, while the detail of faraway buildings is also visible. The transmittance images in column (d) also show these properties, that is the transmittance of pedestrians, vehicles, road and road signs is very high, while that of faraway buildings and sky is low as shown in (d).

The magnified images in Fig. 9 compares the visibility of buildings and pedestrians in the observed images derived from our network trained by F_1 and F_2. As shown in this figure, both F_1 and F_2 enable us to see the detail of buildings, which is not visible in the original camera images. However, the visibility of pedestrians is degraded in F_1 based method, while the F_2 based method preserves their visibility.

From these results, we find that our direct control of incident light is very efficient for human observers to see high dynamic scenes caused by backlight, etc. We also find that the transmittance computed from F_2 provides us higher visibility of important objects in the scene than the standard tone mapping functions.

9 CONCLUSION

In this paper, we proposed a method for avoiding glare caused by strong incident light, such as sunlight and headlight, in driving situations.

Our method controls the transmittance of windshield pixel by pixel according to the intensity of incident light. For computing the transmittance of glass efficiently from saturated camera images, we proposed a method based on a generative adversarial network (GAN).

In our method, the ideal observation images of the driver can be designed freely. Therefore, we can emphasize the intensity of specific objects, such as pedestrians, in the driver's view.

By using our method, the visibility of drivers can be improved drastically, and objects such as pedestrians in dark place become visible even under strong backlight of sun, etc.

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