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Semantic Segmentation of Driving Environment in Fog Conditions Using Pseudo-Fog Images

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Abstract— *Image recognition using a camera can recognize the necessary information for driving, such as object recognition and tracking using deep learning technology, white line detection, signal recognition, sign recognition, and driving area identification. However, the actual camera image often deteriorates due to bad weather such as fog, haze, and dust. We propose pseudo-fog images data augmentation by depth estimation using semantic segmentation databases to improve recognition in fog environment. This method estimates the distance to cars in images from the label image of the databases and creates pseudo-fog images using the fog model formula. This method makes it possible to easily create fog databases from the original databases.*

Keywords— *Semantic segmentation, Deep learning, Data augmentation, Fog model, Distance estimation, Pseudo data.*

I. INTRODUCTION

In recent years, automatic driving has been developed for the purpose of reducing traffic accidents, alleviating traffic congestion, and securing means of transportation for weak people in transportation such as the elderly. Currently, self-driving vehicles on the market are "driving assistance (levels 1 and 2)" represented by autonomous emergency braking and lane keep assist. It is necessary to recognize the road environment around the car in order to realize driving support and automation.

Among them, semantic segmentation, which recognizes images at the pixel level, is used as an advanced autonomous driving technology because it can recognize in more detail than object detection.

Deep learning requires a large amount of training data. Also, semantic segmentation in actual road environment requires versatility that can cope with bad weather such as fog, haze, and dust [1]. In this paper, we propose a pseudo-fog image data augmentation by depth estimation using semantic segmentation database to improve recognition in fog environment.

If there is fog in the atmosphere when taking a camera outdoors, the image will be blurred. This is because, if there is no fog, the light that bounces off the object directly enters the camera lens, but because the fog particles cause Mie scattering, the brightness of the entire image is higher and the contrast is lower than clear image [2][3]. Previous study in this field use the image processing technology of fog removal and are used as preprocessing for semantic segmentation in fog environments [4]. By this method, better results were obtained after fog removal, but good recognition was not possible when the image after fog removal did not resemble the brightness value and contrast information of the training data. Also, since fog removal is used as preprocessing, it cannot be used for automatic driving that requires real-time performance.

In this paper, we focused on database augmentation and created pseudo-fog images so that it can be used in fog environments. The pseudo-fog images were created using our depth estimation that has been applied to the fog removal method. Our method is an application based on data augmentation and is excellent in real-time performance. We also consider that this depth estimation method can be applied not only to pseudo fog image creation but also to object distance estimation by using it from the output results of semantic segmentation.

In this paper, the next section describes the image fog removal model and the fog removal method. Next, we describe our depth estimation algorithm.

II. PREVIOUS STUDY

A. Fog Removal Method

There are many fog removal methods, but the basic method is to use a fog image model formula. The fog image model can be described by the following equation.

$$I(x) = J(x)t(x) + A\big(1 - t(x)\big) \tag{1}$$

Here, x is the pixel position, $I(x)$ is the fog image, and $J(x)$ is the scene radiation, which is seen as a fog-removed (clear) image. $t(x)$ is a transmission map that shows the degree to which the light from the scene radiation reaches the camera without being scattered by the fog particles. A is the environmental light, which is the same for all pixels. In this model, $J(x)\,t(x)$ is called direct attenuation and indicates the degree to which scene radiation reaches the camera without scattering. $A(1\text{-}t(x))$ indicates the degree of environmental light affecting the fog image.

$$t(x) = e^{-\beta d(x)} \tag{2}$$

β is the scattering coefficient of ambient light and $d(x)$ is the distance from the object to the camera. The transmission map shows the fog density, which is high in the distant view and low in the near view. Therefore, it is fog removal to estimate A and $t(x)$ from $I(x)$ and calculate $J(x)$[5].

By applying this method, we thought that a fog image could be created if the distance $d(x)$ of the clear image was known.

III. DEPTH ESTIMATION ALGORITHM

To create a pseudo fog image, the distance $d(x)$ in Eq. (2) is required. There is a method using a stereo camera to estimate the distance from the image. However, this study

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proposes another method because camera calibration is difficult, and it is necessary to recollect the database. That method is a depth estimation method using label images.

A. Semantic Segmentation Database

In this study, considering the road environment in Japan, we decided to create our own database using images captured from the driver's seat around Meijo University. Then, the collected images were annotated using LabelMe, and finally 500 databases in the daytime were created. It has three label lists (vehicle, road, background). Figure 1 shows an example of our database.

Fig. 1. Our Database

B. Distance Estimation Method

Here, we explain the distance estimation method using label images. The method has three steps. The first is the creation of a base depth image. This is a depth image when there are no cars on the road. The in-vehicle camera is photographed from a certain height, and a depth image of only the road can be easily created by a distance experiment which is described later. Next, determine the infinite point in the image. Finally, the distance from the camera to the car is estimated from the relationship between the vector length from the infinite point to the farthest point of the car label and the actual distance. Figure 2 shows an image of infinite points and vectors.

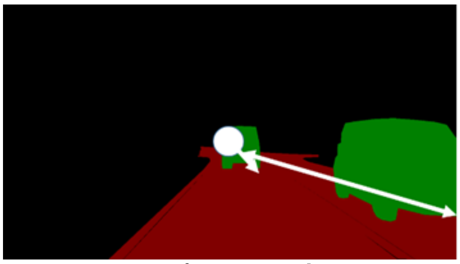

Fig. 2. Infinite point and vector

C. Distance Experiment

Here, we show an experiment to find the relationship between the vector length and the actual distance. An experiment was performed using a tape measure and an object with a camera of the same resolution（640×480） as the onboard camera set on a tripod. The camera height is 1.2 m, and the infinite point is a point 30m from the camera position (image y coordinate:273).

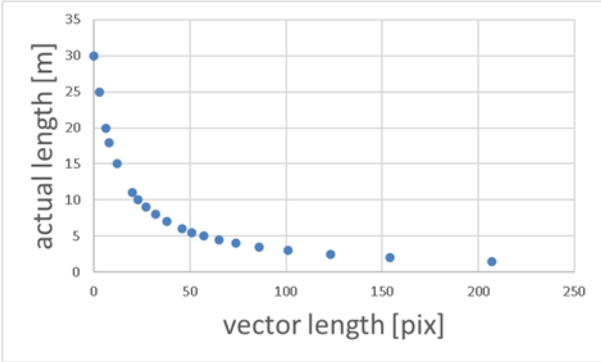

Fig. 3. Relationship between vector and actual length

An approximate expression was obtained from the results in Figure 3. As a result, it was found that when 0 < vector length < 80, it could be approximated by the 6th order equation, and when 80 < vector length < 207, it could be approximated by the 5th order equation.

D. Depth Image

From the distance experiment, the distance from the camera to the car can be estimated, so that depth images can be created when cars are on the road.

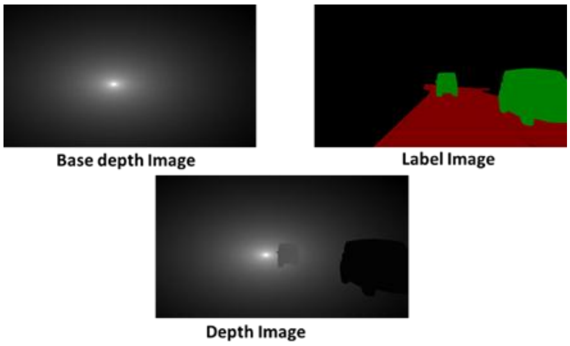

Fig. 4. Our Depth Image

The upper left of Figure 4 is the base depth image when there is no car on the road. At this time, the brightness value is normalized to the actual distance obtained from the distance experiment with 0-255. Therefore, the brightness value around the infinite point becomes bright, and the brightness value becomes darker as it goes away from the infinite point. Using this basic depth image, the distance between the camera and the vehicle can be estimated from the label image, and the brightness value of each car can be copied to the basic depth image to create the entire depth image.

The above is our depth estimation algorithm.

IV. PSEUDO-FOG IMAGE CREATION

Here, a pseudo-fog image is created from the fog image model (Eq.1) by a distance estimation method using a database of semantic segmentation. First, convert the brightness value of the depth image by the proposed method into a distance, and apply it to $d(x)$ in Eq. (2) and solve Eq. (1). The scattering coefficient β is 0.003 and the ambient light A is 255[1].

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Fig. 5. Our Pseudo-fog Image

V. EVALUATION

We evaluate whether the pseudo fog image created by the proposed method is similar to the actual fog image. As mentioned above, the actual fog image has the feature that the brightness of the entire image is higher, and the contrast is lower than clear image because the light causes Mie scattering due to the particles of the fog. In this study, this feature is evaluated using image histograms. The original image is converted to a gray image for comparison of brightness and contrast. The results are shown below.

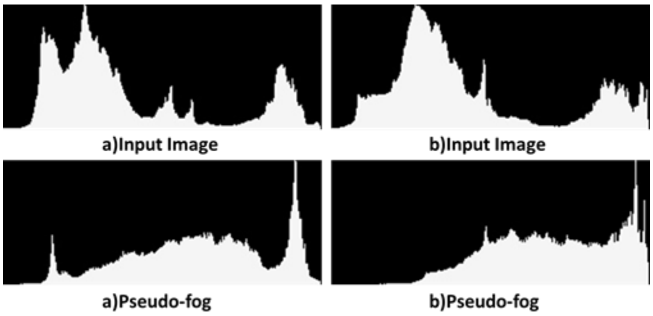

Fig. 6. Change in histograms due to pseudo-fog

Fig. 6 is a histogram of the gray image of Fig.5. From this result, the brightness value increases (graph shifts to the right) and the contrast decreases (graph width narrows). In other words, the pseudo fog image by the proposed method is similar to the actual fog image.

VI. CONCLUSION

From the results in Figure 5, it was found that a pseudo fog image can be created by using the depth image and fog image model formula by the proposed method. The actual fog image has the feature that the brightness value is higher, and the contrast is lower than the image without fog. It was confirmed that all of the databases (500 images) created this time have that feature.

The most important information in creating a pseudo-fog image is the distance. There are several methods for creating depth images. For example, stereo cameras and RGB-D cameras [6][7]. Recently, there is a method using deep learning, and the depth image created by LIDER is learned as a database.[8]

The method proposed in this study is depth estimation using a database of semantic segmentation. Therefore, it is not necessary to create a new database or to use expensive sensors such as LIDER. However, in this study, the number of label classes is only 3, and the depth information of the background is the base depth image. Therefore, in the pseudo-fog image of this study, only depth information of roads and vehicles is created as a depth image. In the future, by increasing the number of label classes, more depth information of objects can be obtained, and more detailed pseudo fog images can be created. There is also the problem of what value the fog density should be when learning a pseudo fog image with a neural network. The fog density is determined by the scattering coefficient β of the ambient light in Eq.2. In this study, 0.003 was used, but it is necessary to consider so that it can cope with various fog density.

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