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A Novel Dark and Light Primary Color Prior Theory for Road Visibility Detection

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Abstract. Aiming at the problems of high complexity and low accuracy of existing visibility detection methods, a road visibility detection method based on monitoring images is proposed. Firstly, the transmittance of dark and bright primary colors is obtained by the theory of dark and bright primary color prior. Then, the atmospheric light value and atmospheric transmittance are optimized by using adaptive fog removal weight and adaptive filtering window, and the transmittance of the first and last end points of the lane line is one-to-one corresponding to the optimized dark and bright primary transmittance. Finally, the atmospheric extinction coefficient and visibility are calculated by combining the distance between the end and end of the lane line. The experimental results show that this method can achieve high precision detection within 100-600m, and the relative error is less than 10%. Compared with other methods, the detection efficiency of this method is faster, the accuracy is higher and the realization is easier.

Keywords: Road visibility detection, Atmospheric light value, Atmospheric extinction.

1. Introduction

In recent years, low-visibility weather such as haze has led to frequent traffic accidents, so real-time monitoring of visibility is particularly important. Compared with other visibility detection methods, visibility detection methods based on monitoring images have been widely studied. Due to the high density and wide coverage of highway surveillance cameras in China, real-time monitoring of sections prone to fog, haze and other weather can effectively prevent and reduce traffic accidents [1-3].

Traditional visibility detection methods include visual estimation method and instrument detection method. Among them, the visibility detection results of the visual estimation method have a large error, while the detection results of the instrument detection method are relatively accurate, but the cost is too high and the maintenance is difficult. It is difficult to realize the construction of the highway in a wide range [4]. Therefore, people focus on the research of visibility detection in the field of image processing, and put forward a wide range of application, good compatibility, low cost video visibility detection method. Based on the idea of template matching, Lincoln Laboratory of Massachusetts Institute of Technology in the United States compares and analyzes real-time captured surveillance video images with those with known visibility, so as to estimate the visibility of the current scene. However, such methods require a large number of sample image libraries and are susceptible to the changes of objects in the scene, making it difficult to apply in actual scenes [5]. Tan et al. [6] dynamically calibrated the internal and external parameters of the traffic camera, and used the average pixel of the area of interest in the moving image to fit the curve to judge the fog, so as to calculate the distance between the point in the road area and the camera. However, the self-calibration model in this method was complicated, and it was difficult to realize real-time monitoring. Tan et al. [7] used the idea of double brightness difference to take the ratio of sky background brightness difference of objects at different distances in the scene in the image region as the basis for visibility detection. This method had strong adaptability and could also detect at night, but it needed to build additional artificial target objects.

In this paper, the image processing method based on atmospheric scattering physical model is improved, and a road visibility detection method based on dark and light primary color prior theory is proposed. The experimental results show that the method has the advantages of strong compatibility, good robustness, fast running speed and high detection accuracy, and can meet the application demand of road visibility detection in our country.

1.1. Visibility Detection Theory

The International Commission on Illumination (CIE) defines visibility as the maximum distance at which the human eye can recognize an object without any auxiliary conditions [8]. Visibility is also defined in relevant meteorological norms in China, that is, the maximum horizontal distance that a person with normal vision (contrast threshold is 0.05) can see and identify a target object (black, moderate in size) from the sky background during the day under the weather conditions at that time [9]. Without considering individual differences, the main cause of visibility change is the state of physical optical propagation. The main reason for reduced visibility in haze weather is that a large number of small particles suspended in the atmosphere (water droplets, dust and other impurities) will absorb the light reflected by the target object, and the reflected atmospheric light will enter the human eye or monitoring equipment. Reduced visibility will cause the driver to be unable to see the surrounding objects and conditions, so as to make wrong judgments about the speed, vehicle distance and braking distance, which is prone to traffic accidents. Therefore, it is particularly important to carry out real-time visibility detection on the road section in haze weather.

According to the Beer-Lambert law, when visible light radiates in an air column of length D, the change of reflected light intensity $I_\lambda(D)$ is determined by the incident light intensity $I_\lambda(0)$ and the atmospheric extinction coefficient β [10], which can be expressed as:

$$I_\lambda(D) = I_\lambda(0) \times exp(-\beta d). \tag{1}$$

Where, d is the scene depth and λ is the wavelength of incident light. Atmospheric transmittance $T_\lambda(D)$ can be expressed as:

$$T_\lambda(D) = exp(-\beta d). \tag{2}$$

Equation (1) and equation (2) are combined to obtain atmospheric transmittance $T_\lambda(D)$.

$$T_\lambda(D) = \frac{I_\lambda(D)}{I_\lambda(0)} = exp(-\beta d). \tag{3}$$

If the distance between the object and the observation point is d, the intrinsic brightness of the object is L, and the ambient brightness is L_0, then

$$L = L_0 exp(-\beta d) + L_\infty[1 - exp(-\beta d)]. \tag{4}$$

Where L_∞ is the brightness of atmospheric light, and $L_\infty[1 - exp(-\beta d)]$ indicates that the reason for the enhancement of brightness is the scattering effect of haze on sunlight, where the brightness of objects decreases with the decrease of exponent $exp(-\beta d)$.

Based on equation (4), Maldonado et al. [11] proposed the law of contrast attenuation, and provided the conditions under haze background that objects could be identified by people. That is, when the distance is d and the actual contrast relative to the environment is C_0, the contrast of the object is C, and the following conditions must be met:

$$C = C_0 exp(-\beta d). \tag{5}$$

$$C = \frac{L_\infty - L}{L_\infty}. \tag{6}$$

$$C_0 = \frac{L_\infty - L_0}{L_\infty}. \tag{7}$$

Assuming that atmospheric illumination and atmospheric particles are uniform, visibility can be calculated according to the above formula. According to CIE definition [12], when the contrast threshold is 0.05, the maximum distance that the human eye can observe the object is the meteorological visibility distance (MVD), assuming the contrast C_0 of the target object relative to the environment. It is known that if the contrast of black objects relative to the sky is $C_0 = 1$, and the normal visual response threshold of the human eye is 0.05, the general distance of MVD can be derived as:

$$V_{met} = -\frac{1}{K_\lambda} \ln 0.05 \approx \frac{3}{K_\lambda}. \tag{8}$$

Where, K_λ is the atmospheric extinction coefficient. Atmospheric visibility is a very sensitive subjective quantity, easy to be interfered by external factors, visual estimation and instrument detection methods such as direct measurement of atmospheric visibility, easy to produce large errors or huge costs. Equation (8) can be used to transform the problem of detecting atmospheric visibility into the problem of estimating atmospheric extinction coefficient. Therefore, the experiment calculated the final atmospheric visibility based on more accurate atmospheric transmittance and atmospheric light value, combined with atmospheric extinction coefficient.

2. An Improved Image Defogging Method Based on Dark Channel Prior Theory

2.1. Atmospheric Scattering Model

The atmospheric scattering model in reference [13] is simplified based on the atmospheric scattering model proposed by McCartney, which is widely used in the field of image fog removal and can be expressed as follows:

$$I(i,j) = J(i,j)t(i,j) + A_{\infty}[1 - t(i,j)]. \tag{9}$$

Where, $I(i,j)$ is the light intensity of the original image of the surveillance video at pixel point (i,j). $J(i,j)$ is the light intensity of the pixel in the recovered clear image. $t(i,j)$ is the atmospheric transmittance of the pixel. A is the atmospheric light intensity at infinity. It can be found that in the influence of haze on atmospheric light propagation, $J(i,j)t(i,j)$ is the direct attenuation term, and $A_{\infty}[1 - t(i,j)]$ is the atmospheric light term.

2.2. Dark Color Prior Theory

The dark color prior theory is a rule [14] based on the statistics of outdoor fog-free image database. The theory states that in local areas other than the sky, there are always special pixels (dark primary colors). It is mainly derived from objects with bright or dark colors, such as the shadows of buildings, trees, cars, brightly colored leaves or flowers of flowers and flowers, and gray trunks or rocks. Dark primary colors are characterized by at least one RGB(Red, Green, Blue) color channel with an intensity value approaching almost zero, which can be expressed as:

$$J^{dark}(i,j) = \min_{i',j' \in \Omega(i,j)} [\min J^c(i',j')] \approx 0. \tag{10}$$

Where J^c is the intensity of a color channel in image J. $c \in R, G, B$ are the color channels of the image. $\Omega(i,j)$ is the local region centered on (i,j).

2.3. Rough Estimation of Atmospheric Transmittance

Haze weather will cause the dark color of the image with low brightness value to change, that is, the atmospheric light scattering caused by haze will increase the brightness value of the dark color. The brightness value of dark color in fog map is directly related to the transmittance, so the affected dark color brightness value can be used to estimate the local atmospheric transmittance.

First, assuming that the atmospheric light value A_{∞} is known, divide both sides of equation (7) by A_{∞} at the same time to get:

$$\frac{I^c(i,j)}{A_{\infty}} = t(i,j)\frac{J^c(i,j)}{A_{\infty}} + 1 - t(i,j). \tag{11}$$

2.4. Optimization of Fog Removal Weights and Atmospheric Transmittance

Based on the classical dark channel prior theory proposed in literature [15], the image after fog removal is prone to Halo effect. The reason is that when there are two objects with depth of field at the same time, the calculation error of transmission is generated. Therefore, the atmospheric transmittance and the fog removal weight ϖ are optimized to make the visibility accuracy of the final detection higher. The simulation found that there was a direct relationship between the de-fogging weight ϖ and the atmospheric light value A_{∞}, and it could be considered that the de-fogging weight ϖ was approximately equal to the normalized atmospheric light value a [16]. Therefore, $\varpi = a - 0.15$ was taken in the experiment.

Based on the dark color prior theory, the transmittance expression of the light primary color can be derived roughly. According to the above analysis, the intensity value of the dark primary color $J^{dark}(i,j)$ approaches 0; based on reverse thinking, the intensity value of the light primary color $J^{light}(i,j)$ approaches 1; combined with the calculation formula of the dark color transmittance, the transmittance of the light primary color can be obtained as follows:

$$t^d(i,j) = 1 - \varpi \frac{\min_{y \in \Omega(x)} [\min I^c(i,j)]}{A_{\infty}}. \tag{12}$$

$$t^l(i,j) = 1 - \varpi \frac{\max_{y \in \Omega(i,j)} [\max_c I^c(i,j)]}{1 - A_{\infty}}. \tag{13}$$

Where $I^{dl}(i,j)$ is the pixel value of dark and bright primary colors in the image (i,j), atmospheric light value A_∞ is taken as the threshold to distinguish the transmittance of dark and bright primary colors, and $t^d(i,j)$ and $t^l(i,j)$ are the transmittance sought by the experiment.

At present, people still take the filter window as a fixed value when de-fogging the image, which leads to excessive error in transmission value. The reason is that the size or size of the selected window will indirectly affect the accuracy of atmospheric transmittance. Therefore, based on the original guided filtering, an adaptive guided filtering method is used to process the image, and the size of the filtering window can be expressed as:

$$R = 4X_{floor}[\max(3, W \times 0.01, H \times 0.01)]. \tag{14}$$

Where X_{floor} is rounded to 0, W and H are the width and height of the original image respectively. This method can adjust the size of the filter window adaptively according to the size of the original image, so as to reduce the error.

3. Visibility Detection Based on Dark and Light Primary Color Prior Theory

The existing detection methods based on surveillance video images need a large number of image samples and calibrate the internal and external parameter characteristics of the camera, and also need to preset the physical target, which is difficult to be laid in practice and easy to be interfered with the external environment. Therefore, a new visibility detection method is proposed based on the reference [17]. First, the transmittance of the upper and lower ends of the lane line is obtained. Without detecting the lane line, the lane line can also be taken as a virtual target object, and the transmittance of the first and last ends of the lane line can be obtained by using the dark and bright primary color prior theory.

Since the lane lines of domestic expressways are all white, the non-lane line areas are cyan black, and the image de-fogging field usually refers to the brighter areas such as the white area, the fog area and the sky area as the bright primary color area, and the colorful, dim objects or the darker color area as the dark primary color area. Therefore, the mean transmittance of the bright primary color region in the image is calculated first and taken as the first point transmittance of the lane line, that is, the bright primary color transmittance $t^l(i,j)$. Then, the mean transmittance of the dark color region is calculated and taken as the transmittance of the tail point of the lane line, that is, the dark color transmittance $t^d(i,j)$. The position of the light and dark primary transmission $t^{dl}(i,j)$ is restricted by the distance between the head and tail of the lane line. The mean point of the bright primary color transmittance may be a certain point of the lane line or other white areas, and a certain point of the unknown bright primary color region is approximately equal to the transmittance $t^l(i,j)$ at the first end of the lane line. The mean dark-color transmittance may be at a point in a non-lane line or other dark area where the transmittance $t^d(i,j)$ at the end of the lane line is approximately equal.

4. Experimental Results and Analysis

Fog map visibility detected by Vaisala PWD10 visibility detector was used as standard data and compared with the detection results of preset target method in literature [18]. Figure 1 is the fog map of different visibility distances detected by VaisalaPWD10 visibility detector. Visibility detection is carried out by this method, and the detection results are compared with those in literature [18], as shown in Table 1. It can be found that when using the same fog map data set, compared with the method in literature [18], this method not only saves the step of setting specific distance, size and color objects on the highway in advance, but also performs better in visibility detection accuracy.

Table 1. Visibility test results of the two methods

Image	Standard visibility/m	Proposed	Reference [18]
Fig 2(a)	126	121	137
Fig 2(b)	145	134	157
Fig 2(c)	199	204	215
Fig 2(d)	90	113	115
Fig 2(e)	324	286	352
Fig 2(f)	124	129	136

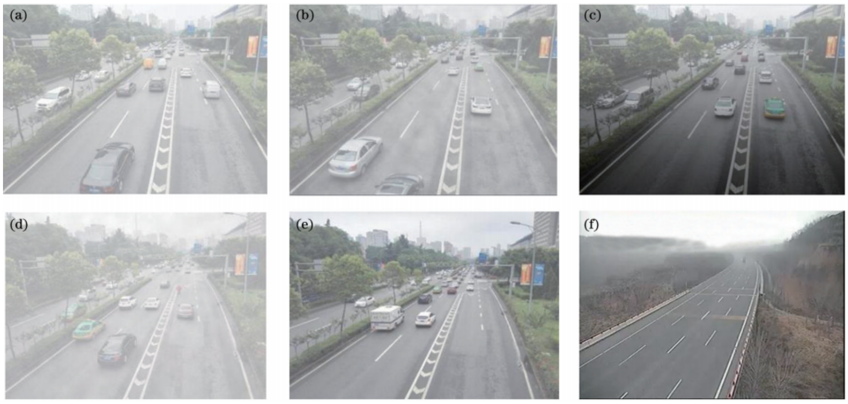

Fig. 1. Visibility image obtained by instrument method. (a) Visibility is 126m; (b) visibility is 145m; (c) visibility is 199m; (d) visibility is 90m; (e) visibility is 324m; (f) visibility is 120m

5. Conclusion

A road visibility detection method based on dark and bright primary color prior theory was proposed. The visibility was detected by using the idea of fog removal with dark and bright primary color prior, and the fog removal weight and adaptive filtering window were optimized by using atmospheric light value and transmittance. The optimized dark and bright primary color transmittance was corresponding to the end points of the lane line one by one, and the atmospheric extinction coefficient was obtained. The test results are compared with the standard visible distance of the instrument method. The results show that the method has a very high detection accuracy in the range of 100-600m visible distance, and the relative error is less than 10%. Compared with other detection methods, this method is faster, more accurate and easier to implement. However, in the case of heavy fog, the detection effect of this method is not good. In the follow-up study, a visibility detection method that can detect heavy fog, fog and heavy fog will be optimized mainly for visibility detection in the case of heavy fog with a visible distance of less than 100m.

6. Conflict of Interest

The authors declare that there are no conflict of interests, we do not have any possible conflicts of interest.

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