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Visibility Detection Based on Object Region Selection

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Abstract: In response to the shortcomings of the dark channel prior and optimization methods in window selection and object depth variation, this paper proposes a visibility detection algorithm based on object region selection. The algorithm introduces superpixel segmentation to divide the image into superpixel blocks and extracts the superpixel blocks containing the target object for visibility calculation. In the visibility calculation, the dark channel and transmission rate extraction can be obtained only from the target object region, without the need to process the entire image region. This improves the accuracy of the target object parameter calculation and speeds up the computation.

Keywords: dark channel prior; visibility detection; superpixel segmentation; object region

1. INTRODUCTION

In recent years, with the popularization of cars, traffic safety has received increasing attention. The reduced visibility caused by haze is an important factor leading to traffic accidents. At the same time, atmospheric transparency is an external manifestation of air pollution. Therefore, detecting atmospheric visibility is an important meteorological observation index, which can guide transportation and environmental management. Currently, visibility detection instruments are relatively expensive and require professional personnel for installation and debugging, making it difficult to be widely promoted. Based on the dark channel prior(DCP), the visibility detection method is simple to use and low in cost, and has great research potential. In the visibility calculation, The dark channel algorithm optimization involves selecting a fixed-size filtering window and optimizing it in the subsequent processing. After two rounds of minimum filtering, a rough estimate of the dark channel image is obtained. The transmission rate image of the scene has a linear relationship with the dark channel image and is usually not directly processed. After obtaining the transmission rate image from the dark channel image, refinement is performed on the transmission rate image. And the dark channel and transmission rate extraction can be obtained only from the target area, without processing the entire image area. Therefore, superpixel segmentation is introduced to segment the image into superpixel blocks, and extract the target object superpixel blocks for visibility calculation. This improves the rigor of the target object parameter calculation and enhances the calculation speed.

2. DCP ALGORITH

Fog imaging model[1][2] is

$$I = Jt + A(1-t) \tag{1}$$

Here, J is haze-free image, I is haze image, t is transmission and A is airlight.

He[3] counted 5000 outdoor haze-free images, and the results showed that in most non-sky areas of the images, there would always be at least one color channel (in the RGB color space) with a very low value. In other words, applying a minimum filter on the RGB color channels of outdoor haze-free images results in a grayscale image where the pixel values are very low. This is the dark channel prior theory. The dark channel refers to the grayscale image obtained by applying the minimum filter on the color channels of any image, which can be represented by formula (2):

$$\begin{cases} I^{dark} = \min_{c\in\{r,g,b\}}\left(\min_{x\in\Omega}\left(I^{c}(y)\right)\right) \\ J^{dark} \to 0 \end{cases} \tag{2}$$

Combining formula (1) and (2) gives the expression for the transmission t:

$$t = 1 - \left(\frac{I}{A}\right)^{dark} \tag{3}$$

The distance d between the observation location and the target object is measured. The target is located in the image and the center pixel position of the target is marked as x. The visibility can be calculated this way[4]:

$$Vis = -\frac{1}{\beta}\ln\varepsilon \tag{4}$$

Where, ε is Visual contrast threshold, β is atmospheric extinction coefficient, which can be represented by formula (5):

$$\beta = \frac{\ln t}{d} \tag{5}$$

The traditional algorithm has a global nature that blurs the boundaries between the target object and neighboring pixels. Processing the input image with a window-based approach actually blends the features of the target object with those of the neighboring pixels. As the window size increases, the interference from neighboring pixels becomes more severe, diluting the features of the target object. Although the traditional algorithm uses optimized transmission[5] to remedy this issue, experimental results show that this optimization only improves but does not solve the problem. It even increases the uncertainty of the results, making the visibility detection results more unreliable.

3. VISIBILITY DETECTION ALGORITHM BASED ON OBJECT REGION SELECTION

3.1 Superpixel segmentation

Image segmentation is a fundamental step in image processing applications, aiming to extract the parts of the image that people are interested in. Depending on the processing task, image segmentation methods include threshold segmentation, region segmentation, etc. In region segmentation, methods such as greedy-based, clustering-based, and graph-based approaches are typically used to segment the image into useful regions for people. Ren et al.[6] proposed the concept of superpixel segmentation, which is a method of image segmentation that groups pixels into superpixels with similar semantic information. By using some features of pixel points, the image is first divided into a large number of irregular pixel blocks, so that the pixels in each region have similar colors, textures, and spatial positions. These pixel blocks are called superpixels. Superpixel segmentation provides a method of image pre-processing that can reduce the complexity of subsequent image processing tasks and has good performance in many computer vision tasks.

Due to the importance of superpixel segmentation, many algorithms have been proposed, but their models are complex and their running times are generally long. To address these issues, Achanta et al.[7] proposed a simple linear iterative clustering (SLIC) algorithm based on the K-means clustering algorithm for superpixel segmentation. The SLIC algorithm has a clear principle, is easy to use, and has a faster processing speed than other superpixel segmentation algorithms. It is a simple and efficient algorithm, and therefore, we chose to use SLIC for superpixel segmentation in this paper.

3.2 Visibility detection algorithm based on object region selection

This paper proposes a visibility detection algorithm based on the selection of target regions. By selecting specific target regions, this algorithm reduces computation and errors, and improves the accuracy and efficiency of detection. Visibility detection is performed specifically on the target region. Due to the selection of target regions, the algorithm only needs to process that region, which can avoid the computational complexity of processing the entire image. The original image and target block are involved in the algorithm calculation, reducing the number of pixels, saving time, and reducing interference from irrelevant pixels in the neighborhood. The algorithm steps are as follows:

(1)Scene setting

In a scene, we need to select a target object, which can be either a colored or a dark object. In the image, the tree trunk is a suitable object, with a dark color and a relatively regular shape. Therefore, we have chosen the tree trunk as our target object and recorded the distance d between the tree trunk and the observation point.

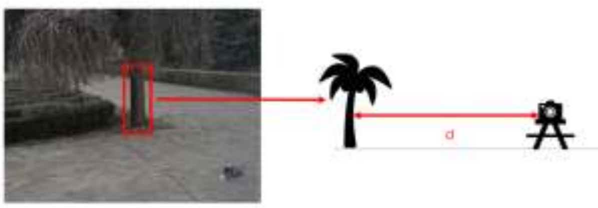

Figure 1. Scene Setting

(2)Segmenting the image.

By performing superpixel segmentation on the image to extract the target object, the superpixel blocks belonging to the target object are labeled as Ω_0. The segmentation result is shown in the figure

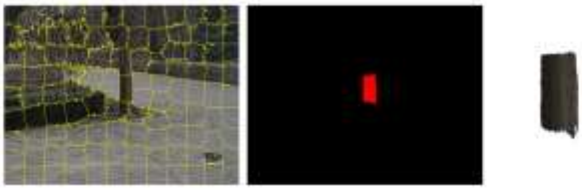

Figure 2. Target Area Segmentation

(3)Calculating the dark channel:

Applying the dark channel prior to Ω_0, by substituting into Equation (2), we obtain the dark channel values within the window of Ω_0.

$$I^{dark} = \min_{c\in\{r,g,b\}}\left(\min_{x\in\Omega_0}\left(I^c(y)\right)\right) \tag{6}$$

In the equation, only the Ω0 window exists in the image. Therefore, for any pixel within the Ω0 window, its corresponding dark channel value is consistent. At this point, I^{dark} is no longer an image of the same size as the input image I, but rather a single numerical value.

(4) Calculating the airlight

For the calculation of airlight value, since the calculation of the dark channel for the entire image is not required in this algorithm, the method of indirectly obtaining the brightest pixel through the dark channel is no longer suitable. Therefore, a quad-tree segmentation method is adopted. The quad-tree segmentation method divides the image into four regions, calculates the mean value of each region, and then divides the region with the highest mean value into four regions again, and calculates the mean value of each region. This process is repeated until the number of pixels in the segmented region reaches a given threshold, and the mean value of this region is taken as the atmospheric light value A. For an RGB image, the quad-tree segmentation method needs to separately obtain A_r, A_g, A_b for each color channel. The illustration below shows the process of obtaining the airlight value A for a single channel (the sky region is not included in the figure, and is only used for illustrative purposes).

Figure 3. Quad-tree segmentation

(5) Calculating transmission

When we know a from fourth step, the formula (3) can be transformed into:

$$t = 1 - \frac{I^{dark}}{\min_{c \in \{r,g,b\}} A^c} \quad (7)$$

Here, t is also a numeric value, not an image.

(6) Calculating visibility

By measuring the distance d in the first step and the transmission rate in the fifth step, we can obtain the value of visibility in this scene by formula (4).

3.3 Experimental results

The algorithm proposed in this paper extracts the target object and places it in a separate window, strictly controlling the window boundary to avoid crossing objects or backgrounds with different depths of field. This theoretically ensures the accuracy of the detection results, and the consistency of the target object itself can also reduce the interference from picture noise.

Assuming the input image size is M×N, and the number of pixels in the target object window is n, in practical visibility detection scenarios, value of n is much smaller than M×N. The following table lists the orders of magnitude of the data volume used in parameter calculations for the two algorithms:

Table 1. Pixels of calculating

Algorithm	I^{dark}	**A**	**t**
DCP	M×N	M×N	M×N
This paper	n	M×N	1

The table shows that the traditional dark channel algorithm requires more computational resources, and as the image size increases, the computational cost of the traditional algorithm increases linearly, greatly reducing its efficiency. The algorithm proposed in this paper is a fast approximation algorithm that is independent of the input image size. As the image size increases, this advantage becomes even more prominent.

4. CONCLUSIONS

The traditional visibility detection algorithm based on the dark channel prior has difficulty in selecting the scale of the filtering window, and optimization methods cannot truly solve this problem, only refining the rough estimated image. This paper introduces superpixel segmentation to solve the window selection problem, making the algorithm results more reliable. Additionally, the algorithm proposed in this paper has lower computational complexity than traditional algorithms, making it more efficient.

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