Structural Surface Identification of Tunnel Face under Complex Conditions

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Abstract. The tunneling engineering plays a pivotal role in infrastructure construction. However, due to the complex construction environment, photographs of tunnel surface are often obscured by dust and smoke, which in turn affects the clarity of the photographs and the accurate identification of the structural surface. In this paper, a joint defogging algorithm based on dark channel prior and light source detection is proposed to enhance the effectiveness of dust removal from tunnel interior images under the environment of limited and concentrated tunnel light sources. The algorithm estimates the atmospheric illumination and transmittance of the image through the dark channel prior principle combined with light source detection, and applies the guided filtering technique for detail preservation and defogging enhancement. Experimental results demonstrate that the algorithm exhibits superior performance in terms of image clarity and detail preservation. Subsequently, structural surface features are extracted by single-scale Retinex image enhancement, image preprocessing and morphological processing. The experiments demonstrate that the method effectively enhances the quality of the image and the accuracy of structural surface identification in practical engineering applications, providing reliable data support for tunnel construction.

Keywords: Tunnel Engineering, Dark Channel Prior, Dehazing Algorithm, Image Enhancement, Structural Surface Identification.

1 Introduction

Tunneling engineering is crucial for infrastructure construction, but the complex environment often results in tunnel face photos being obscured by dust and smoke, impairing clarity and structural surface identification accuracy. High-definition images are essential for accurately analyzing tunnel structural features, directly impacting construction safety and project quality. Therefore, effectively removing

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dust from photos and accurately identifying structural surface information has become an urgent issue.

The current approach to image defogging is based on three main categories of algorithms, namely non-model based image enhancement, model based image restoration, and deep learning algorithms according to statistical learning. Typical image enhancement methods include contrast-constrained adaptive histogram equalisation algorithm [1], Retinex algorithm [2], and various frequency domain filtering methods. Li et al. [3] proposed a depth-adaptive CLAHE by guiding filtering and stripping the atmospheric light correction of the sky. The clipping threshold is affected by the depth of the scene to avoid the near scene being over-enhanced while maintaining the enhancement effect of the distant scene. Deepika et al. [4] used Retinex algorithm to enhance the image, then used the wavelet transform algorithm to enhance the image details, finally obtained a clear image after defogging. The image enhancement algorithm can eliminate some interference information in the image, but sometimes there will be over-enhancement and even color distortion. The image restoration algorithm for image treatment with the inverse of the image degradation process. He et al. [5] initially proposed a dark channel piror algorithm (DCP) for image defogging, which demonstrated satisfactory outcomes. While the method is effective in defogging, it is prone to colour distortion at the edges of colour blocks and is susceptible to loss of luminance information and image details. Consequently, numerous researchers have sought to refine it. In order to address the limitations of the DCP, which is susceptible to colour distortion and artifact in the sky region, Wang et al. [6] proposed a new dark channel confidence calculation method with adaptive parameter adjustment by using the two-dimensional Gaussian function to correct the transmittance of the sky region. Zhao et al. [7] proposed an optimized DCP algorithm combining region growth, correction coefficients and multi-modal detection methods to obtain more accurate transmittance. Li et al. [8] used the Otsu method to divide hazy images into sky and non-sky regions. The regions were then divided into sky and non-sky regions using a transmittance optimization method that combined the DCP with the bright channel prior (BCP). Kil et al. [9] proposed a dehaze algorithm based on a DCP and contrast enhancement to balance the relationship between contrast and colour distortion, thereby removing haze while maintaining colour. The deep learning method has been extensively employed in image processing during recent years [10,11,12,13,14], with a number of representative algorithms, including an end-to-end dehaze model based on a convolutional neural network (CNN). However, deep learning training requires a substantial quantity of test data, a high cost, a more complex process, and a longer processing time. Consequently, research on traditional image processing methods continues to hold significant practical value.

Most of these algorithms are designed for outdoor dehazing. However, there is limited research on tunnel environments, which pose unique challenges such as point light interference, low brightness, high dust levels, and complexity. To address image distortion and Halo effects [15] caused by traditional algorithms near point light sources in tunnels, this paper proposes a tunnel dehazing technique based on a dark channel prior algorithm with light source detection, combined with the Retinex image enhancement algorithm for structural surface identification.

2 The removal of dust from the tunnel image.

This paper proposes a joint defogging algorithm combining DCP and light source detection for removing dust interference from tunnel images. Traditional methods estimate atmospheric light by selecting the brightest pixel region from the dark channel map. In tunnel environments with limited and concentrated light sources, direct extraction from the dark channel map may overestimate atmospheric light due to bright spots from light sources, impacting defogging effectiveness. To tackle this, we use light source location information to improve atmospheric light estimation and transmittance calculation.

2.1 Defogging model implementation

In order to identify the region of the image that corresponds to the light source, the image is converted into a gray-scale image and the threshold segmentation is applied in order to identify the bright spots. The gaussian blurring is applied to the binary image in order to eliminate noise. Subsequently, the bright areas with a large area are detected and labeled in order to form the light source mask. The outcome of the light source detection process is illustrated in Fig 1.

(a) Original image (b) Light source detection image

Fig. 1. The detection and processing of light sources.

The DCP principle is employed to estimate the atmospheric illumination in the image. The dark channel of the image is computed by identifying the local minimum at each pixel point in the image. For image I, the dark channel I_{dark} is calculated as follows,

$$I_{\text{dark}}(x) = \min_{y\in\Omega(x)}\left(\min_{c\in\{r,g,b\}} I^c(y)\right) \tag{1}$$

where, $\Omega(x)$ represents the local window centered on x, and $I^c(y)$ represents the value of pixel y on the color channel c.

In order to estimate the atmospheric light, the pixels in the light source region are excluded using a light source mask, thus obtaining the processed image I1 (x). The brightest pixels in the non-light source region are then selected for atmospheric light estimation. The brightest pixel regions in the light source masked image can be found using the DCP principle, which usually contain a large haze component. The estimation method for atmospheric light is as follows,

$$A = \underset{x \in \Omega_{\mathrm{top}}}{max} I_1(x) \tag{2}$$

where Ω_{top} represents the brightest pixel region in the dark channel image, and the $I_1(x)$ denotes the image processed by the light source mask.

The transmittance of the image is inferred based on the atmospheric illumination estimated after correction for light source detection. This is achieved using the DCP principle. However, during the transmittance estimation process, the light source regions may be incorrectly considered as high transmittance regions, resulting in overly bright images in these regions after dehazing. Therefore, the transmittance of the light source regions is specially treated to avoid excessive defogging. Transmittance is defined as the degree of light attenuation between pixels in an image and the observer. It is one of the main influences on dust fog. The transmittance $t(x)$ is estimated using the atmospheric light A and the input image I. The transmittance $t(x)$ is the ratio between the light source and the observer,

$$t(x) = 1 - \omega \underset{y \in \Omega(x)}{min} \left(\underset{c \in \{r,g,b\}}{min} \left(\frac{I_c(y)}{A_c} \right) \right) \tag{3}$$

where, ω represents the fog retention coefficient, usually taken as 0.95, and A_c is the component of atmospheric light on the color channel c.

The transmittance obtained from the estimation is optimized using a guided filtering technique. The guided filtering process takes the input image as the guide image and the transmittance as the weight of the guide image. Through this process, the transmittance is adjusted to maintain the details and textures of the image while enhancing the defogging effect. The local linear relationship between the output image q and the input image p (initial transmittance) $t(x)$ is established under the guide image I,

$$q_i = a_k I_i + b_k, \forall i \in \omega_k \tag{4}$$

where, a_k and b_k are linear coefficients, and ωk is the local window.

The optimal linear coefficients a_k and b_k can be determined by minimising the following loss function,

$$E(a_k, b_k) = \quad_{i \in \omega_k} ((a_k I_i + b_k - p_i)^2 + \epsilon a_k^2) \tag{5}$$

where, ϵ is the regularisation parameter to control the smoothness.

The final output image q (where q is the optimized transmittance $t(x)$) is obtained by the weighted average of the local linear transformation results.

$$q_i = \frac{_{k|i \in \omega_k}(a_k I_i + b_k)}{|\omega_k|} \tag{6}$$

Finally, the original scene image is restored based on the optimised transmittance and the estimated atmospheric light. The original image is corrected using the transmittance and atmospheric light to recover the true scene information, thereby achieving the defogging process,

$$J(x) = \frac{I(x)-A}{t_1(x)} + A \tag{7}$$

2.2 Experimental validation and result analysis

Evaluating image dehazing performance is crucial for optimizing algorithms, with common methods divided into subjective and objective assessments. Subjective evaluation is based on visual perception, assessing haze residue, image information, detail recovery, saturation, and contrast. Due to differences in human perception, subjective evaluation is usually only a supplementary reference.

Objective evaluation is more precise, with common metrics including Peak Signal to Noise Ratio (PSNR) [16] and Structural Similarity (SSIM) [17].

PSNR is a widely used metric for assessing image quality, measured in dB, which evaluates algorithm performance by computing differences in pixel values. PSNR is computed based on Mean Squared Error (MSE) [18]. Despite not accounting for the influence of pixel distribution on visual perception, PSNR remains a common evaluation standard. In the evaluation of dehazing algorithms, a higher PSNR value indicates better performance.

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{\mathrm{MAX}_I^2}{\mathrm{MSE}}\right) \tag{8}$$

$$\mathrm{MSE} = \frac{1}{mn}\ {}_{\substack{1\le \mathrm{i}\le \mathrm{m}\\ 1\le \mathrm{i}\le \mathrm{n}}} [I(i,j) - J(i,j)]^2 \tag{9}$$

SSIM measures image similarity based on luminance, contrast, and structure, aligning closely with human perception. It's used alongside PSNR in defogging tasks, with values from 0 to 1 indicating higher similarity between images. The SSIM is calculated for a predicted dehazed image I and a reference image J as follows,

$$\mathrm{SSIM}(I,J) = \frac{(2\mu_I\mu_J+C_1)(2\sigma_{IJ}+C_2)}{(\mu_I^2+\mu_J^2+C_1)(\sigma_I^2+\sigma_J^2+C_2)} \tag{10}$$

where μ_I and μ_J represent the mean values of images I and J, σ_I^2 and σ_J^2 represent the variances of images I and J, σ_{IJ} represents the covariance of images I and J, C_1 and C_2 represent represent constants for stabilisation calculations.

In this study, 12 sets of foggy images are selected and processed using the improved DCP, the CLAHE algorithm, the Retinex algorithm, and the traditional DCP for defogging. The PSNR and SSIM for each algorithm are calculated. The results are presented in Fig. 2.

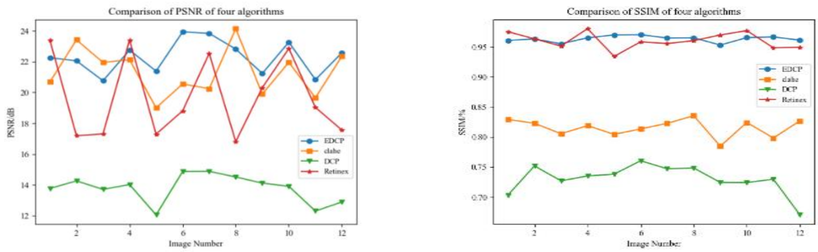


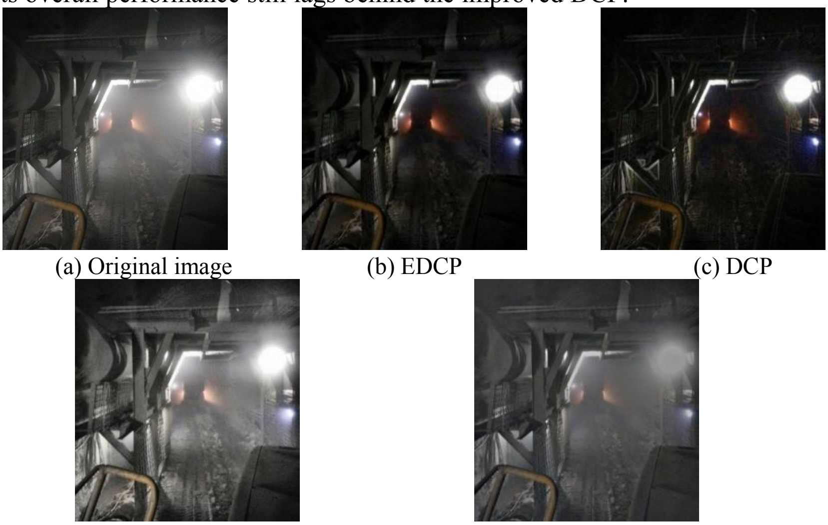
Fig. 2. Comparison of four algorithms PSNR and SSIM.

The enhanced dark channel prior algorithm (EDCP) exhibits superior PSNR and SSIM performance, particularly excelling on images 5, 6, 9, and 10, indicating effective image clarity enhancement and detail preservation during defogging.

In contrast, the traditional DCP shows poorer performance with lower PSNR and SSIM values across all images, though some improvement is seen on images 6 and 7. Its effectiveness in defogging needs further enhancement.

The CLAHE algorithm performs inconsistently, achieving high PSNR and SSIM values on some images but poorly on others, indicating room for improvement compared to other algorithms.

The single-scale Retinex algorithm has certain advantages on images 1, 4, 9, and 10, but its overall performance still lags behind the improved DCP.



(a) Original image (b) EDCP (c) DCP

(d) CLAHE (e) Retinex

Fig. 3. Comparison of 4 algorithms for defogging effect.

Fig. 3 presents a comparative analysis of the defogging efficacy of the four algorithms. The EDCP not only significantly removes haze but also preserves more image details, enhancing fineness and texture. It effectively avoids the Halo effect, and the contrast and saturation are well-balanced, preventing distortion from over-enhancement.

The traditional DCP algorithm shows some improvement in dehazing but suffers from Halo effects on the left side of the image, with poor detail recovery. The CLAHE algorithm has a limited dehazing effect, leading to unstable image clarity and detail. The Retinex algorithm, while performing well in contrast and saturation, does not dehaze significantly, leaving some images still blurry.

In summary, the EDCP performs best in dehazing, with high PSNR and SSIM values, effectively removing haze while preserving details. The traditional DCP and CLAHE algorithms perform relatively poorly, while the single-scale Retinex algorithm shows some advantages in certain cases but has overall performance improvement needs.

3 Identification of the structural surface of the tunnel face

In order to improve the visibility and contrast of cracks in tunnel tunnel face photographs, this paper employs the Retinex algorithm for image enhancement processing, with the intention of assisting in structural surface recognition. The Retinex algorithm is capable of effectively enhancing the contrast and details of the image, by simulating the human eye's perception mechanism of the scene. This is of particular importance in tunnel environments under complex lighting conditions. The Retinex theory, proposed by Land and McCann [19] in 1971, aims to achieve dynamic range compression and colour constancy of images by simulating the human eye's perception of the scene. The classical Retinex algorithms include Single Scale Retinex (SSR) and Multi-Scale Retinex (MSR). In the context of tunnel face image processing, the lighting conditions are frequently suboptimal, resulting in pronounced issues with shadows and uneven brightness. This paper proposes the application of the Single-Scale Retinex (SSR) algorithm to address these challenges. The SSR algorithm employs single-scale lighting estimation and enhancement to enhance the image's details and global contrast.

(1) The logarithmic transformation is applied to the input image *I(x,y)* in order to enhance the detail information present in the low-light regions of the image. The logarithmic transformation is as follows,

$$\mathrm{log\_I}(x,y) = \log\left(I(x,y) + 1\right) \tag{11}$$

the logarithmic transformation maps the pixel values of the input image to a larger dynamic range and improves the sensitivity to low-light details.

(2) The gaussian blurring *G(x,y)* is applied to the image after logarithmic transformation in order to estimate the lighting component *L(x,y)* of the image. Gaussian blurring serves to reduce the high-frequency details present in the image by applying a Gaussian kernel in the spatial domain, thereby smoothing the image and enabling the estimation of the illumination distribution,

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{12}$$

(3) The Retinex component is calculated in order to obtain an estimate of the reflectance *R(x,y)*. This is done by subtracting the logarithmically transformed input image from the logarithmically transformed image that has undergone Gaussian blurring,

$$R(x,y) = \text{log\_I}(x,y) - \log\left(G(x,y) * I(x,y)\right) \tag{13}$$

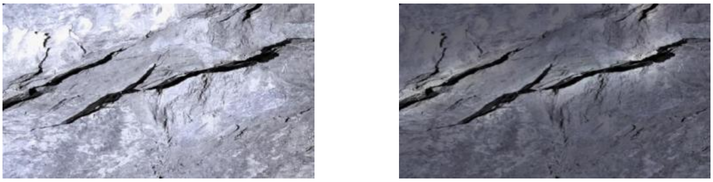
where, *G(x,y) * I(x,y)* represents the element-by-element product of the log-transformed input image *I(x,y)* and the Gaussian blur *G(x,y)*.

(4) The reflectance estimate *R(x,y)* is normalized to a range of pixel values within a reasonable interval,

$$R(x,y) = \frac{R(x,y) - \min(R)}{\max(R) - \min(R)} \tag{14}$$

where, σ represents the standard deviation of the Gaussian fuzzy.

Following the aforementioned processing, the overall contrast of the tunnel face photograph and the clarity of the detail part have been significantly improved. The problem of uneven illumination has been effectively alleviated, making the cracks more obvious, laying the foundation for subsequent image processing. The processing effect of the selected tunnel face photos using the SSR algorithm is illustrated in Fig. 4.



(a) Original image (b) Retinex algorithm enhanced images

Fig. 4. Retinex algorithm enhancement effects.

To highlight the structural features and reduce noise impact, we preprocessed the image optimized by the SSR algorithm. First, we converted it to a grayscale image, then used a Gaussian filter for noise reduction, followed by Otsu threshold segmentation [20] for binary image conversion. Finally, we applied morphological processing [21], including dilation and erosion, to enhance the structural features in the image. After preprocessing and morphological operations, we obtained a binary image highlighting prominent structural features. Using image processing techniques, we extracted the contours of the structural surfaces and performed area filtering to obtain more precise regions. These binary images were input into our custom-developed parameter calculation software, enabling accurate detection and identification of cracks on the tunnel wall in the enhanced images. Geometric features such as maximum width, minimum width, length, and area were extracted accordingly.The final extracted structural surface features and binary image are shown in Fig. 5.

Fig. 5. Results of extraction and binarisation.

4 Conclusion

This paper presents a novel approach to the analysis of tunnel face images, which have been affected by tunnel dust. The methodology is based on the DCP, which is applied to the images using computer vision technology. The principal findings are as follows.

(1) The algorithm optimizes atmospheric light estimation and transmission calculation through light source detection, reducing halo effects in processed images. Furthermore, it enhances fog removal and preserves image details using guided filter techniques.

(2) Both subjective and objective evaluations demonstrate excellent performance of this algorithm in most test images, highlighting its effective fog removal capability and detail preservation.

(3) Integration with single-scale Retinex image enhancement enhances the accuracy of structural feature recognition.

However, tunnel environments present various complexities such as different light source distributions and multiple interference factors. Future research can optimize the algorithm for these complex scenarios to improve its robustness, adaptability, and overall accuracy and reliability in diverse environments.

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