A NEW METHOD FOR DEHAZING OF UAV REMOTE SENSING IMAGES BASED ON IMPROVED DARK CHANNEL PRIOR

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ABSTRACT:

Aiming to solve the problem of loss of important image information, such as blurred details and low contrast, caused by fog, haze and other meteorological influences in the slope monitoring process of UAV remote sensing images, a new method of improving dark channel image dehazing based on channel-weighted analysis and compensation function is proposed by a training of multilayer perceptron (MLP) in this study. First, based on the dark channel prior principle, the original hazy UAV image is mapped to obtain the estimated values of atmospheric light and rough transmittance. Next, by counting the RGB three-channel values of the pixels in the high-brightness regions, and analyzing the scattering of the RGB three-channel values in the haze, a color recovery module of atmospheric light is constructed, and the estimated value of atmospheric light is optimized. Then, according to the global transmittance, the compensation boundary value is determined and a functional relationship between different brightness regions and the increment of transmittance is established as a compensation function to optimize the rough transmittance. Finally, perform secondary optimization on the rough transmittance with the multi-layer perceptron (MLP) to obtain a smoother transmittance value. The experimental results show that the image processed by the proposed method has good contrast. The color saturation and authenticity are effectively maintained. And the detailed information of the mountain recorded by the image is better restored, which can provide a real data basis for slope monitoring.

1. INTRODUCTION

In recent years, UAV aerial photography has been rapidly popularized due to its flexible use, low cost, and good economy. It has been widely used in emergency event processing, map mapping, slope disaster monitoring and other fields (Liu, 2015). The UAV aerial photography system is extremely sensitive to weather conditions. Weather like fog and haze will have a great impact on the quality of aerial photography, such as image grayscale concentration, contrast reduction, and blurred image details. It is difficult for the image to meet the detection requirements. Thus it will affect the reliability of numerical analysis and simulation analysis (Wu, 2015). Therefore, how to dehaze the UAV image in foggy weather is one of the main research directions in the current research field of image dehazing.

At present, image-based dehazing algorithms have made some progresses. Jobson et al. (Jobson, 1997) proposed a multi-scale Retinex algorithm, which eliminated the problem of image color distortion by introducing a color recovery factor, thereby improving the visual effect of dehazed images. He et al. (He, 2011) proposed a dark channel prior (DCP) dehazing algorithm, which was based on the atmospheric scattering model to dehaze the image. And the dehazing effect was better. However, the algorithm had high complexity, long processing time, and cannot adjust the fog parameters adaptively. Cai et al. (Cai, 2016) proposed a trainable end-to-end dehazing algorithm to estimate transmittance. However, the atmospheric light scattering model in this algorithm relied on a single light source model, and did not consider scenes with multiple light sources. Also, the restoration quality in the depth-of-field region needed to be improved. Ren et al. (Ren, 2016) proposed a multi-scale deep neural network transmittance estimation algorithm based on convolutional neural network (CNN). First, a coarse network was used to generate a coarse-grained transmission map. Then a finer network was used to obtain a more detailed image. Li et al. (Li, 2018) proposed a dehazing algorithm based on residual depth CNN, which could estimate the transmittance and atmospheric light separately, and improved the dehazing efficiency. Based on his dark channel prior (DCP) theory, He et al. (He, 2013) proposed to use guided filtering instead of the soft matting method to optimize the transmittance, which improved the dehazing efficiency. However, there were still problems such as incomplete dehazing and slow processing speed after processing. In view of the shortcomings of He et al., Liu et al. (Liu, 2018) proposed to introduce an adaptive threshold in the acquisition process of dark primary colors, which improved the accuracy of transmittance, but the operating efficiency was still relatively low. Han et al. (Han, 2020) proposed an improved atmospheric light estimation method based on quadtree subdivision and an improved guided filter optimization method with adaptive weighting factor added, which reduced the halo effect. But there was also a problem with color overcorrecting.

Compared with traditional hazy images, UAV hazy images have their own characteristics, such as: the transmittance of objects in the scene is roughly the same; the large areas of light color in the scene, like rivers, lakes, wastelands, buildings, etc., will affect image dehazing results; factors such as long-distance shooting fog have a great influence on the image quality (Li, 2018). According to the unique characteristics of UAV images, it is necessary to improve the traditional image dehazing method. By improving the robustness, real-time and intelligence of the algorithm, a higher quality UAV image dehazing effect can be achieved, so as to ensure the engineering research accuracy of post-image processing such as feature extraction, target recognition, and image fusion.

In this paper, we have made some improvements to the traditional DCP algorithm. First, map the original hazy UAV image to obtain the estimated values of atmospheric light and rough transmittance. Next, optimize the atmospheric light values based on Rayleigh scattering and channel weighting analysis. Then, construct a compensation function according to the relatively consistent depth of field of the UAV image, and the rough transmittance is optimized to avoid the color distortion of the restored image in the area of high-brightness objects. Use the Multilayer perceptron (MLP) to establish the mapping between the rough projection rate and the optimal transmittance, so as to obtain the optimal transmittance, improve the block effect and improve the efficiency of the algorithm. Finally, dehaze the image according to the atmospheric light value. The experimental results show that the algorithm can effectively dehaze the UAV image, and the detailed information of the mountain recorded by the image can be restored well, which can provide a real data basis for slope monitoring. And the dehazing quality of the algorithm is evaluated by mean square error (MSE), peak signal-to-noise ratio (PSNR) and structural similarity (SSIM).

This paper is organized as follows. Section 2 presents the theoretical background, which includes atmospheric scattering models, dark channel priors, and multilayer perceptrons. Section 3 presents the improved dark channel dehazing algorithm, including improved atmospheric light estimates and rough transmittance. Section 4 introduces the experiments, followed by conclusions in Section 5.

2. THEORETICAL BACKGROUND

2.1 Atmospheric Scattering Model

The DCP algorithm is based on the atmospheric scattering model for dehazing (McCartney, 1976) , which can be defined as:

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

where $I(x)$ = input haze image
$J(x)$ = output haze-free image
$t(x)$ = transmittance
A = atmospheric light value

By calculating transmittance t(x) and atmospheric light A, the scene image can be recovered.

2.2 Dark Channel Priors

Dark Channel Prior (DCP) theory is an empirical observation of the properties of haze-free images, which believes that in most outdoor non-sky local regions, there will always be at least one color (Red, Blue, Green) channel with the lowest brightness value and approaching 0. According to these statistics, the dark channel of any image can be defined as：

$$J^{\text{dark}}(x) = \min_{y \in \Omega(x)} \left(\min_{c \in \{R,G,B\}} (J^c(y)) \right) \to 0 \ , \tag{2}$$

where $J^{\text{dark}}(x)$ = dark channel value for haze-free images
$J^{c}(y)$ = one color channel of the haze-free image
$\Omega(x)$ = a square area centered on pixel x.

The dark channel prior dehazing method is an important breakthrough in the field of image dehazing, which provides a new idea for researchers in image dehazing.

2.3 Multilayer Perceptron

MLP is derived from the artificial neural network model (Han, 2004), which can map multiple input vectors to a single target vector. The network model includes input layer, hidden layer and output layer. The training of MLP is divided into forward and backward propagation processes. Taking the hidden layer as an example, suppose the input vector of the MLP network is x_i and the target vector is $y_i (1 \le i \le n)$, the output of the *j*-th neuron in the hidden layer is $Z_j (1 \le j \le n)$, Z_j can be expressed as：

$$Z_j = f\left[\sum_{i=1}^{n} (\omega_{ij} x_i + b_j)\right] , \tag{3}$$

where f = activation function
b_j = the bias of the *j*-th neuron in the hidden layer
ω_{ij} = the weight between the *i*-th neuron in the previous layer and the *j*-th neuron in the hidden layer

The MLP is trained by continuously updating the weights and bias values to obtain the desired output dataset through the input dataset.

3. METHODOLOGY

The flow chart of the proposed method is shown in Figure 1. First, based on the dark channel prior principle, the original hazy UAV image is mapped to obtain the estimated values of atmospheric light and rough transmittance. Next, by counting the RGB three-channel values of the pixels in the high-brightness regions, and analyzing the scattering of the RGB three-channel values in the haze, a color recovery module of atmospheric light is constructed, and the estimated value of atmospheric light is optimized. Then, according to the global transmittance, the compensation boundary value is determined and a functional relationship between different brightness regions and the increment of transmittance is established as a compensation function to optimize the rough transmittance. Finally, perform secondary optimization on the rough transmittance with the multi-layer perceptron (MLP) to obtain a smoother transmittance value.

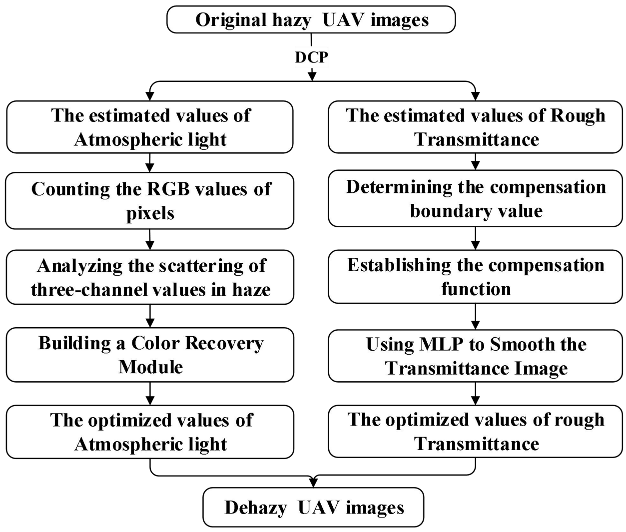

Figure 1. Flow chart of the improved DCP algorithm.

3.1 Atmospheric light value optimization based on color recovery module

Atmospheric light value A is one of the key parameters for image dehazing. If the error of atmospheric light estimation value is too large, the dehazing effect of the whole image will be worse. The dark channel dehazing algorithm proposed by He is to use the top 0.1% pixels in the dark channel image, that is, the brightest part of the image, as atmospheric light A (He,2011). However, this estimation method will be distorted when there are objects with white surfaces in the image. This is because the brightness of objects with white surfaces will be significantly higher than the brightness of atmospheric light after haze scattering, resulting in a large error in the estimation of atmospheric light A. Since the angle of view of drone aerial photography is larger than that of traditional photography, large areas of high brightness are prone to appear in the image, such as lakes and white buildings. Therefore, we proposed an improved atmospheric light estimation method.

According to Rayleigh scattering theory, blue light is more easily scattered than other colors of light, so for the RGB three channels of hazy images, when estimating atmospheric light A, the value of B (blue) channel will be smaller due to scattering. In this paper, the channel-weighted method proposed by Lee (Lee,2018) is used to compensate for the low value of the B channel due to scattering during atmospheric light estimation, so as to avoid the darkening of the restored image and even the color distortion of some objects. The main calculation steps are as follows:

(1) Select the brightest top 0.1% pixels in the dark channel image, and calculate the sum of the RGB three-channel values of these pixels respectively, namely R_{sum} , G_{sum} and B_{sum} .

(2) Calculate the color averages Z_R , Z_G and Z_B of any two pairs of channels of the three RGB channels:

$$Z_R=(G_{sum}/N+B_{sum}/N)/2 , \tag{4}$$

$$Z_G=(R_{sum}/N+B_{sum}/N)/2 , \tag{5}$$

$$Z_B=(R_{sum}/N+G_{sum}/N)/2 , \tag{6}$$

(3) According to formulas (4), (5), (6), a suitable S^C can be obtained:

$$S^C = q*(avg_C + Z_C)/2, c \in \{R,G,B\} , \tag{7}$$

where $q = 0.1$
Z_C = three-channel color image composed of Z_R , Z_G and Z_B
avg_C = three-channel color image composed of R_{sum} , G_{sum} and B_{sum}

(4) Substitute it into the atmospheric light estimation as a color recovery module, and the final atmospheric light estimated value is as follows:

$$A = A^C - S^C , \tag{8}$$

where A^C = Atmospheric light value estimated by He.

3.2 Coarse transmittance optimization based on compensation function

For UAV aerial images, the existence of large areas of high-brightness objects makes some areas in the image do not meet the prior knowledge of dark channels $J_{\text{dark}}(x) \to 0$, resulting in a small overall transmittance, which makes the restored image distorted in color.

In this paper, we constructed a compensation function to increase the transmittance of the highlight area as a whole. Since there are other non-high-brightness areas in the image, the compensation function needs to ensure that the transmittance of the high-brightness area increases, and the transmittance of the non-high-brightness area is basically unchanged. The transmittance $t(x)$ processed by the compensation function can be expressed as:

$$t(x) = t'(x) + \Delta t(x) , \tag{9}$$

where $t'(x)$ = raw estimated coarse transmittance
$\Delta t(x)$ = compensation function
$t(x)$ = optimized coarse transmittance

When using $\Delta t(x)$ compensation for high-brightness areas, $t'(x)$ needs to be fully boosted in the high-brightness area, to prevent the invalidation of DCP theory in the high-brightness area, and at the same time, At the same time, it is necessary to prevent $t(x)$ from being over-lifted in non-high-brightness areas.

According to the DCP principle, it can be known that the estimated rough transmittance $t'(x)$ can reflect the depth of field to a certain extent, that is, the rough transmittance $t'(x)$ and the depth of field $d(x)$ are inversely proportional as shown in equation (10) :

$$t'(x) = e^{-\beta d(x)} , \tag{10}$$

Since the depth of field of the drone image does not change much, according to the original method, as the depth of field increases, the transmittance of distant objects will decrease; removing the haze in the larger depth of field , the transmittance of near objects will be estimated to be high, and the dehazing effect will be poor. Therefore, in the process of UAV image dehazing, it is necessary to ensure that the estimated values of transmittance in each area of the image are basically consistent, which is in line with the characteristics of UAV images.

In this paper, we firstly performed global scale compensation for the UAV image, and adjust the scale according to the maximum value of the sky area as the boundary value. The specific adjustment formula is as follows:

$$p = \frac{\max(t') - t'}{\max(t') - \min(t')} , \tag{11}$$

where p = global scale compensation function constructed
$t'(x)$ = original estimated coarse transmittance, [0.1]
$\max(t')$ = maximum value of $t'(x)$, [0.1]
$\min(t')$ = maximum value of $t'(x)$, [0.1]

Then a nonlinear function is constructed to ensure that when the depth of field is large or the brightness of the object itself is high, $t'(x)$ is small, At this time, no compensation function is needed, and $\Delta t(x)$ will be adaptively reduced. Conversely, when the depth of field is small, in order to ensure the dehazing effect in the distance, the $t'(x)$ will increase, and the $\Delta t(x)$ will increase accordingly to ensure the dehazing effect in this area. Specifically as follows:

$$\Delta t(x) = t'(x) - e^{-kp} , \tag{12}$$

where k = compensation function coefficient, and the optimal value range is in [7, 20]

After many attempts, k=11 works best. Substitute Equation(12) into Equation (9) to obtain the optimized transmittance map. From b and c in Figure 2, it can be seen that after optimization, the transmittance is more uniform, which is in line with the depth of field change characteristics of UAV images.

Figure 2. Transmission optimization comparison: (a) Hazy image. (b) Initial coarse transmittance. (c) Optimized coarse transmittance.

3.3 Coarse transmittance optimization based on MLP

The coarse transmittance estimation by Equation (9) is pixel-level, lacks integrity, and the output image has block effect. Since the transmittance changes slowly within a certain range, the overall smoothing of the transmittance map can be performed (Huang, 2021). He uses soft matting to optimize the rough transmittance to improve the visual effect of the image (He, 2013). The difference between the exact value of the transmittance $\tilde{t}$ and the rough transmittance t is as follows:

$$E(t) = t^T L t + \lambda (t - \tilde{t})^T (t - \tilde{t}) , \tag{13}$$

where L = Laplace operator
λ = regularization parameter

The Laplace operator is as follows:

$$\sum_{k|(i,j)\in\omega_k} (\delta_{ij} - \frac{1}{|\omega_k|}(1 + (I_i - \mu_k)^T (\sum\nolimits_k + \frac{\varepsilon}{|\omega_k|} U_3)^{-1} (I_j - \mu_k))) \ ,(14)$$

where I_i = the color of the pixel at i in the input image
I_j = the color of the pixel at j in the input image
δ_{ij} =Kronecker function
$|\omega_k|$ =the number of pixels in the area ω_k
μ_k =Mean matrix of colors
$\sum_k$ =covariance matrix of colors
U_3 = 3×3 identity matrix
ε =regularization parameter

However, the dehazing effect of the soft matting algorithm is not obvious when there are large areas of high brightness in the image. And through Equation (13) and Equation (14), it can be seen that the Laplacian operator is related to the large-scale sparse linear equation, which leads to the high computational complexity of the algorithm (Pu, 2021) . In order to smooth the transmittance map, further remove residual haze and refine the contour of ground objects, ensure the efficiency of the algorithm, this paper uses MLP method to refine the coarse transmittance map.

First, the transmittance map obtained by Equation (9) and Equation (12) is used as the input vector of MLP, and the optimized transmittance is used as the target vector of MLP. By training the MLP to learn the soft matting algorithm, the mapping relationship between the coarse transmittance and the fine transmittance is directly established. The experiment is based on Pu's MLP algorithm (Pu, 2021) , and uses a three-layer neural network structure to optimize the coarse transmittance. The size of the image generated each time is the same, and it is the center of (x, y) , the side length is 16, a sliding window is set, and the number of input and output neurons is 256 each time. After optimizing the coarse transmittance with MLP, the obtained transmittance map tends to be smoother, as shown in Figure 3.

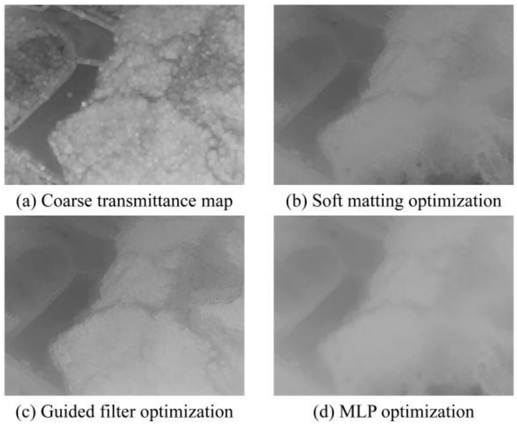

Figure 3. Coarse transmission optimization comparison: (a) Coarse transmittance map. (b) Soft matting optimization. (c) Guided filter optimization. (d) MLP optimization

4. EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Subjective Effect Evaluation

Some traditional dehazing algorithms are selected for comparative analysis with the method proposed in this study: ① Dark channel prior dehazing algorithm proposed by He(He, 2011). ② Improved dark channel prior algorithm proposed by Pu (Pu, 2021). ③ Wang's fast adaptive histogram equalization algorithm(Wang, 2006). ④Cai's DehazeNet algorithm based on Convolutional Neural Networks(Cai, 2016). It can be seen from Figures 4-6 that the overall visibility and contrast of the image have been greatly improved after several methods of dehazing.

However, He's DCP algorithm had obvious color distortion when dealing with urban gravel roads and white buildings in the distant view. there was also a halo phenomenon in the depth of the scene when dealing with the river part view. When dealing with the bare ground, due to the high brightness of this part of the ground, the estimated value of transmittance was low, and there was haze residue after He's processing. The result of processing with Pu's improved dark channel prior algorithm, had haze residue in the foreground view. and the color is darker. The Fast adaptive histogram equalization by Wang, was an image enhancement technology. It did not rely on atmospheric scattering models for processing, and directly enhanced photo details by enhancing image contrast. It also had the problem of color distortion. Cai's DehazeNet dehazing algorithm relied on the convolutional neural networks(CNN), directly calculated the mapping relationship between the input hazy image and the dehazed image. But the obtained image after this method was darker and the details of the mountain texture were lost.

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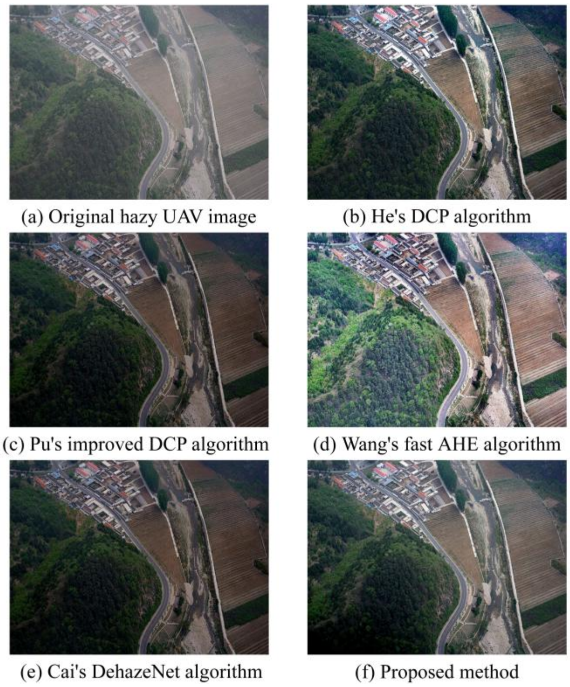

Figure 4. Comparison of different methods on images of buildings: (a) Original hazy UAV image. (b) He's Dark Channel prior algorithm. (c) Pu's Improved DCP algorithm. (d) Wang's fast adaptive histogram equalization algorithm. (e) Cai's DehazeNet algorithm. (f) Proposed method

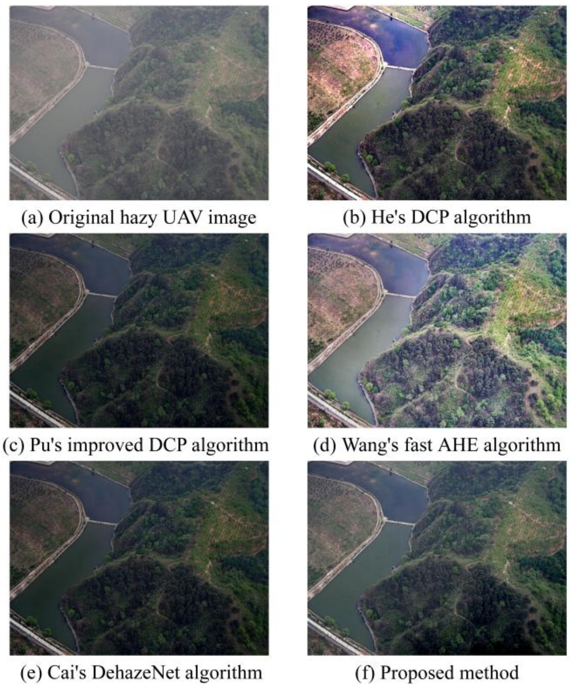

Figure 5. Comparison of different methods on images of river: (a) Original hazy UAV image. (b) He's Dark Channel prior algorithm. (c) Pu's Improved DCP algorithm. (d) Wang's fast adaptive histogram equalization algorithm. (e) Cai's DehazeNet algorithm. (f) Proposed method

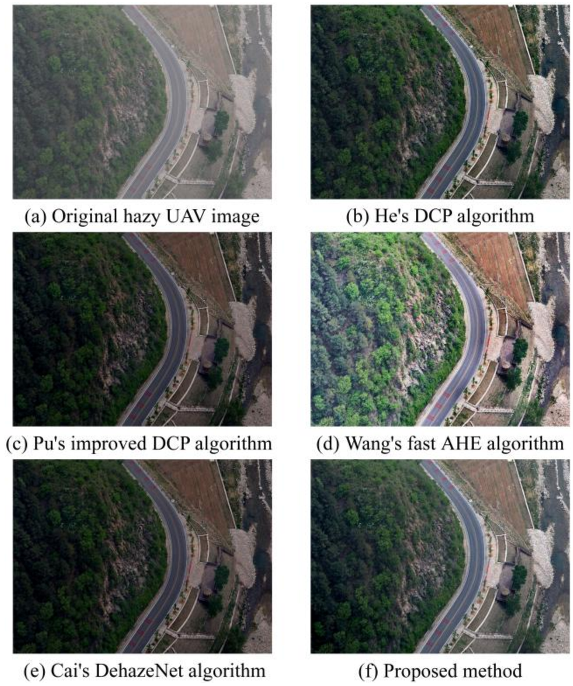

Figure6. Comparison of different methods on images of mountains: (a) Original hazy UAV image. (b) He's Dark Channel prior algorithm. (c) Pu's Improved DCP algorithm. (d) Wang's fast adaptive histogram equalization algorithm. (e) Cai's DehazeNet algorithm. (f) Proposed method

The dehazing effect of the algorithm proposed in this study was better than that of the commonly used image dehazing algorithms. Due to the introduction of the color recovery module, the overall picture brightness is basically appropriate, and the colors of red and blue buildings in the distance are more natural. The hazy on the mountain was completely removed, and the red markings on the road were clearly restored.
The rough transmittance estimate was optimized by a compensation function, which eliminates haze in the mountain section. The MLP algorithm was used to make the coarse transmittance estimation among the pixels more average, and the halo phenomenon in the depth of field was obviously eliminated. The image processed by the proposed method had natural color, in addition to having a good dehazing effect, it was more in line with the brightness of human visual habits.

4.2 Objective Numerical Analysis

In this study, three indicators commonly used in image dehazing quality evaluation were selected to evaluate the effective of the proposed. They were the mean square error (MSE), the peak signal-to-noise ratio (PSNR), and the structural similarity (SSIM). Where MSE represents the root mean square error between the original image and the enhanced image. The smaller the value, the better the algorithm. The formula is as follows:

$$MSE = \frac{1}{\text{mn}} \sum_{i=0}^{m=1} \sum_{j=0}^{n=1} [I(i,j) - P(i,j)]^{2} , \tag{15}$$

where m = the length of the image
n = the width of the image
I = enhanced image
P =original image

PSNR is a method to measure the relationship between the original image and the processed image from a statistical point of view, and calculate the difference between the corresponding pixel gray values of the original image and the processed image. The larger the value, the smaller the degree of image distortion and the smaller the noise. Since MSE is the average energy of the difference between the real image and the noisy image, and the difference between the two is noise, PSNR is the ratio of the peak signal to MSE, and its formula is as follows:

$$PSNR = 10 * \log_{10}(\frac{MAX_I^{\ 2}}{MSE}) , \quad (16)$$

PSNR is simple to calculate, but it only depends on the statistical point of view to consider the difference between the corresponding pixels of the processed image and the original image, while ignoring the relationship between pixels and pixels, which makes it different from the subjective evaluation results. SSIM unifies image brightness, contrast and features as image evaluation parameters, because it is more in line with the visual structure of the human eye, and this method can obtain evaluation results that are basically consistent with subjective evaluation. The principle is to define the images before and after processing as X and Y, and calculate and obtain the brightness information $L(X,Y)$, contrast information $C(X,Y)$ and structural information $S(X,Y)$ of the image according to the following formula:

$$L(X,Y) = \frac{2\mu_X \mu_Y + C_1}{\mu_X^{\ 2} + \mu_Y^{\ 2} + C_1} , \quad (17)$$

$$C(X,Y) = \frac{2\sigma_X \sigma_Y + C_2}{\sigma_X^{\ 2} + \sigma_Y^{\ 2} + C_2} , \quad (18)$$

$$S(X,Y) = \frac{\sigma_{XY} + C_3}{\sigma_X \sigma_Y + C_3} , \quad (19)$$

where μ_X = mean of image X
μ_Y = mean of image Y
σ_X = standard deviation of image X
σ_Y = standard deviation of image Y
σ_{XY} = covariance of image X and image Y
C_1 , C_2 , C_3 = constant

In summary, the SSIM formulas of the images X and Y are defined:

$$SSIM = L(X,Y)^{\alpha} * C(X,Y)^{\beta} * S(X,Y)^{\gamma} , \quad (20)$$

where α , β , γ = parameters for adjusting specific gravity settings

The value of SSIM is between 0 and 1, and the closer it is to 1, the smaller the distortion is when the processed image is compared with the original image.

The effect of the proposed method was better than the above image dehazing algorithms, as shown in Table 1.

Algorithms	(a)Rivers			(b)Buildings			(c)Mountains		
	MSE	PSNR	SSIM	MSE	PSNR	SSIM	MSE	PSNR	SSIM
Dark Channel prior	1933.7	15.2669	0.2862	1923.4	15.2902	0.3127	2408.9	14.3127	0.3188
Improved Dark Channel	5253.5	10.9263	0.1520	3269.9	12.9855	0.6209	3906.5	12.2129	0.5745
Adaptive Histogram	1249.3	17.1641	0.2889	1810.5	15.5527	0.2525	1775.5	15.6377	0.2599
DehazeNet	4230.9	11.8665	0.6036	3269.9	12.9855	0.6209	3906.5	12.2129	0.5745
Proposed method	1700.7	15.8245	0.6991	1117.5	17.6485	0.7341	1090.7	17.7536	0.7310

Table 1. Evaluation results of each algorithm on UAV images dehazing of ground objects: (a) In the processing of rivers. (b) In the processing of buildings. (c) In the processing of mountains.

In the processing of rivers, the PSNR of the proposed method was inferior to the adaptive histogram equalization and the SSIM value was the highest. It showed that the PSNR indicator only measured the relationship between the original image and the processed image from a statistical point of view, but lacked the consideration of the relationship between pixels, which made the evaluation results have certain errors. In the image processing of buildings and mountains, the three evaluation indicators (MSE, PSNR and SSIM) of dehazing effects selected in this paper are all optimal. Especially in the image processing with mountains, the SSIM of the proposed method was 0.731, which was much higher than the other four dehazing methods. It indicated that the proposed method can more effectively achieve dehazing and improve the accuracy of subsequent processing when monitoring mountain landslides.

5. CONCLUSION

Starting from the principle of dark channel, this study clarifies the degradation of UAV images caused by haze weather. By optimizing the estimated value of atmospheric light and transmittance value, it makes up for the problem of image color distortion caused by the traditional dark channel dehazing method for large-area rivers, buildings and other objects. Using MLP to refine the contour of the ground object while improving the efficiency of the algorithm, thereby further improving the overall effect of image dehazing. The experimental results show that the image processed by the proposed method has natural color, more vivid details, and more prominent detail intensity and tone restoration effect. The contrast of the processed image is good, the color saturation and authenticity are effectively maintained, and the detailed information of the mountain recorded by the image is better restored, which can provide a real data basis for slope monitoring. However, the results of the proposed method is not ideal when processing images with rivers. This aspect has yet to be further studied.

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