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ENHANCEMENT OF SAND DUST IMAGES USING HISTOGRAM AND L-CLAHE TECHNIQUE

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Abstract : In sand-dust weather conditions, images often suffer from low contrast, color distortion, and blurriness, severely impacting their clarity. To address this, we introduce a method that adjusts pixel colors adaptively using the mean and standard deviation of chromatic histograms. This method ensures that each color component is corrected based on the statistical properties of the green component, preserving the mean green value. Additionally, we employ a green-mean-preserving color normalization technique. Furthermore, we utilize the YCbCr color space method to enhance contrast and accuracy. By separating the image into its Hue, Saturation, and Intensity components and enhancing them individually, we can retain detailed information. Finally, we enhance the luminance component using CLAHE (Contrast Limited Adaptive Histogram Equalization), resulting in the output termed L-CLAHE. Through quantitative evaluations, our method demonstrates significant improvement in images captured during sand-dust weather compared to other techniques.

***IndexTerms* - Sand-dust image enhancement, color normalization, green-mean preserving, maximum overlapped histogram, coincident chromatic histogram**

1. INTRODUCTION

Adverse atmospheric conditions significantly impact the performance of outdoor vision systems, including intelligent surveillance, human and vehicle tracking, image-based remote monitoring, and traffic monitoring systems. Inclement weather leads to outdoor images and videos with diminished quality, characterized by poor contrast, color distortion, reduced visibility, blurriness, and darkness. Among the primary culprits for image degradation is haze or fog, which has prompted extensive research into haze removal techniques. In recent decades, sand dust has emerged as a considerable threat to both human health and outdoor vision applications. In sand-dust weather conditions, the rapid absorption of blue and green light by sand-dust particles causes captured images to exhibit an overall yellow or red hue. Additionally, the larger radius of sand-dust particles, compared to haze and fog particles, renders direct application of traditional haze removal methods ineffective for sand-dust image enhancement. Consequently, enhancing images affected by sand dust proves to be a more challenging task compared to conventional dehazing and underwater image enhancement. Despite these challenges, there has been a notable lack of active research in the field of sand-dust image enhancement. The block diagram of the proposed work flow is as shown in Figure 1.
Adversities in Sand dust Images are as follows

1. Outdoor images and videos captured in inclement weather conditions have poor contrast, color cast, low visibility, fuzz, and darkness.
2. The main reason for this phenomenon is the scattering and absorption of light by sand-dust particles.
3. Therefore, the sand-dust-degraded images have directly reduced the processing capacity of monitoring systems, automated driving and remote sensing systems.
4. The main problems of sand-dust image enhancement are severe color shifts or casts.
5. To improve the processing ability of computer vision systems in sand-dust environments, researchers have proposed some visibility restoration algorithms.

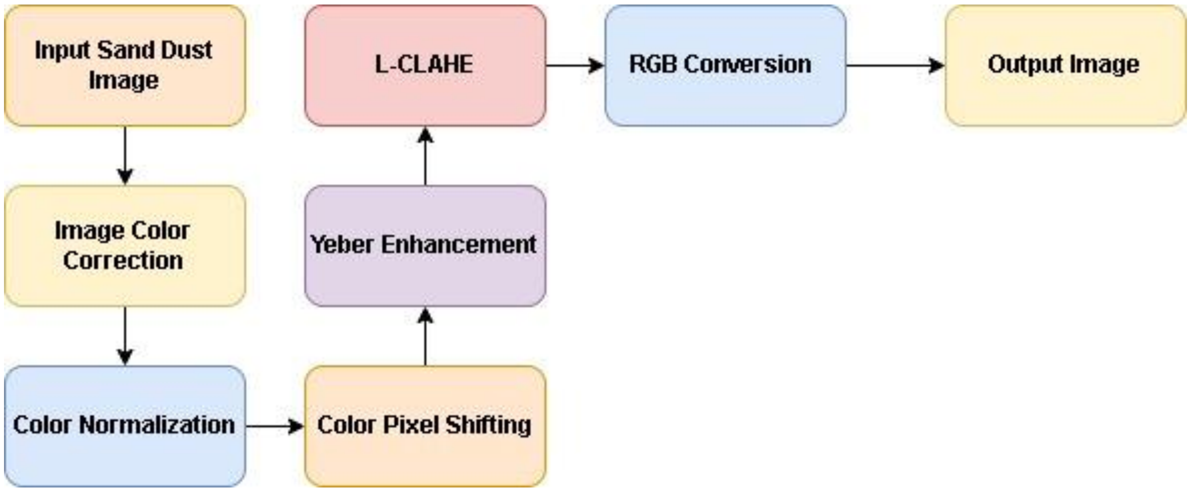

Figure 1. Block Diagram of the proposed work flow

2. RELATED WORK

Yazhong et al. introduced a distinctive enhancement method utilizing a fusion strategy for sand and dust images [1]. Addressing these challenges, this paper presents a novel enhancement algorithm also based on fusion strategy. The algorithm comprises two sequential components: first, sand removal through an enhanced Gaussian model-based color correction algorithm, followed by dust elimination utilizing a residual-based convolutional neural network (CNN). One of the main issues with underwater imaging is color distortion, which is caused by light being absorbed and scattered as it travels in the water. Another major issue is underexposure, which is caused when the light is not properly exposed to the surface of the water. In this article, we will look at a novel approach to enhance one underwater image using a retinex based enhancing technique. This technique was developed by Fu et al[2]. It is expected that the medium transmission coefficient of each pixel is different according to the dust removal method according to HuichengLai et al[3]. It is difficult to achieve good image quality, correction of color casts, and good running time in the current sand dust image processing method. In this paper, we introduce a new compensation coefficient, effective intensity difference before, which results in an effective and reliable sand dust removal. In the paper by Jong-Ju Jeon et al. [4], a pioneering approach to enhancing sand-dust images through innovative dehazing and color correction is introduced. The method begins with a novel color correction technique designed to uphold the constancy of chromatic variances while ensuring alignment of chromatic means. Ali Hakem Alsaeedi et al. [5] propose an enhanced model for refining sand dust photographs, integrating color correction alongside a novel membership feature. The model delineates three key stages: haze elimination, rectification of color shifts, and enhancement of contrast and brightness. Guxue Gao et al. [6] introduce a method for enhancing sand-dust images through a two-step unsupervised approach. Initially, they present a pragmatic and efficient color correction method aimed at tackling color shift problems. Subsequently, they devise an unsupervised generative adversarial network that enhances picture clarity and details without the need for paired data during training. Zhongwei Hua et al. [7] outline a technique wherein the color cast of the initial degraded image is rectified using a novel color balance and compensation formula. This formula effectively offsets the impact of sand-dust scattering, specifically by compensating for excessive yellow channel information with adjustments to the blue and green channels prior to white balance calibration. Fei Shi [8] presents a method for enhancing sand dust images, aiming to efficiently address color casting issues and enhance visibility in such photographs. This technique involves two key modules: the Red Channel-based Correction (RCC) function and the Blue Channel-based Dust Particle Removal (BDPR). The RCC module corrects color casting errors, while the BDPR module focuses on the removal of sand dust particles. In his work, "Sand and Dust Storms: Underrated Natural Hazards," Miileton, N. [9] delves into the hazard perspective of Sand and Dust Storms (SDS), exploring their multifaceted impacts across economic, physical, and social domains. The analysis centers on their implications for agriculture, health, transportation, utilities, households, as well as the commercial and manufacturing sectors. He, K. and Sun [10] introduce a straightforward yet powerful method for single image haze removal, leveraging the dark channel prior. The dark channel prior relies on a statistical analysis of outdoor images devoid of haze. Their approach is grounded in a crucial observation: most local patches within such images contain pixels with notably low intensity in at least one color channel. T. Gevers [11] explores edge-based color constancy, revealing two distinct scenarios where achieving color constancy is feasible. Within this framework, color constancy necessitates the estimation of the illuminant present during image capture. S. Agaian [12] investigates underwater image quality measures inspired by the human visual system. Underwater images commonly experience blurring, reduced contrast, and desaturated colors due to absorption and scattering effects in water. Numerous algorithms have been devised to enhance the visual quality of underwater images in response to these challenges. X. Yang [13] introduces a novel no-reference quality metric for contrast-distorted images, grounded in the principle of information maximization. The primary objective of viewing an image is to extract information to the fullest extent possible. In this study, we propose a new no-reference/blind metric for assessing image quality in cases of contrast distortion.

3. PROPOSED METHOD

The proposed method consists of four steps as follows.

- Step 1: Adaptive initial color correction.
- Step 2: Green mean-preserving color normalization technique.
- Step 3: Color pixel shifting based on maximum histogram overlapping.
- Step 4: Image adjustment for obtaining brighter image.

Overall, the proposed steps aim to obtain a coincident chromatic histogram. The goal of our method is to remove color veils due to sand dust, and to improve the brightness and contrast of the sand-dust image.

3.1 Initial Color Correction

We use an initial color correction algorithm based on weighted green component compensation. Let IC (c ϵ{r, g, b}) be the color channel of the given sand-dust image, and IC(X) be the pixel value of IC at the position X=(x, y) within the image. The color correction is achieved as follows.

$$IC1\,(X)=IC\,(X)+\Delta C\,Ig\,(X) \qquad (1)$$

Where IC1 (X) is a color corrected pixel, and ΔC is the weight of the green pixel. Here we proposed three factors to construct Δ^c. That is

$$\Delta C = \delta^{C}_{md} * \delta^{C}_{sr} * \delta^{C}_{wm}(X) \qquad (2)$$

Whereδ^{C}_{md}, δ^{C}_{sr} are global weighting factors based on the mean difference and standard deviation ratio, respectively. $\delta^{C}_{md}(X)$ is the pixel based local weighting factor that controls the amount of color correction by measuring the strength of a colour pixel.

The proposed pixel-based initial correction step slightly changes the color histograms. However, this initial correction step plays an important role in the next green-mean preserving step. In this paper, we propose a pixel-wise weight$\delta^{C}_{mc}(X)$, which is a generalized form of the weight used in the conventional method. This $\delta^{C}_{mc}(X)$is defined as follows,

$$\delta^{C}_{mc}(X)=1-kIC\,(X) \qquad (3)$$

3.2 Green-mean-preserving Image Normalization

The color values across all channels exhibit remarkable similarity, resulting in an overall average hue that approximates gray across the entire image. . Therefore, to stretch color components according to the mean of the green component, we present a green-mean-preserving image normalization algorithm. This step is simple, but very effective. Let $I^{C}_{2}(X)$ be the normalized image, which is defined as

$$I_2{}^{C}(X) = \frac{I_1{}^{C}(X) - m(I_1{}^{C}(X))}{max I_1{}^{C}(X) - \min I_1{}^{C}(X)} + m(I^{g}\,(X)) \qquad (4)$$

Using the image normalization process, the color veil of many sand-dust images can be removed. In addition, this process is affected by the previous initial color correction step. A strong Color Pixel Shift Based On Maximum Histogram Overlappingor weak color components prevent the proper stretch of color values.

3.3 Color Pixel Shift Based On Maximum Histogram Overlapping

To remove the minor color cast and enhance the brightness of the color-corrected image this operation is performed. Because sand-dust images have a predominant color, such as red, the gray-world algorithm, which has the same color mean, can cause color casts. After initial color correction and green-mean-preserving normalization the histogram of red channel is narrow and has a high peak. Because of the narrow and high-peak histogram, the processed image has a reddish artifact. This is caused by equating the red or blue mean to the green mean. A color pixel shifting algorithm using the maximum histogram overlapping method as in Step 3. To avoid the effect of background luminance, we use normalized color values. Using the histogram shift, we can achieve the maximum overlap of the three color channels. The narrow red channel distribution is expanded, this eliminates the reddish artifact.

3.4 Luminance Chrominance Colour Analysis

The output after performing Color Pixel Shift Based on Maximum Histogram Overlapping is having little colur variations, to enhance the quality of image this step is performed. Color spaces comprising luminance and chrominance typically consist of three components .Luminance contains the overall brightness of the image. It is a bit like a greyscale image - if you looked at just the luminance component it would look similar to a black and white photograph. Two chrominance components. These indicate the colour once the lightness component has been removed. The two chrominance components contain information akin to the hue and saturation components of HSL. There are several standards defined for the conversion at different context.

$$Y = 0.299R + 0.587G + 0.114B \qquad (5)$$
$$C_b = 128 - 0.1687R - 0.3312G + 0.5B \qquad (6)$$
$$C_r = 128 + 0.5R - 0.4186G - 0.0812B \qquad (7)$$

The luminance information is given to adaptive histogram equalization for enhancing the intensity level. Finally converted to RGB to obtain the original image.

3.5 L – CLAHE

The L-CLAHE (Limited Contrast Adaptive Histogram Equalization) technique is a variation of the traditional Contrast Limited Adaptive Histogram Equalization (CLAHE) method. CLAHE is a method used in image processing and computer vision to improve the contrast of images. It divides the image into small blocks called tiles and performs histogram equalization on each tile. This local operation helps in enhancing the contrast of images with varying intensity levels. Traditional CLAHE has a parameter called clip limit which restricts the amplification of the histogram bins. This helps in preventing noise amplification but can also lead to under-amplification in certain areas, resulting in suboptimal contrast enhancement. L-CLAHE introduces a modified way of setting the clip limit. Instead of a uniform clip limit for the entire image or tile, L-CLAHE adjusts the clip limit based on local image characteristics. This adaptive adjustment aims to achieve more balanced contrast enhancement across different parts of the image. Algorithmically, L-CLAHE involves calculating the histogram for each tile, adjusting the clip limit based on local characteristics (such as mean intensity), and then performing histogram equalization. This process is repeated for each tile to ensure local adaptiveness.

4. RESULTS AND DISCUSSION

The suggested sand-dust image enhancement method was tested on a variety of sand-dust photographs retrieved from the Internet to ensure its efficacy. There is a comparison of our method's performance with that of five state-of-the-art approaches, as shown in [14], and with the SCBCCH. The suggested procedure was put into action using an Intel i7 4790 CPU running at 3.60GHz with

8GB of RAM. Coding took place in MATLAB. In Fig. 2, we display a qualitative comparison between our 10 sand-dust photos and the results obtained from SCBCCH image enhancement approaches. Figure 8 shows that when it comes to sand-dust photos, SCBCCH fails miserably. Despite the strong contrast, the restored results look artificial due to color casts and faded hues. In a sand-dust environment, the suggested method produces the greatest qualitative results with minimal color veils, excellent brightness, and high contrast

In Table 1, we can see a comparison of the five average quantitative measure values across all ten pictures. using far, the most effective UIQM score was achieved using the suggested algorithm. STME's UIQM score is second-best, even though it has highly distorted colors. See Figure 2 for examples of how FBE, TFIO, HRDCP, and NGT provide UIQM ratings that are comparable to the subjective picture attributes. On average, our technique outperformed STME for NIQE, PIQUE, and BRISQUE scores.

The suggested L-CLAHE algorithm achieved the best NIQMC scores, as demonstrated in Table 1. Taking into account the results of five quantitative criteria, the suggested strategy emerges as the clear winner. Consequently, when comparing NIQE scores, the suggested enhancement scheme can create improved photos that look more natural, and images that are more vivid and have a high contrast from a UIQM standpoint. Furthermore, by comparing the NIQMC values, we can determine that our method exhibits lower contrast distortion compared to previous methods.

Table 1: Average Quantitative metric values and Execution times for ten images

IMAGE NUMBER	METHOD	Quantitative metrics					
		UIQM	NIQE	PIQE	BRISQUE	NIQMC	TIME
1	SCBCCH	0.623036	3.278877	55.482739	22.259188	6.738650	2.650377
	L-CLAHE	0.648294	2.868399	51.200369	21.950135	7.062361	0.235574
2	SCBCCH	1.060621	2.110327	37.975420	13.053924	7.145283	2.593234
	L-CLAHE	1.155025	2.049839	35.415868	5.467276	7.581478	0.227748
3	SCBCCH	1.243774	4.360392	41.752040	29.275206	7.665313	2.393279
	L-CLAHE	1.516496	4.173841	39.109453	23.004183	7.726223	0.227188
4	SCBCCH	0.915255	1.982041	40.342302	18.867382	6.478050	2.732389
	L-CLAHE	1.005228	1.937752	40.269761	14.230062	6.894835	0.243228
5	SCBCCH	1.221080	2.251525	25.291515	28.813925	7.364231	2.644998
	L-CLAHE	1.270028	2.233201	19.999491	22.322594	7.522685	0.249395
6	SCBCCH	0.788267	2.623019	47.195119	29.785769	6.829613	1.959768
	L-CLAHE	0.791793	2.616378	42.560603	25.489216	7.086513	0.208041
7	SCBCCH	0.601540	4.403303	66.884150	41.984640	6.419547	1.948111
	L-CLAHE	0.627105	3.605159	59.245798	37.470146	6.432427	0.248753
8	SCBCCH	0.770015	2.122292	37.910358	16.459089	6.672192	2.590260
	L-CLAHE	1.023419	1.466796	35.368026	8.585696	6.810791	0.569104
9	SCBCCH	1.027740	2.705800	44.073276	31.173386	7.094687	1.981785
	L-CLAHE	1.063264	2.515174	41.627536	25.030927	7.320065	0.209164
10	SCBCCH	0.707125	2.963898	54.026518	22.838286	7.094710	1.952232
	L-CLAHE	0.763875	2.686208	49.370901	15.385594	7.203276	0.204483

Sl no	Input image	Image after Step-2	SCBCCH	L-CLAHE
1				
2				
3				
4				
5				
6				
7				
8				

Figure 2. Enhanced results of various Sand-dust Images

5. CONCLUSION

Using a successive color balancing to obtain a coincident chromatic histogram, we suggested an efficient approach in this study for sand-dust image improvement. A color correcting method that uses the standard deviation and mean of color histograms was first introduced. The second step was to normalize the colors of the red and blue histograms such that they looked like the green histogram. This was done by retaining the green mean. Because many sand-dust photos' red or blue components have a narrow histogram with a strong peak, this approach could provide undesired output. We utilized the YCbCr color space method to improve contrast and accuracy, and we advocated a histogram shifting approach that maximizes the overlap of the red and blue histograms with the green histogram. Individually improving the image's Hue, Saturation, and Intensity components allows us to preserve detailed information. Prior art sand-dust picture enhancing techniques were tested against the suggested method to determine its efficacy. The suggested improvement scheme beats state-of-the-art methods in terms of subjective and objective aspects, according to the simulation findings.

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