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An Optimized Stationary Wavelet Fusion Technique for Image De-hazing

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ABSTRACT- Nowadays, the amount of smoke and dust in the air is increasing significantly due to industrialization. The smoke and dust particles accumulate in the relatively dry air and cause haze in the surrounding area, impairs visibility. This haze also affects photography, which reduces the images' quality and looks unnatural. The hazy atmosphere affects even pictures taken with a cell phone in everyday life. There are many methods to remove this haze content from the image, but they have not yielded great results. The long-time and short-time shots constantly differed while attempting to eliminate atmospheric haze from the images. To solve this problem, a fusion rule was proposed to fuse the luminance and dark channel prior (DCP) methods. The transmission estimated with the DCP method contributes mainly to the foreground regions, while the luminance model deals with the celestial regions. The fusion technique is a pixel-level fusion approach in the transform domain. The proposed approach combines the transmittance values obtained from the dark channel in front of the foreground region (background) and the luminance model for the sky region in the transform domain using the Stationary Wavelet Transform (SWT) with the optimized level of decomposition. The proposed algorithm was subjected to quantitative analysis of some statistical measures. The result shows that the proposed method successfully maintains the maximum visual truth content by effectively removing atmospheric haze from the images.

Keywords: Haze; Fusion Rule; Dark Channel Prior (DCP); luminance; Stationary Wavelet Transform.

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1. INTRODUCTION

In recent years, industrialization and urbanization have increased in India. At the same time, pollution has increased, resulting in a very hazy atmosphere. The deferred elements in the atmosphere, such as dust, smoke, and other pollutants, linger between the sky and the ground. This leads to a deterioration in the quality of captured images, which in turn leads to difficulties in analysis, such as CCTV surveillance, aerospace object tracking and detection, advanced driver assistance systems (ADAS), and especially in taking artistic images in daily life with cell phones [1]. Therefore, the technique of image enhancement is of practical importance. Image Restoration is ultimately about enhancing an image in a certain way. The degradation phenomenon should be known in advance to restore the original image efficiently. Restoration models have been developed to treat haze and insignificant colours in close-up images [2-4]. However, dealing with atmospheric haze and the lack of a basic standard for measuring atmospheric thickness in long-distance images is difficult.

Haze removal using a physical atmospheric scattering model has recently gained much popularity. Numerous single-image haze reduction techniques have been proposed based on the atmospheric scattering model first described and derived in 1999 [6,7]. An atmospheric veil, like dark channel matting with a median filter, was suggested in [8] as a quick way to process dehazing. To get satisfactory results, though, many factors must be changed. A model for the prior likelihood of scene radiance dehazing was developed [9]. As statistical priors on the depth and albedo, it made it possible to integrate structural restrictions. The authors in [10] suggested combining the intrinsic boundary restriction for image dehazing with the contextual regularized weighted L1-norm to estimate an optimal transmission map. All other approaches are ineffective for the sky treatment effect, except the method used in [11]. An innovation in the dehazed field is the dark channel prior method put out by [1]. Nevertheless, it still has limits regarding colon distortion following haze removal and processing the sky area. Luminance prior haze removal was used in certain works to preserve the image's natural appearance following haze removal. According to the authors in [12], there is a significant variation in intensity value when the concentration of haze changes. There was almost no residual error in the relationship between intensity and haze concentration. Consequently, the whole image's haze was removed by simulating the depth using the linearly converted luminance. Several techniques were used to segregate and process the sky and non-sky regions to create a natural sky in dehaze images. The study in [2] used an intensity gradient to divide the sky and non-sky regions. In [3], transmission map and intensity data were utilized to divide the sky and non-sky regions using a constant threshold. The depth

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map was clustered to sky and non-sky regions in [4] using the Gaussian Mixture Model (GMM). A context-adaptive super pixel segmentation technique was presented by Yoon [5] to separate an image into labels such as ground and sky. Images with much haze tend to have a connection between the sky and distant background. With these methods [2–5], it is difficult to determine the precise border between sky and non-sky regions in a strong hazy image. In [14], a supervised learning method by learning the parameters of the dehaze model was presented, whereas in [13], a learning framework for dehazing in tandem with the growing body of research on deep learning was proposed. A multi-scale deep network was used in [15] to forecast a holistic transmission map. In [16] a Dehaze Net model utilizing Convolutional Neural Networks (CNN) was proposed. The CNN layers were created specifically to embody the pre-existing priors in the field of image dehazing. The outcome was dismal but natural.

The prior model for the dark channel is a widely accepted technique for image rectification. This model assumes that the pixel value tends to be higher in the hazy region while it approaches zero in the haze-free region. The value of the dark channel in the haze-free sky region is higher than zero. Therefore, the output image of this model is usually distorted. Another fundamental problem with this method is the evaluation of atmospheric light. Since there is no standard measurement procedure, the estimated value corresponds to a factor of 0.001 of the main intensity value of the dark channel [1]. This leads to a colour shift in the resulting image, i.e., the higher the value, the darker the restored image.

The restored image's effectiveness is increased using the luminance model [13, 19]. The sky region requires more luminance, i.e. high transmission values. Therefore, the luminance model replicates the scene depth for higher transmission values. To improve the visualization of the output image, the appropriate and useful amount of information from both transmission models is fused in the transformation domain. Image fusion is a valuable method of consolidating images of the same scene to obtain the greatest information content from the final, restored image. Image fusion can be performed at three basic levels: the pixel, feature, and decision levels [20, 21]. In feature-level image fusion, features are extracted, and then a fusion algorithm is applied based on the extracted features. In decision-level image fusion, the extraction and classification of useful information from the input images are performed independently. In pixel-level image fusion, each pixel is determined from a set of pixels in different source images. Thus, pixel-level images have shown remarkable success in image denoising.

There are different approaches to image fusion. The basic classification is spatial domain fusion and transformation level fusion. In spatial domain fusion, local spatial features such as gradient, local standard deviation, angle, etc. are used for image fusion, resulting in spatial distortions in the fused image. Transformation domain fusion, on the other hand, uses three basic steps: Images in the spatial domain are converted to the transform domain, the fusion rule required by the proposed method is applied to obtain the required coefficients, and then the fused coefficients of the transform domain are fed back to the spatial domain to obtain the fused image. There are various pyramid-based declinations, such as the discrete wavelet transform (DWT), the stationary wavelet transforms (SWT), etc., to obtain such changes.

The transformation used in this work is the stationary wavelet transform (SWT), which is quite like the DWT, with the fundamental difference that no down-sampling of images between hierarchy levels in the SWT [22-24]. Therefore, the resolution of the sub-images obtained after the decomposition process of the transformation is well preserved.

This paper proposes a fusion approach in the transform domain for effective and natural recovery of haze-free sky images that considers the yields of the two basic recovery models.

The paper is structured as follows: Section 2 briefly overviews the image degradation model, the DCP model, and the luminance model. Then, the proposed SWT-based fusion approach is explained in Section 3, and finally, simulated results along with performance analysis are shown in Section 4.

2. IMAGE DEGRADATION MODEL

The following expression indicates the degradation model widely used in computer vision [25]:

$$\mathrm{H_I(w) = R_I(w)T_m(w) + L_A(1 - T_m(w))} \tag{1}$$

Here H_I is the original blurred image, $\mathrm{R_I}$ is the restored defocused image and T_m describes the mean transmission, which expresses the strength of the light intensity that survives the path between the viewer and the sight in the visual view and L_A describes the global atmospheric light.

Various atmospheric degradation factors and even increasing distance from an object lead to an increase in opacity. Since the proportion of light reaching the object is determined by the transmittance due to the reflection of light from the object, a greater attenuation is observed for light traveling over a greater distance [26]. The transmission is therefore given as

$$\mathrm{T_m(w) = e^{-\beta d(w)}} \tag{2}$$

Here β is the coefficient of scattering. It depends on the wavelength of the light, its polarization state, etc., and d represents the scene's depth.

2.1. Dark Channel Prior Model (DCP)

The DCP is based on detecting dark channel values in 'haze-free' images and the absence of the sky. As a rule, pixels with low intensity are observed in haze-free image fields in at least one colour channel, *i.e.*, the dark channel of the haze-free image normally has zero values. It is mathematically expressed as,

$$\mathrm{R_I}^{\mathrm{dark\_ch}}(\mathrm{w}) = \min_{\mathrm{y}\in\Omega(\mathrm{w})}\left(\min_{\mathrm{c}\in\{\mathrm{r,g,b}\}} \mathrm{R_I^c(y)}\right) \rightarrow 0 \tag{3}$$

Here, R_I^c is the value of R_I in one colour channel and $\Omega(w)$ a regional patch with w was center. The coefficients of

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transmission, determined by the DCP model with normalization, are defined as:

$$\widetilde{T}_d(w) = 1 - \omega \min_{y \in \Omega(w)} \left(\min_{c \in \{r,g,b\}} \frac{{H_I}^c(y)}{{L_A}^c} \right) \quad (4)$$

Here, ω defines the degree of de-hazing to present depth with its value ranging as ($0 \leq \omega \leq 1$).

The guided filter can also be used to refine the dark channel transmission defined by Td to increase computational speed, improve image quality, and even remove artifacts and halos [18].

2.2. Luminance Model

The DC estimate in the sky area is much higher than zero, which makes the sky area look unnatural. Therefore, the use of the DCP method is unsuitable for covering the sky area. Similarly, the DCP method fails when the atmospheric light and the objects' colour match and there are no shadows.

Based on model *equation (1)*, the transfer is modified as follows:

$$T_{actual}(x) = \frac{1 - H_{I_c}(x)/L_{A_c}}{1 - R_{I_c}(x)/L_{A_c}} \quad (5)$$

As assumed in *equation (3)*, the denominator of *equation (5)* must be set to one to obtain the estimated transmission value. The estimated transmission in the sky region is lower than its actual value. Therefore, the efficiency of the haze removal technique is lower in the sky region because the demand for transmission values is larger. It is difficult to estimate the actual depth of the sky because it is uncertain. According to the luminance distribution in the HSL colour space, hazy images are justified with a change in depth. Luminance is therefore used to imitate the depth of the scene.

Based on luminance, estimated transmission is given as:

$$T_L(x) = e^{-\beta \tilde{L}(x)} \quad (6)$$

Here T_L defines the estimated luminance transfer. L is the revised luminance. There are various models such as the Henyey and Greenstein phase function [7], the Mie scattering model [27] and the Rayleigh scattering model [16] to describe atmospheric scattering. In a hazy atmosphere, the Mie scattering model is most suitable. The Mie scattering model states that the angle of the camera, the amount of haze and the distance of the object together determine the scattering coefficient β. To capture the sky images, a camera angle of 60° is sufficient. Therefore, we used the corresponding values of β in the Mie scattering model [27] for a camera angle of 60°. The values of the scattering coefficient are given as:

$$\beta = \begin{cases} 0.3324, \lambda = 700\mu m(\text{red}) \\ 0.3433, \lambda = 520\mu m(\text{green}) \\ 0.3502, \lambda = 440\mu m(\text{blue}) \end{cases} \quad (7)$$

To obtain the actual depth, the luminance is expanded as follows:

$$\tilde{L}(x) = \frac{\tau}{l^*} l(x) \quad (8)$$

Where τ is a range of real depth determined based on an optimization procedure, l is the luminance of the input image, and l* is set to 95% of the luminance value, which describes the range of available luminance.

This parameter is set so that the difference between the transmission maps of DCP and luminance, P(τ), is the smallest. The difference is calculated as

$$P(\tau) = \frac{1}{n} \sum_n (T_L(\tau) - T_d)^2 \quad (9)$$

Here T_L is the luminance transmission, T_d is a transmission of DCP and the total number of images is represented by n, which is used to calculate the mean square error P. The higher the value of τ, the greater the haze removal in strong haze. However, a lower value provides a more natural visual effect in less hazy conditions.

3. PROPOSED FUSION METHOD FOR IMAGE DE-HAZING

This piece of work presents a Fusion of Luminance and Dark Channel Prior method to effectively and organically restore the sky region by de-hazing the hazy image. The medium transmission correction and atmospheric light estimate in the image degradation model are the primary steps of the suggested technique. While examining hazy images, it is observed that the shift in luminance from the foreground to the sky often corresponds well with the change in depth. It is suggested that the transmission of sky and background regions be determined from the luminance model. The dark channel prior is the main basis for estimating the foreground region's transmission. A transmission weight is utilized to fuse the transmissions from the luminance and dark channel prior models. An atmospherically degraded image's visual quality can be greatly improved by the suggested fusion technique by maintaining colour distortion and processing the sky area more organically. Furthermore, in the process of refining raw transmissions, a novel technique called Fast Guided Filter [9] is used instead of the more time-consuming and memory-intensive Guided Filter [10] by down-sampling to estimate the dark channel prior transmission map. Due to this, the proposed approach is faster than other equivalent methods currently in use and saves computing time.

The proposed approach combines the transmission values obtained from dark channel prior for foreground (background) region and luminance model for sky region in transform domain using SWT. The fusion of the transmission values is done at pixel level in this proposed approach. The framework of the proposed fused transmission model is depicted in *figure 3*.

- Initially the dark channel prior transmission model was applied on the original hazy image to obtain a haze-free image. This method was carried out to obtain the transmission values for foreground or background region. The output image was further passed through guided filter to remove artifacts and halos. Similarly, to obtain the transmission values for sky region, luminance model was used.

- Then, both the haze-free images obtained were transferred to transform domain by use of 2-D stationary wavelet decomposition, and we get approximate detail coefficient along with horizontal, vertical, and diagonal coefficients for both the images.

- The approximate detail coefficient obtained from both the images were fused using the fusion rule as follows:

$$F_A(x,y) = p(x,y).C_{A_d}(x,y) + q(x,y).C_{A_l}(x,y) \quad (10)$$

Where

$$p(x,y) + q(x,y) = 1 \quad (11)$$

Here p and q are the weighted coefficients and C_{A_d} represent the approximate coefficients from the dark channel prior and C_{A_l} is the approximate coefficient from the luminance model.

The horizontal, vertical, and diagonal coefficients for the fused image were selected considering the lowest value from the respective decomposed sets.

In the end, the image was restored by an inverse stationary wavelet transform of the fused image.

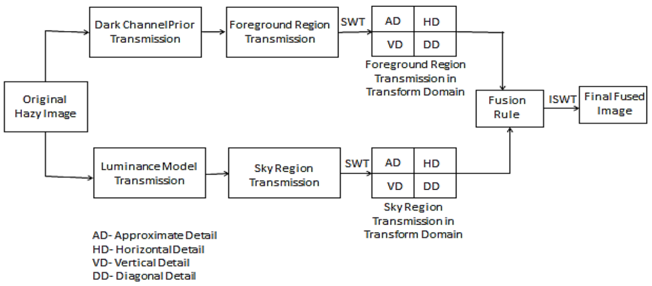

Figure 1. Framework of the proposed transmission model based on fusion

4. RESULT AND DISCUSSION

In this section, the effectiveness of the proposed fusion method in the transformation domain is presented based on various statistical parameters.

The quantitative analysis shown in *table 1* is based on the analysis of seven different hazy images, namely A, B, C, D, E, F and G. The seven initial images with the respective de-hazed images corresponding to the different methods are shown in *figure 2*. The performance of the proposed method is evaluated using statistical parameters such as PSNR, deviation index, and correlation and structural similarity measurement indices. A brief description of the parameters is given below.

4.1 Peak Signal to Noise Ratio (PSNR)

PSNR is an important tool to quantify the acceptability of the image. PSNR [28] is dependent on the Root Mean Square Error (RMSE), which can be mathematically determined as follows:

$$RMSE = \sqrt{\frac{\sum_{u=1}^{m}\sum_{v=1}^{n}[R_{img}(u,v) - R_{Fimg}(u,v)]^2}{m*n}} \quad (12)$$

R_{img} serves as the model image and R_{Fimg} is the fused image that was restored. The corresponding PSNR is:

$$PSNR = 10 * ln(\frac{P\,max * P\,max}{RMSE^2}) \quad (13)$$

P_{max} is the maximum intensity in the fused image. A higher PSNR value indicates a better fusion process.

4.2. Deviation Index (DI)

The deviation index is measured as follows:

$$D_{index} = \frac{1}{p*q}\sum_{s=1}^{p}\sum_{t=1}^{q}\frac{|Img_H(s,t) - I_F(s,t)|}{Img_H(s,t)} \quad (14)$$

Img_H stands for the intensity of the blurred image and I_F for the intensity of the fused image. A better fusion process is achieved if the value of DI is lower.

4.3. Correlation Coefficient (CC)

It is calculated as follows:

$$CC(I_f, I_g) = \frac{\sum_{s,t}\left|(I_{f_{s,t}} - \mu_f)\times(I_{g_{s,t}} - \mu_g)\right|}{\sqrt{\sum_{s,t}(I_{f_{s,t}} - \mu_f)^2 \times \sum_{s,t}(I_{g_{s,t}} - \mu_g)^2}} \quad (15)$$

$I_{f_{s,t}}$ and $I_{g_{s,t}}$ are the intensities at the position (s,t) of the original and the fused image. μ_f and μ_g are the mean values of the fused and original image. A higher CC value means a better fusion result.

4.4. Structural Similarity Index (SSIM)

The structural similarity index essentially measures three basic properties of an image: luminance, contrast, and structure. The SSIM is the multiplicative combination of all these three terms [28].

$$SSIM(p,q) = [I_l(p,q)]^{\alpha}.[I_c(p,q)]^{\beta}.[I_s(p,q)]^{\gamma} \quad (16)$$

I_l, I_c and I_s are the terms for luminance, contrast, and structure respectively. A higher value of SSIM indicates a better performance of the fusion process.

Table 1. Results of several de-hazing methods

Image	Method	PSNR	DI	CC	SSIM
A	DCP model	15.5435	0.4274	0.8856	0.7126
	Luminance model	16.7449	0.4062	0.9306	0.7456
	Proposed model	19.2181	0.2135	0.9445	0.8139
B	DCP model	15.5824	0.5219	0.9327	0.5799
	Luminance model	20.5913	0.3136	0.9448	0.7506
	Proposed model	23.2350	0.2203	0.9641	0.7657
C	DCP Model	16.1545	0.3387	0.9444	0.6394

	Luminance model	20.8178	0.2607	0.9693	0.6687
	Proposed model	20.9928	0.1875	0.9867	0.6960
D	DCP Model	20.1898	0.4471	0.8916	0.7415
	Luminance model	24.7872	0.2613	0.9136	0.8976
	Proposed model	32.4007	0.099	0.9292	0.9609
E	DCP model	19.1817	0.5375	0.9693	0.6960
	Luminance model	24.0105	0.3882	0.9649	0.5544
	Proposed model	26.0968	0.2173	0.9797	0.6845
F	DCP model	20.1898	0.4471	0.9136	0.7415
	Luminance model	24.7872	0.2613	0.9263	0.8976
	Proposed model	27.4007	0.1903	0.9692	0.9609
G	DCP model	25.5824	0.5219	0.9327	0.5799
	Luminance model	28.5913	0.3136	0.9641	0.7506
	Proposed model	33.2350	0.2203	0.9848	0.7656

The proposed method is compared to two existing popular de-hazing methods. The first method is dark channel prior, and the other one is the luminance model. The results of the models are in the second column and column of *figure 2* respectively. In addition to the visual analysis, the suggested algorithm is evaluated by the analysis of four quantitative assessment parameters. The original, haze-free images served as the ground truth for comparison with the final de-hazed images because it was challenging to obtain the corresponding ground truth data for the input haze images. The two metrics used to assess the variations between each pair of ground truth haze-free image and de-hazed result were PSNR (Peak Signal to Noise Ratio) and SSIM (Structural Similarity Index). The CC (Correlation Coefficient) and DI (Deviation Index) were the other two evaluation metrics that were measured using the haze image as the reference. *Table 1* presents a summary of the results of the objective assessment. The highest PSNR, SSIM, and CC values are obtained using the suggested strategy. It attests to the fact that that outcome is the most accurate. Additionally, it is evident that the predicted outcome, which is consistent with the ground reality, maintains the optimal natural weather conditions in the sky region. The PSNR score of the luminance model approaches that of the suggested method, although the output is typically a little fuzzy and the foreground is excessively dark. Their score illustrates that their results have a lot of black points. The results of Luminance model and DCP model have large DI values than the proposed method. This is because the suggested method does not result in over-sharpened edges, but the outputs of these methods have a lot of noise in the sky region. The result shows that the proposed algorithm treats both the sky region and the foreground region more naturally and restores the details of the scene well.

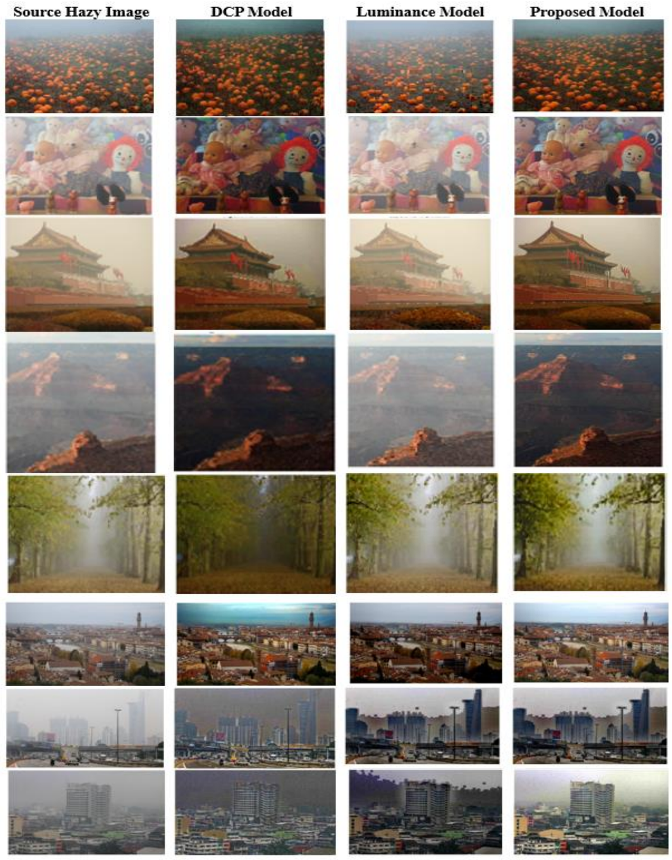

Figure 2. Hazy Images (A, B, C, D, E, F, G) and results based on different de-hazing methodologies

5. PROCEDURE FOR LEVEL OPTIMIZATION FOR WAVELET DECOMPOSITION

The total number of decomposition levels must be optimized to obtain an optimal fusion result for the restoration since changing the scale of the decomposition levels leads to a different performance of the fusion technique. The performance of wavelet-based image fusion depends on the number of decomposition levels in the wavelet transform. To obtain the optimal fusion results, the number of decomposition levels need to be optimized using optimization algorithm. As shown in *figure 3*, the flow is as follows.

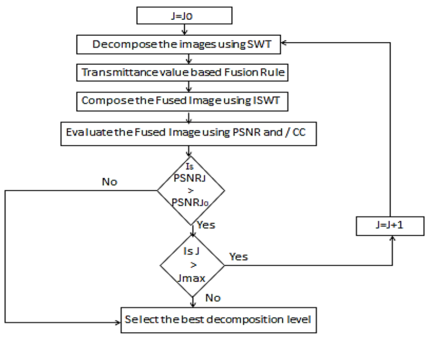

Figure 3. Flowchart for Optimization of Decomposition Level of SWT

- Let the number of the decomposition levels for the wavelet-based image fusion is J. The value range of J is

$$0 \le J \le \log_2(N-1) \tag{17}$$

where the size of original images is N by N.

- Thereafter, SWT of the resulted DCP model output and luminance model output images A and B were found up to specified decomposition level. Each coefficient sub-image is divided into non-overlapping blocks with the size of m x n. The i^{th} image blocks of A and B sub-images are referred to as A_i and B_i respectively.
- The transmittance values of two corresponding blocks A_i and B_i, given by T_a and T_b are compared to determine the sharper image block and i^{th} image block F_i of the fused image can be constructed as:

$$F_i = \begin{cases} A_i & \text{if } T_i^a > T_i^b \\ B_i & \text{if } T_i^b > T_i^a \\ (A_i + B_i)/2 & \text{otherwise} \end{cases} \tag{18}$$

Subsequently, using inverse transform, all the fused coefficients are coupled to get final fused image employing hybrid approach and then optimization algorithm, as shown in the above flowchart, is developed under the condition of obtaining maximum PSNR and CC to achieve the optimal degree of decomposition of SWT. The termination criterion for the algorithm is set so that the decomposition level with the maximum PSNR value has the largest similarity value so that maximum information content can be recovered in the restored image.

6. CONCLUSIONS

In this work, a simple but innovative and very efficient method for reducing haze in single images was proposed. The main problems of the DCP method were investigated and a novel strategy was proposed to solve the haze reduction problems of images with sky. In the proposed approach, dark channel prior and luminance models were first used to find the transmission coefficients for each hazy source image, and then SWT was applied to each transmission coefficient. To obtain better results, the estimated transmission coefficients were fused and reconfigured using inverse wavelet processing. The visual impact and quantitative evaluation of the statistical parameters show that the proposed transmission model-based image fusion provides significant added value in preserving the structural features of the objects and the resolution of the image compared to other currently used restoration methods. It was also found that the method also improves the colour and contrast and removes the colour cast from the images. The suggested method could help improve the technical and aesthetic results of denoising sky images from a long distance. The approach has been tried on high-resolution images captured by drones and the result is successful within a reasonable computational time. It is also observed from the result that the method has advantages in preserving the authenticity of images with the sky, as a comparison with analogous modern methods.

Conflicts of Interest: The authors declare no conflict of interest.

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