



Multi-Focus Image Fusion using Non-Local Mean Filtering and Stationary Wavelet Transform

Kapil Joshi, N.K.Joshi, Manoj Diwakar, A.N. Tripathi, Himanshu Gupta

Abstract: *Today's research era, image fusion is a actual step by step procedure to develop the visualization of any image. It integrates the essential features of more than a couple of images into a individual fused image without taking any artifacts. Multi-focus image fusion has a vital key factor in fusion process where it aims to increase the depth of field using extracting focused part from different multiple focused images. In this paper multi-focus image fusion algorithm is proposed where non local mean technique is used in stationary wavelet transform (SWT) to get the sharp and smooth image. Non-local mean function analyses the pixels belonging to the blurring part and improves the image quality. The proposed work is compared with some existing methods. The results are analyzed visually as well as using performance metrics.*

Keywords: *Image Fusion, Stationary Wavelet Transforms (SWT), Non-Local Mean Filter (NLM).*

I. INTRODUCTION

Now a days, researchers have been searched a lot of ways to enhance the quality of human visual level and its performance [5]. In this imaging field, image fusion is the best technique with the couple of input images [1] and combines them to generate best vision quality input image. The goal of image fusion [4] [8] [17] [21] is having more improving informative resultant images in terms of edges, sharpness, clearness etc. Fusions with two input images are based on multi-sensor, multi-focus [20], multi-modality and multi-temporal etc.

Further the classification of image fusion is categorized into three segment levels [4] [7] with pixel i.e. low level, features i.e. average level and decision i.e. high level [6]. Pixel level generally operates on spatial and frequency domain and works directly on the various pixels [3]. While features level fusion deals only with all the features of an image. Decision level fusion treated as high level fusion to compress the image with the best quality perception [22].

Image fusion can be treated as generating [5] [9] as relevant information from meaningless data [22].

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The useful information is enrolled all in focus information. Image fusion [2] [7] [8] technique has become more strongly [9] [12] and widely used technique to enhance the human visual elucidation of any image in different application such as multi-focus [20] image, military affairs fields, robotics, medical health diagnosis area, biometric machine, remote sensing fields, monitoring application, surveillance area, computer vision etc [11][12][15]. The major objective of image fusion is to retain important, comprehensive and accurate information than the separate source of images [21].

The image has suitable essential information for processing task but the limitations of focusing problem of image in multi focus images are used by many researchers [20]. It is very challenging task in recent years. Processing system can be implemented for better visualization because of individual image that cannot contain much more information. Sometimes it is very difficult to focus all the objects in a single image due to the limitations of profundity of focus.

Mostly imaging system represents a limitation of depth of field. The scene of an image using a limited set of distance always remains in proper focus while images are closer and appears as blurred or we can say those are out of focus in an image. Bin yang et.al. [1] [2016] introduced demoicing method for raw information and also produced a single chip camera. Further the final results are obtained from the sparse coefficients and the given method is also tested on quantitative and qualitative performances factors. Many color images in the form of book, rose and flowers being used during the experimental work. It measures the following parameters like SWT, NSCT, SOMP and GFF. The experimental stage was also cleared into ground truth color images, random CPA images and sensed images. This model is explored with the joint share model but the problem is to implement on 3D medical images. Most of the time we discuss about medical images and its modality to display the useful information in terms of CT, MRI and PET images. Xiaojunxe et.al. [2][2016] also discussed on multimodal concept and presented a multimodal scheme based on discrete fractional wavelet (DFRWT). They decomposed source images by this DFRWT technique in various order and further applied inverse DFRWT to get the resultant fused images. The proposed flow chart has some fusion rule and generated fusion coefficient. In future work, image enhancement will be fully focused on more formats of medical images which include x-ray and ultrasound modalities. Caiping Liu et. al. [3] [2016] found the problem of the discontinuity of fusion area so they proposed a new multi-focus image fusion method based on energy-efficient concept.

The latest multi-scale neighbour distance method can also be affected on the detail of images.

They also used mathematical morphology for processing operation.

This experimental work will be better and usable in the analysis of multi-focus fusion regions. They applied different source images like as flower, lab & tiger images data sets. The problem of this study is all about the pixels in the border area is not solved yet. Further they will optimize and resolved in next study.

zhangbaohua et. al. [4] [2016] discussed a problem about artifacts and blurred edges so they proposed a algorithm of novel fusion for multi-focus based on robust principal component analysis(RPCA) as well as guided filter to preserve edges of images and background enhancement using the extraction of essential structure information. They also described the morphological algorithm used to get precise fusion decision map. The proposed method gives the best performance of fusion on different scales of images are pepsi, flower, clock, calendar and stone images. The proposed scheme is also useful in noisy image due to guided filter. Jinshengxiao et.al. [5] [2016] improved the best quality of observed general color images. They proposed multi-focus fusion algorithm of depth extraction and this algorithm can exclude the blocking artifacts and submerge the state of the art in both cases that are subjectively & objectively. The outcomes of this proposed work will generate few fused images with respect to clear and sharpe edges having better performance. N.K. kaplan et. al. [6] [2016] proposed latest scheme algorithm on lifting wavelet transform technique belongs to second generation.

They also proposed to use the lattice structure filter for multi-scale transform (MST). In between, spatial domain is used for low and high passes both operations. Through this, lattice structure is composed with decomposition and reconstruction based concepts. Various color scales are utilized on different resolutions. These color source images are simply decomposed by undecimated lattice filters and the sub-bands are fused with few fusion rule. The conclusive results are obtained for clear, sharp and noisy images. Further the advantage of the proposed work is capable for hardware implementation using arithmetic operations by increased durability to noise.

Fanjiemeng et.al. [7] [2016] launched an algorithm for a couple of images those are visible light and infrared images. They combined object region detection through non-subsampled contourlet transform (NSCT). The comparisons are established between the current implemented method and other previous existing methods. Using the proposed algorithm an improved performance can be achieved through experimental work. In the future, the proposed work will be applicable for video fusion.

Hassan ghassemian [8] [2016] reviewed some fusion method at pixel level. He focused pixel level fusion based on remote sensing. Four various classes: CS, MRA, Hybrid, and Model based approaches are simply located in reviewed method. If we explain these four then CS method is very fast to implement. MRA method is all about top spatial distortion but now a best spectral consistency. To grab the benefits of both methods hybrid method is introduced. The ultimate results need to be rescaling of all images at native scale.

The approach of image fusion has been driven to all medical images A.P. james et. al. [9] [2014] did a survey on all kind

of images. They discussed five major imaging modalities based on medical era such as magnetic resonance imaging (MRI), computerized tomography (CT), positron emission tomography (PET), single photon emission computerized tomography (SPECT) and ultrasound. They also compared the different organs of human body like brain, breast, prostate, lungs and many more. This review study will be more effective for any diagnosis and monitoring in medical field. Fatma el-zahraet. Al. [10] [2015] again considered medical images with registration and fusion. They presented the current challenges with medical image registration as well as fusion. They also classified the diagnostic images. These are following radiology, visible light photography printed signal (waves), microscopy and reconstruction. Complete procedure of medical images is also discussed whereas MRI to PET images, MRI to SPECT images simultaneously CT. This discussion is very helpful and useful in any medical diagnosis in future.

Yong yang et. al. [11] [2010] presented a wavelet based approach for medical image fusion. They simply applied wavelet transform on medical images and used other fusion schemes for merging various coefficient low frequency band are selected using a visibility based scheme and other high frequency band are in variance based method. They have used been gray scale medical brain type images for their research's work. This experimental work shows the high spatial scale resolution in any fused image.

This paper is organized in different sections. After introduction, rests of sections are segmented as: section 2: Described preliminaries. In Section 3: Proposed work is described. Section 4: Performance Evaluation Metrics are discussed. Section 5: Results and analysis are explained. Finally the conclusion is mentioned in section 6.

II. PRELIMINARIES

A. Stationary Wavelet Transform (SWT)

Stationary Wavelet Transformation is an algorithm of wavelet transform [5] designed to solve the problem of translation-invariance of the discrete wavelet transform (DWT).

SWT is basically an inherently redundant based scheme as the particular output of every level of SWT having the similarratio[2] of samples similar as the input so for a decomposition phase of N levels and there is a kind of redundancy of N in the wavelet based coefficients[3].

Stationary Wavelet Transform (SWT) is also known as Un-decimated wavelet transform that does not destroy coefficients at each transformation level. SWT can be applying on low and high pass filter [7] [10] to the data at each and every level. Stationary Wavelet Transform existing with complex problem based on computationally parts.

It deals with one dimensional using decomposition steps, filter computation and initialization factors.

B. Non-Local Mean Filter (NLM)

Non local mean is applicable for the redundant data of the image in pixel [2] or spatial domain to reduce the noise very [14] [16] effectively and each neighbourhood in a general image have various duplicate copies in similar images.

Generally non local mean is a kind of filter where it estimates the intensity of pixel noise frees [15].

Non local mean algorithm is a kind of self-similarity method introduced by efros and leung. Apart from this, the non-local mean [15] method is proposed by buades is totally based on the same concept.

Each pixel p of the non-local means denoised image is computed with the following formula:

$$NL(V)(p) = \sum_{q \in V} w(p, q) V(q) \quad (1)$$

Where, V is the noisy image, and weight, $w(p, q)$ meet the following conditions $0 \leq w(p, q) \leq 1$ and $\sum_q w(p, q) = 1$. Each pixel is a weighted average of the entire pixel in the image.

Non local mean algorithm can be defined as

$$NL[v](i) = \sum_{j \in I} w(i, j) v(j), \quad (2)$$

Where, the family of weights $\{w(i, j)\}_j$ depend on the similarity between the pixels i and j , and satisfy the usual conditions $0 \leq w(i, j) \leq 1$ and $\sum_q w(i, j) = 1$.

The similarity between two pixels i and j depends on the imilarity of the intensity gray level vectors $v(\mathcal{N}_i)$ and $v(\mathcal{N}_j)$, where \mathcal{N}_k denotes a square neighbourhood of fixed size and cantered at a pixel k .

The actual limitation of non-local mean filter is just time consuming process and that is all about the calculation of Euclidian distance [14] between same windows in any image. Whole square calculation computational complexity can be $m^2 \cdot n^2$.

Where m^2 define the size of same window and n^2 tells about the number of pixels in any noised image [15].

III. PROPOSED WORK

We take two images then convert these into gray scale with the format of double integer. Resize these two images with the size of 256. While sub plotting we decompose the images into stationary wavelet transform (SWT).

The whole decomposition process is performed with approximation, horizontally, vertically and detailed part. In the next phase, we fuse all four decomposed part and apply inverse operation and getting the better results than previous visualization. To find the similarities between two images, we implemented coefficient correlation and obtained the noise ration using PSNR.

The summary of proposed algorithm is given below:-

Step 1: Initially we take two blurred images i.e. X and Y .

Step 2: After Applying Stationary Wavelet Transform (SWT), we find four decomposition parts low low (LL), low high (LH), high low (HL), high high (HH).

Step 3: Combined the low low (LL1) part of image X and low low (LL11) part of image Y in Fusion Using Average Operation and remaining level has been considered in Fusion of Coefficients.

Step 4: We generated LL' , LH' , HL' , HH' part from fusion using average operation and fusion of coefficients and applied inverse stationary wavelet transform (ISWT) with the variable of Z .

Step 5: We subtracted the fused part Z from X and Y and stored in another variables i.e. X' and Y' .

Step 6: After getting X' and Y' , we apply non local mean (NLM) filter to improve the edges and increase the sharpness of any image.

Step 7: Filtered image can be treated as fused resultant image.

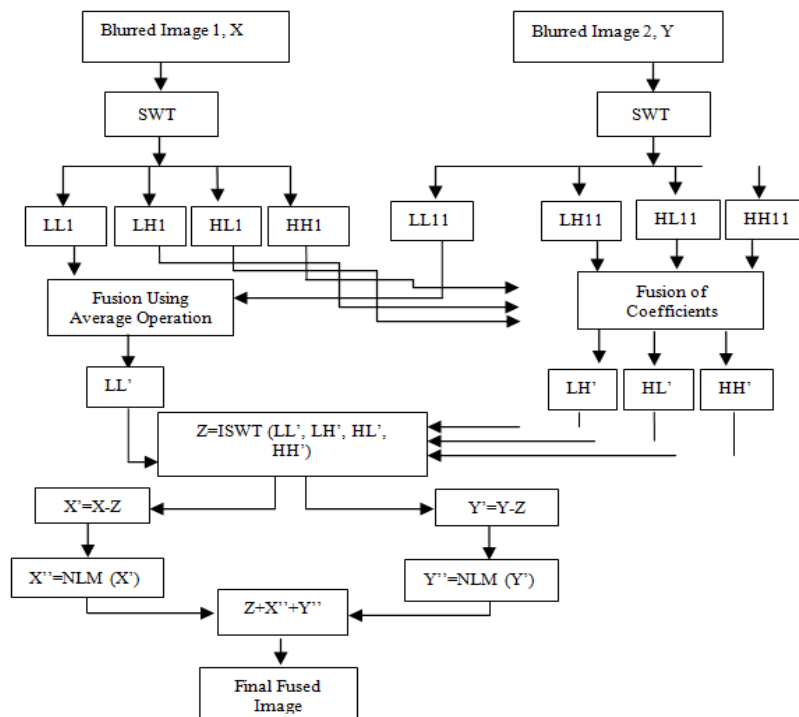


Fig. 1: Proposed Algorithm

IV. PERFORMANCE EVALUATION PARAMETERS

A. Mean

Mean formula can be defined as:-

$$\text{Mean } \mu(I_f) = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (I_f(i, j)) \quad (3)$$

Where $i=1$ to N and N shows the actual number of values in image matrix form.

B. Signal Noise Ratio (SNR)

Signal Noise Ratio (SNR) is calculated in between

$$\text{SNR} = 10 \log_{10} \left\{ \frac{\sum_{i=1}^M \sum_{j=1}^N (I(i, j) - F(i, j))^2}{\sum_{i=1}^M \sum_{j=1}^N I(i, j)} \right\} \quad (4)$$

In this equation, I and F defined the actual input and output image.

C. Peak Signal Noise Ratio (PSNR)

Peak Signal Noise Ratio (PSNR) tells about the ratio among different pattern of images. It is based on Mean Square Error (MSE). The formula is defined as:-

$$\text{PSNR} = 10 \log_{10} \left\{ \frac{(2^n - 1)^2}{\text{MSE}} \right\} \quad (5)$$

$\text{MSE} = \sum \sqrt{\epsilon^2}$ with treated as error values.

D. Cross Entropy

The quantity of any image is measured in cross entropy. It is defined as:-

$$\text{CE}(I_1, I_2, I_f) = [\text{CE}(I_1, I_f) + \text{CE}(I_2, I_f)]^{1/2} \quad (6)$$

E. Normalized Mutual Information

Normalized Mutual Information (NMI) calculates the mutual dependence between two random variables. In image fusion concepts, it estimates the data shared between the original images and the final resultant image. NMI is computed as:-

$$\text{NMI} = \frac{\text{MI}(A, F)}{H(A) + H(F)} + \frac{\text{MI}(B, F)}{H(B) + H(F)} \quad (7)$$

Where source images are treated as A and B and F will be as fused image, $\text{MI}(A, F)$ and $\text{MI}(B, F)$ show the mutual information between images A , F and B , F . $H(\cdot)$ gives the entropy of the image.

F. Feature Mutual Information

Feature Mutual Information (FMI) exploits basically visual image features and makes use of the mutual information to calculate the better quality of the final fused images. Given the multi-focus source image A and B , and F fused image. The mutual information between A and F is calculated as average local information.

$$I(A, F) = \frac{1}{n} \sum_{i=1}^n \frac{I(A, F)}{H_i(A) + H_i(F)} \quad (8)$$

Where the $I(A, F)$ and $I(B, F)$ are the factors and averaged to compute the FMI metric.

$$\text{FMI} = \frac{1}{2} [I(A, F) + I(B, F)]$$

G. Nonlinear Correlation Information Entropy

Nonlinear Correlation Information Entropy (QNCIE) is a kind of theory-based quality metric. It uses the concept of

nonlinear correlation coefficient (NCC) between the original images i.e. A , B and the fused image is treated as F and constructs a nonlinear correlation matrix in the form of R :

$$R = \begin{bmatrix} 1 & \text{NCC}_{AB} & \text{NCC}_{AF} \\ \text{NCC}_{BA} & 1 & \text{NCC}_{BF} \\ \text{NCC}_{FA} & \text{NCC}_{FB} & 1 \end{bmatrix} \quad (9)$$

Q_{NCIE} is computed as:

$$Q_{\text{NCIE}} = 1 + \sum_{i=1}^3 \frac{\lambda_i}{3} \log_{256} \frac{\lambda_i}{3} \quad (10)$$

Where λ_i are the eigen values of matrix i.e. R .

H. Fusion loss

The complete information is incomplete during the process of fusion is measured.

$$L_{AB/F} = \frac{\sum_{\Delta n, m} r_{n, m} [(1 - Q_{n, m}^{AF}) + (1 - Q_{n, m}^{BF}) w_{n, m}^B]}{\sum_{\Delta n, m} w_{n, m}^A + w_{n, m}^B} \quad (11)$$

Where $r_{n, m}$ is flag where it indicates the value of 0 or 1.

I. Fusion Artifacts

Fusion artifacts are computed as weighted integration of the fusion noise estimate over the overall fused image. It characterized unwanted data added during the process of fusion. It is defined as:-

$$N_{AB/F} = \frac{\sum_{\Delta n, m} N_{n, m} (w_{n, m}^A - w_{n, m}^B)}{\sum_{\Delta n, m} w_{n, m}^A + w_{n, m}^B} \quad (12)$$

$N_{n, m}$ shows the fusion loss at various locations implanting fused gradients that are stable than input is computed.

J. Petrovic's metric

Petrovic's metric ($Q_{AB/F}$) is treated as a gradient fusion metric. It measures the actual amount of gradient data or it can be information i.e. transferred from the original images to the resultant fused image.

$Q_{AB/F}$ is calculated as:-

$$Q_{AB/F} = \frac{\sum_{x=1}^W \sum_{y=1}^H Q^{AF}(x, y) w^A(x, y) + Q^{BF}(x, y) w^B(x, y)}{\sum_{x=1}^W \sum_{y=1}^H (w^A(x, y) + w^B(x, y))} \quad (13)$$

Where, W and H denoted as the width and the height of any image.

K. Total Fusion Performance Measure

The total fusion performance parameters $Q_{AB/F}$ is estimated as a weighted sum of rationale images A and B 's edge information. The absolute information or data conveyed from input images to resultant images are completely obtained.

$$Q_{AB/F} = \frac{\sum_{\Delta n, m} Q_{n, m}^{AF} w_{n, m}^A + Q_{n, m}^{BF} w_{n, m}^B}{\sum_{\Delta n, m} w_{n, m}^A + w_{n, m}^B} \quad (14)$$

L. Yang's Metric

Yang's metric (Q_Y) is a fusion quality metric based on structural similarity and it measures the sharp amount of structural information fended in final fused image in the form of F from the basic source images A and B .

$$Q_Y = \begin{cases} \lambda(w) \text{SSIM}(A, F|w) + (1 - \lambda(w)) \text{SSIM}(B, F|w), & \text{if } \text{SSIM}(A, B|w) \geq 0.75 \\ \max(\text{SSIM}(A, F|w), \text{SSIM}(B, F|w)), & \text{if } \text{SSIM}(A, B|w) < 0.75 \end{cases} \quad (15)$$

Where w was a local window and $\lambda(w)$ is treated as:

$$\lambda(w) = \frac{s(A|w)}{s(A|w) + s(B|w)}$$

and s as a local measurement of saliency image.





















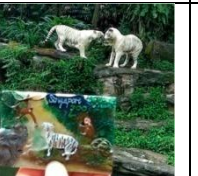
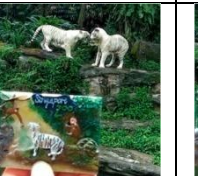

















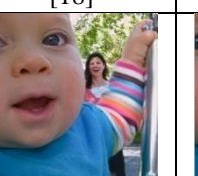


V. SIMULATION RESULTS AND ANALYSIS

The following data set represents the results of DWT and

SWT based images where we focus the blurring problem and resolve it with the new proposed visualization results.

We calculate and compare the following visual results and derived the final fused image that gives the better information than source images.

Table- I: Results on Color images using Existing methods and proposed method

					
A1	A2	[17]	[18]	[19]	Proposed work
					
B1	B2	[17]	[18]	[19]	Proposed work
					
C1	C2	[17]	[18]	[19]	Proposed work
					
D1	D2	[17]	[18]	[19]	Proposed work
					
E1	E2	[17]	[18]	[19]	Proposed work
					
F1	F2	[17]	[18]	[19]	Proposed work
					

G1	G2	[17]	[18]	[19]	Proposed work
					
H1	H2	[17]	[18]	[19]	Proposed work
					

Our visualized experiments are fully focused on quality of image in terms of sharp edges, smoothness and clarity of image. In particular dataset from A1, A2 to C1, C2 having good texture and contrast features. Specially B1 and B2 having extra brightness with a single focused objects. Apart from this D1, D2 and E1, E2 contains better contrast with homogeneous region E1, E2 still having some blurring

factors. Rest of datasets F1, F2, G1, G2, H1, and H2 are based on good results where edges are very sharp and clarity of images is good as we can see the better information than existing work. Specially F1, F2 produced the good contrast features using brightness. The proposed scheme gives the better outcomes in terms of sharpness and smoothness.

Table- II: Performance Metrics using existing methods and proposed method

	Methods	Mean	SNR	PSNR	Cross entropy	Normalized Mutual Information	Feature Mutual Information	Nonlinear Correlation Information Entropy	Fusion loss	Fusion Artifacts	Petrovi c's metric	Total Fusion Performance Measure	Yang's Metric
Data Sets													
Set 1(A1 to H1)	17	0.1081	6.0558	20.6755	0.6251	1.2092	0.6630	0.8459	0.1039	0.0220	0.7643	0.8920	0.9867
	18	0.1083	6.0343	20.7097	0.6193	1.2097	0.6626	0.8458	0.1046	0.0231	0.7645	0.8928	0.9895
	19	0.1095	6.0528	20.2091	0.6154	1.2081	0.6632	0.8473	0.1046	0.0254	0.7656	0.8919	0.9871
	Proposed work	0.1098	6.0242	20.6018	0.6198	1.2087	0.6638	0.8470	0.1053	0.0279	0.7655	0.8932	0.9887
Set 2(A2 to H2)	17	0.1081	6.0558	20.6755	0.6251	1.2049	0.6620	0.8410	0.1029	0.0245	0.7641	0.8924	0.9852
	18	0.1052	6.0560	20.3092	0.6061	1.2097	0.6626	0.8458	0.1070	0.0238	0.7645	0.8938	0.9895
	19	0.1077	6.0592	20.6129	0.6153	1.2059	0.6618	0.8420	0.1046	0.0254	0.7678	0.8919	0.9875
	Proposed work	0.1080	6.0590	20.6899	0.6129	1.2099	0.6645	0.8479	0.1050	0.0268	0.7680	0.8944	0.9888

In dataset 1 that is range from A1 to H1. Proposed work is evaluated using mean function. Mean value is concluded with better results. After it signal noise ratio is very less than existing work so that images show the detailed information. Further we analyzed the value of peak signal noise ratio that is increasing the capability of image pattern. Cross entropy is measured with the quantity of an image. Its value shows the correct measurement. In experimental work, data sharing capability is also done in normalized mutual information parameters. The proposed value of feature mutual information defines the quality of fused image. The quality metric of nonlinear correlation information entropy is evaluated efficiently as compared to previous work. Correlation data can be generated through final resultant work. The proposed result protects the loss of data by fusion loss and added more information to increase more artifacts during the process of fusion as we can see in table 2. When we consider the gradient data then all gradient metric's values also increased at large scale using petrovic's metric. The weighted sum of rationale images examined in our proposed method. It gives the extraordinary features. The structural information of fused image also improved in our practical work using yang's metric.

The final results from table 2, we can analyze that the proposed scheme provides better outcomes as compare to existing method.

VI. CONCLUSION

In multi-focus image fusion method, sharp regions are focused in multiple set of images of similar scene with pixel levels. All objects are focused to obtain the clarity of images. This paper introduced multi-focus fusion algorithm having two operation fusion using NLM technique. The objective of work is to remove the blurring problem and increasing the quality of image pattern using specific parameters like cross entropy, peak signal noise ration and Normalized Mutual Information (NMI) etc. The tested results are visualized through multiple datasets. The metrics gives the excellent performance. We employ a non-local mean technique to further refine the focused region maps. The final results show better performance measurement. In future, more filtering techniques can be applied to obtain quality images which generate fewer artifacts and preserve the color pattern.

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