Due to the limited range of focusing length of digital imaging system (camera) the poor quality of image is formed or it is not capable to form all-in-focus image of substances at varying distance in a scene. To get an image of enhanced quality or all in focus image a multi-focusing system is used. In this paper, we propose a novel method for multi focus image fusion using improved dual tree complex wavelet transform (DT-CWT) with kernel padding and filtering technique. Firstly, wavelet transform is applied to decompose the source image into different components. Then, apply the kernel padding and high pass filter to sharpen the image and diminish the noise after filtering apply fusion rule to reconstruct the decomposes image to obtain fused image of enhanced features. Our proposed work is executed on MATLAB2012a and its comparative analysis is performing using performance measuring parameters such as MSE and PSNR. The experimental result reveals that our proposed method is very appropriate for multi-focus image fusion and also outperformed than other existing techniques.

Keywords: MSE, PSNR, DWT, PCA, DTCWT, DTWTKHF, Image Fusion

1. Introduction

In advanced picture transforming framework, different picture securing strategies have been developed from past decade to enhance the nature of picture and these procedures is sought different application, for example, medicinal imaging, remote detecting, satellite imaging et cetera. These days the boss center of specialists is picture on picture combination process. Picture combination is the procedure of obtaining better picture determination by joining two or more pictures and structures a solitary picture. By Piella [1], a combination procedure is only a change of unmistakable data so as to blend a picture with more data than individual picture and incorporated picture is more fitting for visual observation. The picture combination technique is isolated into two classifications [2]: spatial area and change space. In spatial area, it specifically manages the picture pixels. The pixel qualities are controlled to attain to wanted data. This technique includes taking after methodologies, for example, PCA, averaging system, pyramid strategy and so forth. In recurrence space systems are in light of the control of the orthogonal change of the picture as opposed to the picture itself. This procedure contains wavelet change and Fourier change. Fourier change is respected as second dialects portrayal of picture data. Lamentably, Fourier change can't recreate the neighbourhood recurrence normal for picture. The DWT has some confinement, for example, associating, movement invariance, less directional affectability furthermore requires more computational expense than others. Such confinement of discrete wavelet change is overcome by double tree wavelet change yet this methodology is some intricate to outline. In this paper, we utilize altered double tree wavelet change to disintegrate the data picture into sub picture after that apply portion cushioning and high channel to get upgrade nature of pictures and afterward apply distinctive combination principle to recreate the decay picture to frame unique picture of more data. The layout of picture combination procedure is indicated is fig. 1
A. Multi-focus Image Fusion

Multi-center Image combination is procedure of consolidating data of two or more pictures of a scene and subsequently has “in with no reservations center” picture. At the point when one scene contains protests in diverse separation, the cam can be centred around every article consistently, making arrangement of pictures. At that point, utilizing picture combination method, a picture with better concentrate over all region can be produced. There are numerous multi-center picture combination strategies, today. One of them is Empirical Mode Decomposition based multi-center picture combination.

B. Dataset

One of the issues in this examination was making multi-center picture dataset that will be accessible for testing combination systems. For that reason, we utilized Nikon D5000 cam, and made in-house multi-center picture dataset. All pictures are in .jpg design. For our testing procedure, we utilized 27 sets of pictures, where 21 of them are from in-house dataset, while 6 sets are standard for testing multi-center picture combination strategies. Standard pictures are in .bmp position. Each of the 27 sets of defocused pictures are making Testing Image Dataset. The pictures gave here are to research purposes just. In Case of All-in-center picture utilizing proposed picture combination calculation.

Figure 2 Example of two defocused images from in house dataset
local energy is applied to bi-dimensional intrinsic mode function components of the corresponding frequency subdivision. If phase of bi-dimensional intrinsic mode function coefficients decomposed by bi-dimensional empirical mode decomposition on two source images is same, local energy maxima standard is used in frequency coefficients of fused image, else if corresponding phase is reverse, bi-dimensional intrinsic mode function coefficients of fused image is determined by weighted average method based on local energy. In conclusion, fusion outcome is received by contrary bi-dimensional empirical mode decomposition transform on fusion coefficient. Simulation demonstrates that the proposed algorithm is considerably done better than the traditional methods, such as maximum criterion, weighted average and wavelet fusion rules. In [4] proposed a fresh spatial domain multi focus image fusion method. The developed method, initially, calculate the point spread functions (PSF) of the source images. Subsequently, the images are artificially distorted by convolving them with the estimated PSFs. After that, the artificially blurred images are used to conclude the sharpest pixels of the source images. Lastly, the all-in-focus image of the prospect is constructed by assembling the sharpest pixels of the source images. The experiments are carried out on numerous multi-focus image sets. The proposed method and additional well-known image fusion techniques are compared in terms of visual and quantitative assessment. The results obtained illustrate the feasibility of the developed method. In [5] proposed a discrete wavelet transform (DWT) based fusion technique with a novel coefficients selection algorithm is presented. After the source images are decomposed by DWT, two different window-based fusion rules are separately employed to combine the low frequency and high frequency coefficients. In this system, the coefficient in the low frequency domain with maximum sharpness focus determine are selected as coefficients of the fused image, and a maximum neighbouring energy based fusion technique is proposed to choose high frequency sub-bands coefficients. In order to guarantee the homogeneity of the resultant fused image, a consistency verification procedure is applied to the mutual coefficients. The performance appraisal of the proposed method was conducted in both synthetic and real multi-focus images. The comprehensive index was proposed, in which the comprehensive index was on basis of spatial frequency and entropy. The comprehensive index is better with the higher spatial frequency and entropy. Firstly, the registered original images were divided into a series of blocks of which the sizes were proper and the same, and then the comprehensive index for each block of source images was calculated as the focus criterion function to select an optimal block for each corresponding block of the fused image. In view of the relevance between pixel and pixel in one image, the optimal blocks selected were fused with a global fusion function. Furthermore, the sum-modified-Laplacian of fused image was used as the measure function to supervise the adaptive blocking, in which the optimal block was obtained when SML of the fused image had reached a high value or the iteration had achieved the specified numbers. Finally, the optimal size of the sub-block was automatically obtained, which was used to fuse the source images. As it was shown in the experimental results, the proposed method which was simple, but more effective compared with the traditional multiscale decomposing methods such as wavelet transform, wavelet packet transform, contour let transform and so on. At the same time, the proposed method was also superior to the method in the literature for it could remove boundary discontinuities between image blocks. Contemporarily, much more details and edges information of the source images were reserved in the fused image. In [7] presented a new framework for the fusion of multi-focus images unambiguously designed for visual sensor network (VSN) environments. Multi-scale based fusion methods can frequently acquire fused images with excellent visual effect. Conversely, because of the defects of the fusion rules, it is approximately impracticable to completely circumvent the loss of constructive information and hence obtained fused images. The proposed fusion system can be divided into two processes: primary fusion and absolute fusion. The primary fusion is based on a dual-tree complex wavelet transform (DTCWT). The Sum-Modified-Laplacian (SML)-based visual contrast and SML are employed to fuse the low- and high-frequency coefficients, correspondingly, and primary composited image is obtained. In the absolute fusion process, the image block residuals technique and consistency authentication are used to perceive the focusing areas and next a decision map is obtained. The map is used to direct how to attain the final fused image. The performance of the proposed system was broadly tested on a number of multi-focus images, including no-referenced images, referenced images, and images.
with dissimilar noise levels. The experimental consequences clearly designate that the proposed system outperformed a range of state-of-the-art fusion methods, in terms of cooperation of subjective and objective appraisals, and is more appropriate for VSNs. In [8] explored two exclusive characteristics of multi-focus images: (1) The self-similarity of a solo image and the communal similarity among manifold source images (2) The distances from entity to focal plane. The earlier characteristic is used to recognize image structure-driven regions whereas soon after distill the image clarity by robotically estimating depth information of blurred images. Experimental consequences exhibit that the proposed method does better than the state-of-the-art fusion methods on image excellence and objective fusion criterion. In [9] proposed a fresh multi-focus image fusion method based on human visual system (HVS) and back propagation (BP) neural network is presented. Three features which replicate the transparency of a pixel are initially extracted and used to educate a BP neural network to conclude which pixel is comprehensible. The comprehensible pixels are then used to assemble the preliminary fused image. Thirdly, the focused areas are detected by measuring the resemblance among the source images and the preliminary fused image followed by morphological opening and closing operations. Lastly, the final fused image is obtained by a fusion rule for those focused regions. Experimental results demonstrate that the proposed method can present better performance and outperform numerous existing popular fusion methods in terms of both objective and subjective appraisals.

3 PROPOSED WORK

This section, explore our research work to extort the indispensable features by fusing the multiple images from image dataset. In our work modified DTCWT and Filtering techniques (high pass filter) is used to fuse the images for getting more information.

A. Discrete Wavelet Transform (DWT)

Wavelet transforms are multi-resolution image decomposition tool that provide a variety of channels representing the image feature by different frequency sub-bands at multi-scale. It is a famous technique in analyzing signals. When decomposition is performed, the approximation and detail component can be separated 2-D Discrete Wavelet Transformation (DWT) converts the image from the spatial domain to frequency domain. The image is divided by vertical and horizontal lines and represents the first-order of DWT, and the image can be separated with four parts those are LL1, LH1, HL1 and HH1[10]. Let s(n1,n2) is input image with size N1xN2 then scaling and wavelet function are:

\[ W_0(j_0,k_0) = \frac{1}{\sqrt{N_1 N_2}} \sum_{n1=0}^{N1-1} \sum_{n2=0}^{N2-1} s(n1,n2) \delta_{j_0}(n1,n2) \]  \[ (1) \]

\[ W_s(j_s,k_s) = \frac{1}{\sqrt{N_1 N_2}} \sum_{n1=0}^{N1-1} \sum_{n2=0}^{N2-1} s(n1,n2) \delta_{j_s}(n1,n2) \]  \[ (2) \]

B. DT-CWT (Dual Tree Complex Wavelet Transform)

The Dual-tree Complex wavelet transform (DT-CWT) [2, 3] is complex valued extension of the standard wavelet. Complex transform uses complex valued filtering that decomposes the image into real and imaginary parts in transform domain. The real and imaginary coefficients are used to compute magnitude and phase information. The prime motivation for producing the dual-tree complex wavelet transform was shift invariance. In normal wavelet decomposition small shifts of the input signal are able to move energy between output sub-bands. Shift invariance can also be achieved in DWT by doubling the sampling rate. This is affected in the DT-CWT by eliminating the down sampling by 2 after first level filter. Two fully decimated trees are then produced by down sampling, affected by taking first even and then odd samples after the first level of filters. To get uniform intervals between the two trees samples, the
subsequent filters need half a sample different delay in one tree. Application to image can be achieved by separable complex filtering in two dimensions. The real 2-D dual-tree DWT of an image x is implemented using two critically-sampled distinguishable 2-D DWTs in parallel. Afterward for each pair of sub-bands they had taken the sum and difference. The complex 2-D DT-DWT is also given augment to wavelets in six distinctive directions. The complex 2-D dual-tree is executed as four critically-sampled distinguishable 2-D DWTs operating in parallel as shown in figure (5). 2-D structure needs four trees for analysis and synthesis. The pair of conjugate filters applied to two dimensional images (x, y) can be expressed as:

\[(h_x + jg_x)(h_y + jg_y) = (h_x - jg_x)h_y - g_xg_y, j(h_xg_y - g_xh_y)...(3)\]

The complex wavelets are able to distinguish between positive and negative the diagonal sub-bands can be distinguished and horizontal and vertical sub-bands are divided giving six distinct sub-bands in each scale at orientations ±150, ±450, ±750. The oriented and scale dependent sub-bands are visualized spatially in figure (6). The DWT have three sub-bands in 00, 450 and 900 directions only but DT-CWT having six sub-bands in ±150, ±450 and ±750, thus DT-CWT improves the directional selectivity which is the prime concern in the application like image fusion.

C. Fusion Rule

Entropy is the determination of information content in the image. A high value of entropy represents more information content and vice versa. Consequently this statistical determination could be used in making a decision to choose the fusion coefficient [14].

\[H(S) = - \sum p(x) \log p(x) \ldots \ldots \ldots (4)\]

Entropy is premeditated on the low frequency components of the input images surrounded by a 3-by-3 window and either having higher values of entropy were selected or the fusion coefficients among the low frequency components.

Subsequently the coefficient is selected as the fuse coefficient when the region energy of it is better shown as formula.
In conclusion the fused image is reconstructed using the fused coefficients using the inverse NSCT transform.

D. Smoothening

The objective of image smoothing is to moderate the cause of camera noise, counterfeit pixel values, missing pixel values etc. two methods is used for image smoothing that are neighbourhood averaging and edge preserving smoothing. In neighbourhood smoothing, every points in the smoothed image \( F(x, y) \) is obtained from the average pixel value in a neighbourhood of \((x, y)\) in the input image. The outcomes of medial filtering are that pixels with outlying value are forced to become more like their neighbour, but at the identical time edges are preserved. Consequently it is known as edge preserving smoothing.

E. High pass filters

A high pass filter is mostly used for sharpening purpose. When an image is sharpened and contrast is superior between bordering areas with little variation in brightness or low eminence information.

High pass = \( f(x, y) – \text{low pass} \) ...............(6)

F. Proposed Algorithm

1. Select First Image A
2. Select Second Image B
3. Decompose images into sub-bands
   \((\text{LL, LH, HL, HH})\) using wavelet transformation
4. Wavelet coefficient into A and B
5. Apply transform function on A, B
6. Apply kernel function separately into all wavelet coefficients
7. Apply zero padding in kernel function process
8. Then apply high pass filter into decomposed \( A_{\text{LL}}, B_{\text{LL}} \) to improve intensity of each decomposed layers
9. Apply fusion rule:

\[
F^k_p(i, j) = \begin{cases} 
A^k_p(i, j), & \text{if } A^m_p(i, j) > B^m_p(i, j) \\
B^k_p(i, j), & \text{Otherwise}
\end{cases}
\]  

10. Fused improved wavelet coefficients
11. Apply DTCWT\(^{-1}\) function
12. Now Compute MSE is as follows:

\[
\text{MSE} = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} (A_{ij} - B_{ij})^2
\]

13. And compute PSNR as follows:

\[
\text{PSNR} = 10 \times \log_{10} \left( \frac{\text{peak}^2}{\text{MSE}} \right)
\]
Here block structure of proposed methodology shows that initially, we have taken the input of two images from the dataset and then decomposes it in the form LL, LH, HL, HH sub bands by applying DT-CWT technique. Later then, apply high pass filter into decomposed layer of input image A and B. Again introduce Gaussian filter to sharpen or eliminating the extra noise from the decomposed layer. After applying Gaussian filter apply High Boost filter to improve the intensity of each decomposed layers.

Then apply fusion rule to blend the decomposed layer and finally apply inverse DT-CWT to get the fused image with more information.

4. EXPERIMENTAL RESULTS

This section of the paper explores the experimental results and analysis of our proposed methodology. For simulation of the method MATLABr2009b [13] tool is used and this tool comprises of many database function. The comparison of modified DTCWTKHF (dual tree complex wavelet transform with kernel padding high pass filter) with other method PCA and DWT shown in the tables and graphs as well. The experiment of the method is performed on two image pattern. MSE (mean square error) and PSNR (peak signal to noise ratio) performance measuring parameter is used for effective analysis of proposed method among existing methods. Here fig. 8.1 shows the GUI environment for multi-focus image fusion. We take similarly 4 more images and perform the experiment on them and experimental results are shown in the table 1 and table 2 as below.

Here table 1 shows the comparison of different images with PCA, DTCWT and DTCWTKHF and in which we observe that our method gives better result than the PCA and DTCWT. Our method is more capable to detect the error than others. The MSE result of our method is depicted through graph.

Figure 7 Block diagram for proposed methodology

![Figure 7 Block diagram for proposed methodology](image)

Figure 8 GUI environment of p27b

![Figure 8 GUI environment of p27b](image)
Table 1: Comparison of MSE with PCA, DTCWT and DTCWTKHF

<table>
<thead>
<tr>
<th>Method/image</th>
<th>PCA</th>
<th>DTCWT</th>
<th>DTCWTKHF</th>
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<tr>
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</tbody>
</table>

In Table 2 illustrates the comparison of dissimilar images with PCA, DTCWT and DTCWTKHF and in which we found that our method gives improved result than the PCA and DTCWT. Our method is more proficient to detect the error than others. The PSNR result of our method is depicted through graph.

Table 2: Comparison of PSNR with PCA, DTCWT and DTCWTKHF

<table>
<thead>
<tr>
<th>Method/image</th>
<th>PCA</th>
<th>DTCWT</th>
<th>DTCWTKHF</th>
</tr>
</thead>
<tbody>
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5. CONCLUSION

From single focusing system of image it is not possible to obtain better quality of image. In this paper we use multi-focusing system to get improved intensity of image. We propose dual tree complex transform with kernel padding and high pass filter technique to retain important edge information. The comparison of our method is done among PCA and DTCWT and found that it gives better result. The effective performance of our methodology is perform using measuring parameter MSE and PSNR and simulation result of MSE and PSNR gives better than existing technique. Overall concluded that our method outperform and offers more essential information.

References


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