Multi-Focus Image Fusion Using Transformation Techniques: A Comparative Analysis

Ali Alferaidi
a.alfredi@uoh.edu.sa
College of Computer Science & Engineering, University of Hail, Saudi Arabia

Summary
This study compares various transformation techniques for multi-focus image fusion. Multi-focus image fusion is a procedure of merging multiple images captured at unalike focus distances to produce a single composite image with improved sharpness and clarity. In this research, the purpose is to compare different popular frequency domain approaches for multi-focus image fusion, such as Discrete Wavelet Transforms (DWT), Stationary Wavelet Transforms (SWT), DCT-based Laplacian Pyramid (DCT-LP), Discrete Cosine Harmonic Wavelet Transform (DC-HWT), and Dual-Tree Complex Wavelet Transform (DT-CWT). The objective is to increase the understanding of these transformation techniques and how they can be utilized in conjunction with one another. The analysis will evaluate the 10 most crucial parameters and highlight the unique features of each method. The results will help determine which transformation technique is the best for multi-focus image fusion applications. Based on the visual and statistical analysis, it is suggested that the DCT-LP is the most appropriate technique, but the results also provide valuable insights into choosing the right approach.

Keywords:
Multi-focus image fusion, comparative analysis, Transformation methods, DCT-LP, qualitative and quantitative evaluation

1. Introduction

Image fusion is a valuable method that helps simplify a large amount of data while preserving important information from multiple source images. The goal of image fusion is to merge a couple of or more source images into a more comprehensive one, thereby reducing the data volume. There are four categories of image fusion including combining multiple modality images, multiple view images, multiple temporal images, and multiple focal images [1].
This comparative research studies the methods of multi-focus or multifocal image fusion. Only things at a specific depth in the scene are in focus with the multi-focus image due to the restricted depth of focus in optical lenses; any objects in front of or behind the focus plane will be out of focus [2]. The resultant image will be "all in focus," more informative, and meaningful once the multi-focus images have been combined. Too many methods have been developed for multi-focus image fusion over the past couple of decades.

The two primary classes of image fusion are frequency-based (FD) and spatial-based (SD). Spatial-based approaches focus on manipulating the pixels of the image directly to accomplish the desired result. Basic fusion techniques can be found in this domain and can be applied to individual pixels or groups of pixels. The advantage of using spatial-based techniques is that they are less affected by noise and are more tolerant of registration errors. However, these techniques can lead to spectrum distortion and spatial degradation in the resulting image. Some of the techniques used in the spatial domain include HSI [3], averaging [4], Brovey [5], PCA, and maximum selection [6]. In the transform domain, the image is converted firstly from the spatial domain to the frequency domain. After all, operations are performed, the inverse transformation process is applied to obtain the final product. Frequency-based techniques are more comprehensive than spatial-based techniques and are commonly used in digital image processing for tasks such as noise reduction, image filtering, and image enhancement. Methods such as DWT) [7], SWT [6], DC-HWT [8], DT-CWT [9], and DCT-LP [10]. are examples of frequency-based approaches. These techniques are preferred due to their simplicity in a calculation, ability to modify the frequency composition of the image, and ease of viewing [11]. Instead of working with pixels in the spatial domain, frequency-based techniques operate on the frequency elements of the image in the frequency domain, taking advantage of the visual characteristics that are present in this domain [12].

The goal of this research is to analyze and assess the popular multi-focus fusion techniques used in the frequency domain. The study aims to increase our understanding of how these transform techniques operate and to differentiate the high-performing method from the traditional ones. To achieve this, the study evaluates the techniques using grey-scale and colour image datasets and a couple of performance evaluation criteria, which include qualitative, and quantitative.

The article's structure is outlined as follows. The second section offers a concise summary of the multi-focus fusion approaches. In the third section, a comparison of the various approaches is presented. Section fourth presents a comparison of the experimentation results with real datasets. Finally, the conclude the article last section

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2. Frequency Domain Methods

This study compares the use of image fusion transformation methods for multi-focus applications. Although there are both spatial and frequency domain approaches for multi-focus techniques, frequency domain methods tend to be more advantageous. Thus, five commonly used frequency domain techniques are selected and analysed for performance results. A brief overview of the transformation methods is provided.

2.1 Discrete Wavelet Transform

The most commonly utilized transformation approach in multi-focus image fusion is DWT. This mathematical tool was developed in the 1980s and allows for the hierarchical decomposition of an image [7]. DWT, like other transformation methods, utilizes pixel frequency information while addressing the issue of spatial distortion. The DWT decomposes the image into four frequency sub-bands: HH, HL, LH, and LL. These sub-bands are decomposed at various scales, which are then reconstructed to produce the final image using Inverse Discrete Wavelet Transform (IDWT). DWT separates the signal into low and high-frequency components. The low-frequency portion of an image presents the coarse information or outlines of the signal, although the high-frequency portion presents detailed information about the edges in the image. The separation and decomposition process involves down-sampling and using high and low-pass filters. Several fusion techniques have been applied to create the fused wavelet coefficients, one of which is averaging. The image is decomposed and the coefficients are acquired. The multi-focus images are processed in the same sub-bands, for instance, the fused image's HH band is created by averaging the first image's HH band and the second image's HH band. Figure 1 illustrates the process [13].

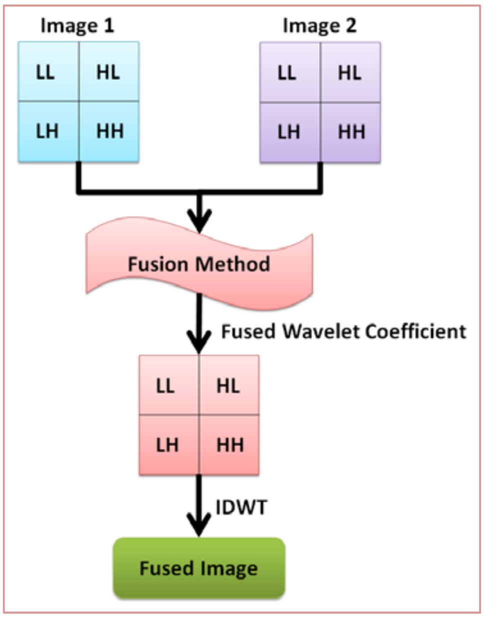


Fig.1 DWT image fusion process

2.2 Stationary Wavelet Transform

The DWT lacks translation invariance, which led to the development of Stationary Wavelet Transform (SWT) to address this issue. SWT circumvents the down-sampling step in the decimated method by up-sampling the filters by inserting zeros among the filter coefficients. This design provides better time-frequency localization and is simple to implement. The data is processed by appropriate high-pass and low-pass filters at each level, resulting in the creation of multiple sequences at the next level. The filters are first applied to the rows in the decimated algorithm and then to the columns. Figure 2 shows the structure of SWT.

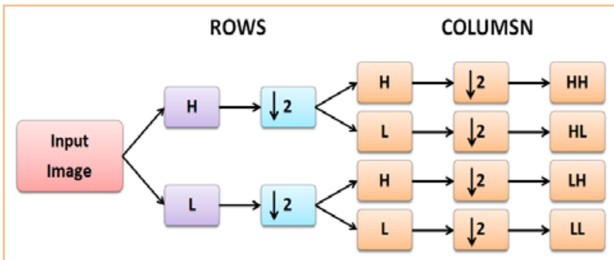


Fig.2. Structure of SWT

The actual image is decomposed into vertical and horizontal approximations by using column-wise and row-wise low-pass and high-pass filters [16]. The same filtering process is applied to break down the components row-by-row and column-by-column to approximate vertically, horizontally, and diagonally. Low-pass and high-pass filters provide detailed information at the appropriate frequencies, preserving both low and high frequencies [17].

2.3 Discrete cosine transform (DCT) Based Laplacian Pyramid

DCT-LP fusion is based on the idea of multiresolution analysis. The input images are decomposed into a set of lower-resolution versions using a Laplacian Pyramid [1]. The DCT is then applied to each subband in the pyramid to obtain the frequency representation of the image. In this representation, the images are decomposed into different frequency subbands, which contain information about different scales and orientations of the image. Once the images are transformed into the frequency domain, the information in each subband is combined using a fusion rule. This can be a simple average, a weighted average, or a more sophisticated rule that takes into account the importance of different subbands. The fused information is then reconstructed into a single image using the inverse DCT and Laplacian Pyramid. The resulting image is a composite of the information from all of the input images.

2.4 Discrete Cosine Harmonic Wavelet Transform

DC-HWT image fusion is based on the idea of multiresolution analysis. The technique involves transforming the input images into the frequency domain using the DC-HWT [19]. In this representation, the images are decomposed into different frequency subbands, which contain information about different scales and orientations of the image. The DC-HWT is used because it has the ability to preserve both high- and low-frequency information, which is important for image fusion applications. Once the images are transformed into the frequency domain, the information in each subband is combined using a fusion rule. This can be a simple average, a weighted average, or a more sophisticated rule that takes into account the importance of different subbands. The fused information is then reconstructed into a single image using the inverse DC-HWT. The resulting image is a composite of the information from all of the input images [8].

2.5 Dual-Tree Complex Wavelet Transform

DT-CWT is first proposed by Boykov and Kolmogorov [20]. The Wavelet-based fusion algorithm is associated with the DT-CWT image fusion algorithm [9]. The DT-CWT method is based on two parallel trees, the first of which represents the odd samples created at the first level and the second of which represents the even samples. The parallel trees eliminate data redundancy problems and achieve shift invariance by generating the signal delays required for each level [22]. The filter structure of the DT-CWT has CWT filters which have complex coefficients and make complex output samples in which each block is a complex filter and contains down-sampling by 2 at its outputs. Afterward, the DWT is unaffected by the output sampling rates but every sample has two parts, the real and imaginary, a redundancy joined. The complex filters can be designed such that the orders of magnitude of their step reactions are down with input [9, 21].

3. Advantages and disadvantages of Frequency Domain Methods

Table. 1 The advantages and disadvantages of Frequency Domain Methods

Techniques	Advantages	Disadvantages
DWT	• In the wavelet transformation process, the DWT is an effective method in image fusion. • The DWT reduces the spectral distortion in an image [23]. • In image fusion, the DWT-based method is more favorable and provides better results. • The input images are combined with magnified information used to create the resultant image. • Multiresolution representation: DWT provides a multiresolution representation of an image, which allows it to extract both low- and high-frequency information from the image. • Simplicity: DWT is a relatively simple technique that is easy to understand and implement. • Widely used: DWT is a widely used technique in image processing [28]	• Only the vertical and horizontal characteristics are preserved by DWT. • Absence of shifted invariance • It encounters ringing abnormalities, which lowers the resolution of the resultant image • Absence of dimensional shift • Because the edges were missed during the process, it is undesirable for edge areas [23] • Artifacts: DWT can introduce artifacts into the fused image. • Computational complexity: DWT is a computationally complex technique, which can make it difficult to use in real-time tools [28]

SWT	• The SWT has overcome the lack of translation invariance. • The SWT, a full shift-invariant transform, prevents the decimated algorithm's down-sampling stage by either up-sampling the filters or inserting zeros among the filter coefficients [23].	• Computational complexity • Parameter selection: SWT requires the selection of several parameters, such as the number of stages in the wavelet decomposition and the choice of wavelet filters. • SWT is Less efficient
DCT+LP	• Complexity Reduction and decomposing images into a series of waveforms. • This method is suited for many real-time applications. • Efficient computation: DCT-LP is a fast and efficient image fusion technique, as it only involves simple arithmetic operations such as addition and multiplication [10, 29]. • Good performance: DCT-LP has been shown to produce fused images that have good visual quality and preserve the significant features of the individual images. It has been involved in various image fusion areas, including medical images and remote sensing [29, 30]	• It is typically slower • Sensitivity to noise: DCT-LP is sensitive to noise in the input images, and the presence of noise can lead to the introduction of artifacts into the fused image [29] • Limited spatial resolution: DCT-LP is a low-pass filter-based technique, which means that it can only preserve low-frequency information from the source images [30].
DC-HWT	• The scalability of the built-in interpolation and decimation processes. • Image rejection and band-limiting filters are not required. • The accessibility of quick method built on the DCT [24]. • Additionally, because DC-HWT uses only real operations, it is computation easier than Fourier-based HWT and even simpler than convolution [19]. • To maintain the fused image's visual quality and performance by using minimal calculations [8]	• It is not only suffering from the leakage effect but also is complex [26]. • Parameter selection: DC-HWT also requires the selection of several parameters, such as the number of stages in the wavelet decomposition and the choice of wavelet filters. • Computational complexity: DC-HWT is a computationally complex technique, which can make it difficult to implement in real-time applications
DT-CWT	• It is shift-invariance and directional sensitivity [21] • DT-CWT is focused on enhancing the visual appearance of images • Gives the best results for images under criteria like natural appearance, and brilliant contrast. • Robustness: DT-CWT is a robust technique that is able to handle nonlinearities and singularities in the data.	• DT-CWT has Computational complexity [21]. • Sensitivity to noise: DT-CWT is sensitive to noise in the input image, and the presence of noise can lead to the introduction of artifacts into the fused image.

4. Experiments

4.1 Evaluation measures

Quantitative measurements play an essential part in evaluating the performance of image fusion techniques, and they help to determine the best-performing technique. There is a wide range of quantitative measures with different characteristics, and to accurately assess the fused images, ten metrics are used. The following is a brief explanation of the performance measures.

Root Mean square error (RMSE): The most commonly employed approach for comparing the difference between the actual and resultant images is known as the RMSE. It computes the variation in pixel values dynamically, providing information about the quality of the final image. If the RMSE value is close to zero, it shows that the resultant image is likely to be highly accurate [27].

$$RMSE = \sqrt{\frac{1}{MN}\sum_{a=1}^{M}\sum_{b=1}^{N}(lr(a,b) - lf(a,b))^2} \quad (1)$$

Mean square error (MSE): By averaging the sum of the squares of the error among the actual and resulting images, MSE calculates the error concerning the values at the centre of the image, such as the mean of the pixel values of the image.

$$MSE = \frac{1}{MN}\sum\nolimits_{a=1}^{M}\sum\nolimits_{b=1}^{N}(I_x(a,b) - I_f(a,b))^2 + (I_y(a,b) - I_f(a,b))^2 \quad (2)$$

Percentage Fit Error (PFE): PFE calculates the difference between the actual and resulting images and compares it to the true image's norm. The resulting image and true image will likely be similar if the value is near 0 [27].

$$PFE = \frac{norm(Ir - If)}{norm(Ir)} * 100 \quad (3)$$

Mean Absolute Error (MAE): The associated pixels in the actual and resultant image have been determined using MAE. Higher image quality is indicated by a lower MAE score. If the value is 0, the real image and the resultant image will both be identical [23].

$$MAE = \frac{1}{MN}\sum\nolimits_{i=1}^{M}\sum\nolimits_{i=1}^{N}\left|I_x(i,j) - I_f(i,j)\right| + \frac{1}{MN}\sum\nolimits_{i=1}^{M}\sum\nolimits_{i=1}^{N}\left|I_y(i,j) - I_f(i,j)\right| \quad (4)$$

Entropy (E): Entropy is the texture of the image that may be characterized using randomness. High entropy scores provide more information about the resultant image [23].

$$E = -\sum_{i=0}^{L-1} P_i \log P_i \quad (5)$$

Whereas, L is the number of grey levels:

$$P_i = \frac{number\ of\ \ pixels\ Di\ of\ \ each\ graylevel\ i}{number\ of\ \ pixels\ D\ \text{in}\ the\ image} \quad (6)$$

Signal Noise Ratio (SNR): The SNR performance metric is applied to find the ratio among the information and noise of the resultant image. If the SNR value is higher, that shows both resultant and true images are identical [27].

$$SNR = 10\log_{10}\left(\frac{\sum_{a=l}^{M}\sum_{b=l}^{N}(lr(a,b))^2}{\sum_{a=l}^{M}\sum_{b=l}^{N}(lr(a,b) - l(a,b))^2}\right) \quad (7)$$

Peak Signal to Noise Ratio (PSNR): The PSNR is a widely used performance metric to calculate the number of grey levels in an image by comparing the corresponding pixels in the true and resultant images. A larger PSNR value shows better image fusion. Higher PSNR values show that the actual and resultant images are similar [27].

$$PSNR = 20\log_{10}\left(\frac{L^2}{\frac{1}{MN}\sum_{a=l}^{M}\sum_{b=l}^{N}(lr(a,b) - lf(a,b))^2}\right) \quad (8)$$

Correlation Coefficient (CC): CC is applied to calculate the closeness of spectral features among the actual and resultant images. If the score is close to 1, that demonstrates the actual and resultant images are similar [27].

$$CC = \frac{2C_{rf}}{C_r + C_f} \quad (9)$$

Mean: The average intensity value of an image is shown by the mean (μ). High mean values indicate good fusion results [23].

$$\mu = \frac{1}{X \times Y}\sum_{x=0}^{X-1}\sum_{y=0}^{Y-1} fused(x,y) \quad (10)$$

Standard deviation (STD): The variance's square root is known as STD. If the STD of the resultant image is higher then will be good fusion results [23].

$$St_l = \sqrt{\frac{\sum_{a=1}^{x}\sum_{b=1}^{y}\left(f(a,b) - \mu\right)^2}{xy}} \quad (11)$$

Where $f(a,b)$ is pixel intensity (a,b) and $x \times y$ is the size of the image.

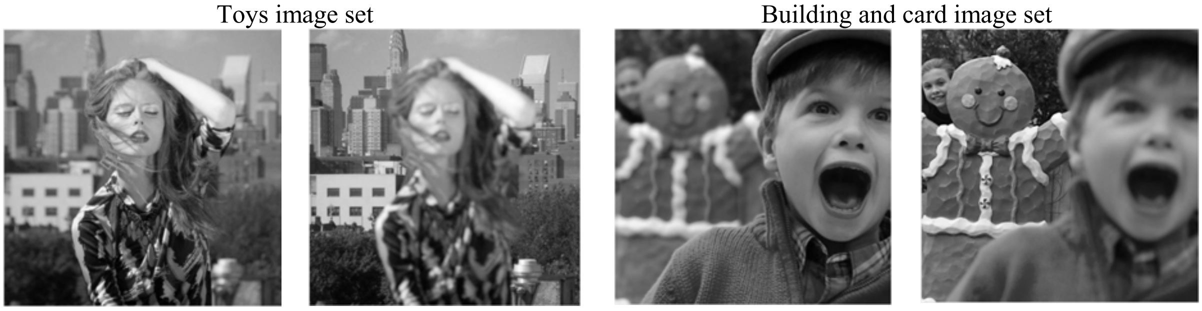
4.2 Datasets

In this study, experiments are conducted using four datasets of multi-focus grey-scale and color images, namely Toys, Building and Card, Girl, and Boy. These images are commonly used in research and are easily accessible online. The Toys and Building and Card datasets are 512 x 512 pixels in size, while the Girl and Boy dataset is 640 x 480 pixels. The experiments are performed using MATLAB 2018b software.

4.3 Results and Discussion

In this article evaluate various methods in the frequency domain for their effectiveness in multi-focus image fusion. They compare the methods based on both visual appearance and quantitative metrics. The source images used in the study are presented in Figure 3, and the resultant fused images can be seen in Figure 4. To evaluate the visual differences between the resultant images produced by all five techniques, the human eye examines them closely to identify any variations. The analysis reveals that the DCT-LP method results in a clearer and more informative fused image compared to the others. The comparison is further supported by statistical data presented in tables 1, 2, 3, and 4.

Toys image set Building and card image set



Girl image set Boy image set

Fig. 3 Four distinct image sets of Multi-focus colour and grey scale images

(a) (b) (c) (d) (e)

(a) (b) (c) (d) (e)

(a) (b) (c) (d) (e)

(a) (b) (c) (d) (e)

Fig. 4 Fused images using five distinct methods on colour and grey scale image sets (a) DWT, (b) SWT, (c) DCT-LP, (d) DC-HWT, (e) DT-CWT

In light of the above evaluation metrics, it can be concluded that the DCT-LP technique is superior to the other techniques. However, this conclusion is definitively established through a statistical analysis. This statistical evaluation is considered a more reliable and authentic method in image fusion research and is conducted using ten performance metrics. The use of ten metrics, as opposed to just a few, is intended to provide a comprehensive evaluation of the final image based on different properties and expectations. For instance, RMSE is applied to assess the difference among the true and resultant images, with a smaller value indicating that the images are similar. MSE and PEF are used to find the error between the images. MAE is used to find the absolute error between the two images. Entropy is applied to depict the texture of the image. SNR is applied to determine the ratio among the information and noise in the fused image. PSNR is applied to determine the number of grey levels in the fused image. CC is used to recognize the spectral features among the true and resultant images. The mean (μ) represents the average intensity of the image, while STD is the square root of variance. These are the properties of each performance metric. In tables 1, 2, 3, and 4, the optimal values are indicated by bold text and a dark gray highlight for easy identification. Different colors are used to distinguish the best and worst results in all methods. For the Toys image set, the entropy value is better for the DWT method than the others, indicating that the texture of the Toys image is better. The mean and STD values are better for DT-CWT, indicating that the average intensity and variance are better for both images in the Toys data sets, as well as the other two data sets. Based on all performance measures, it can be easily concluded that the DCT-LP method outperforms all popular methods for multi-focus fusion applications.

Table 1. The statistical comparison of "Toys image set" over five transformation approaches

Matrices	***DWT***	***SWT***	***DCT-LP***	***DC-HWT***	***DT-CWT***
RMSE	7.1951	6.9554	**6.1223**	7.0144	8.3876
MSE	39.3858	36.700	**28.4634**	52.9112	54.7122
PFE	4.0718	3.9432	**3.0042**	5.9212	6.3820
MAE	0.3956	0.3802	**0.1675**	0.3782	0.3944
entropy	**6.9111**	0.0843	0.4432	0.0832	0.9852
SNR	22.1406	22.3970	**24.3455**	22.7512	21.1994
PSNR	40.9998	40.3211	**40.8657**	39.9237	39.1117
Correlation	0.9975	0.9976	**0.9981**	0.9964	0.9965
Mean	99.2934	98.6154	99.6343	99.1155	**99.8933**
STD	47.0112	48.1143	48.3244	47.8343	**52.6343**

Table 2. The statistical comparison of "Building and card image set" over five transformation approaches

Matrices	***DWT***	***SWT***	***DCT+LP***	***DCHWT***	***DTCWT***
RMSE	6.5662	6.8360	**2.9976**	6.9355	11.3323
MSE	42.3304	46.7311	**6.8067**	42.8171	72.1250
PFE	3.5625	3.7676	**1.2943**	3.6561	6.1072

MAE	**0.0337**	0.0346	0.0429	0.0462	0.0347
entropy	**7.1112**	0.1161	0.4205	0.0220	0.0366
SNR	23.0393	23.3998	**31.6769**	22.9121	19.1378
PSNR	41.0315	41.8168	**43.0001**	37.9902	37.7887
Correlation	0.9982	0.9983	**0.9997**	0.9951	0.9957
Mean	97.6311	96.5681	**98.2066**	96.3284	97.7958
STD	50.4176	51.496	**52.5312**	50.1222	39.0232

Table 3. The statistical comparison of "Girl image set" over five transformation methods

Matrices	***DWT***	***SWT***	***DCT+LP***	***DCHWT***	***DTCWT***
RMSE	7.5738	7.6612	**5.7362**	6.3200	7.7932
MSE	53.3629	53.6944	**32.9041**	43.8123	53.5491
PFE	2.0399	2.0517	**1.2242**	3.2991	3.3009
MAE	1.7490	1.7500	**1.0837**	1.6023	1.7110
Entropy	6.8756	0.0002	0.0049	**7.4311**	6.3072
SNR	24.2168	24.2472	**26.7296**	24.8713	24.3600
PSNR	39.3716	39.3918	**40.5786**	39.2001	39.0029
Correlation	0.9983	0.9984	**0.9991**	0.9911	0.9962
Mean	98.2756	98.4809	**98.4999**	98.4421	98.3921
STD	55.7632	55.8321	**57.6321**	56.4432	55.3223

Table 4. The statistical comparison of "Boy image set" over five transformation methods

Matrices	***DWT***	***SWT***	***DCT+LP***	***DCHWT***	***DTCWT***
RMSE	8.5738	8.6612	5.7362	**5.3200**	9.7932
MSE	52.3876	40.6004	**36.8765**	43.8643	50.4321
PFE	2.9911	3.1721	**2.0065**	3.2991	3.0943
MAE	2.8790	1.7654	1.7887	**1.7023**	2.8790
Entropy	5.8756	0.8802	**7.4311**	0.1149	5.3072
SNR	24.2268	24.2332	**26.9876**	25.8553	24.0000
PSNR	39.0006	39.3128	**42.8766**	39.9901	38.0029
Correlation	0.9965	0.9975	**0.9976**	0.9900	0.9962
Mean	87.2756	98.4898	**99.4999**	97.4421	99.3021
STD	49.7982	50.0921	**50.9821**	50.4872	52.3093

5. Conclusion

In conclusion, multi-focus image fusion is an essential technique in the area of image processing, its combination of multiple images with unlike focus levels into a single image with an increased depth of image. This study provides a comprehensive comparison of various transformation-based techniques including DWT, SWT, DCT-LP, DC-HWT, and DT-CWT, for multi-focus image fusion. The results are evaluated using qualitative measure, and quantitative measure. This study adopts a comprehensive approach to evaluating frequency-domain methods by using ten performance metrics instead of just a few. The aim is to provide a more accurate and authentic evaluation of these methods. The use of multiple metrics helps to give a broader perspective and ensure that the results are dependable. Moreover, having a range of metrics enables the identification of both the strengths and limitations of the methods and highlights areas that require improvement. However, it is crucial to select the metrics carefully and make sure they are relevant to the problem and data being analysed. The results of all measures show that the DCT-LP method is the best-performing method among all the frequency-domain techniques. Future work, efforts will be made to overcome the limitations of frequency-domain methods

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