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A review of various image fusion types and transforms

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ABSTRACT

Utilizing multiple views of an image is an important approach in digital photography, video editing, and medical image fusion applications. Image fusion (ImF) methods are used to improve an image's quality and remove noise from the image signal, resulting in a higher signal-to-noise ratio. A complete assessment of the literature on the different transform kinds, techniques, and rules utilized in ImF is presented in this paper. To assess the outcomes, a white flower image was fused using discrete wavelet transform (DWT) and discrete cosine transform (DCT) techniques. For validation of results, the red, green, blue (RGB) and intensity hue saturation (IHS) values of individual and fused images were evaluated. The results obtained from the fused images with the spatial IHS transform method give a remarkable performance. Furthermore, the results of the performance evaluation using DWT and DCT fusion techniques show that the same peak signal to noise ratio (PSNR) of 114.04 was achieved for both PSNR 1 and PSNR 2 for DCT, and different results were obtained for DWT. For signal to noise ratio (SNR), SNR 1 and SNR 2 achieved slightly similar values of 114.00 and 114.01 for DCT, while a SNR of 113.28 and 112.26 was achieved for SNR 1 and SNR 2 respectively.

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1. INTRODUCTION

A digital image is a grid of small elements called a pixel. An image can be represented in both the spatial and spectral domains. To obtain a better quality of an image containing both spectral and spatial domains, multiple input images are fused. This process is known as image fusion [1]-[3]. Spectral representation defines the edge features of the image while spatial representation indicates space. For a 2D image space (x, y-plane), direct modification of the properties of the pixels can be achieved. Multi-view fusion, multi-focus fusion, multi-tier fusion, multi-exposure fusion, multi-modal fusion, hyperspectral fusion (HSF), single sensor fusion, and multi sensor fusion are the different types of image fusion (ImF) techniques [4], [5]. When different views of the same scene are taken from multiple cameras and fused, the process is known as multi-view fusion. Multi-sensor fusion is mainly used in remote sensing where the fusion of panchromatic (PAN) mode (high spatial resolution image which has no color information: gray) and multispectral (MS) mode (low spatial resolution image in which color information is present) [6], [7]. PAN and MS modes are usually used simultaneously in order for some information of the object not to be lost. Multi-sensor image fusion is the fusion of different satellite images [8], [9]. There is another fusion procedure called HSF in which multispectral images with high spatial resolutions enhance spatially a hyperspectral image. High spectral (hyperspectral) images have a low spatial resolution and high geometric (multispectral) images have a high spatial resolution [10]. When images are obtained from diverse modalities of a similar scene and fused, this is known as multi-modal image fusion [11], [12]. Multi-modal image fusion also focuses on different scenes whether they are foreground or background scenes. For multi-modal image fusion, medical image fusion (MIF) is the best example.

Nowadays, a wide number of physicians fuse the lesions taken from different modalities of medical images [13], [14]. This processes most times involves the application of computer vision, image processing, machine learning, pattern recognition, or artificial intelligence [11]. MIF uses positron emission tomography (PET), single photon emission computed tomography (SPECT), computerized tomography (CT), magnetic resonance imaging (MRI), and ultrasound modalities. There are several advantages and disadvantages of the different MIF techniques. For instance, ultrasound imaging is extensively used because of its low cost and its negligible side effect on patients. CT images provides a 3D imaging technique with a high imaging resolution and short scan time with limited characterization of soft tissues. MRI images encompass soft tissues and high geometric images, and provides limited movement information such as body metabolism. SPECT images give the information of blood flow in tissues and organs while PET images have a high sensitivity and a low resolution [15]. There are different types of image fusion approaches that are used to fuse two or more images. They can be characterized into Morphological, knowledge, neural network, wavelet, fuzzy logic, and various other approaches.

Authors in [4], [5], presented a PAN sharpening method which employed pyramid-based ImF and wavelet-based ImF. In this approach, discrete wavelet transform (DWT) with principal component analysis (PCA) methods were combined to give a better image fusion outcome. Mifdal *et al.* [8] used an Optimal Transport method which was used to fuse the spectral information of a hyper image with spatial information. The method is known as the hyperspectral and multispectral Wasserstein barycenter (HMWB) method. Authors in [16], [17], have used wavelet transform to fuse high spectral and high geometric images, while the non-sample contourlet transform (NSCT) domain was used instead of wavelet transform in [18], [19]. In [20], [21], non-sampled directional filter bank (NSDFB) and non-sampled directional pyramid filter bank (NSPFB) techniques were adopted. A pulse coupled neural network (PCNN) model was presented in [22]. In [23], Shearlet transform was introduced for the fusion process; while for PCNN model parameter estimation, gamma distribution in Shearlet domain was used. There are several techniques used for discrete wavelet transform (DWT) based ImF. These include gamma enhancement [24], histogram equalization [25], and contrast enhancement using gamma correlation (GC) with weighted functions [26]. Zhang *et al.* [14] used wavelet-based Bayesian function and [27] employed the use of blurring method and quaternion wavelet transform (QWT) on multispectral and hyperspectral images. Reid *et al.* [28] proposed a method that can propagate information from high-resolution images to low-resolution images using different spectral channels. In this case, both resolution images are nonlinear, non-stationary, and non-deterministic. The authors used Gaussian process (GP) regression as the main approach. GP is a non-parametric Bayesian framework. In this approach, there are two challenges: the first is to define the covariance function and the second is to define image prior structure. Yang *et al.* [29] introduced Red black wavelets with principal component analysis (PCA) for multi-spectral image fusion.

For features that originate from image sensors, fusion is required. Each attribute in a multimodal system is composed of many feature matrices. However, we cannot process or save them in a database at the same time because it takes a lot of time to compute and it is also time-consuming. As a result of this, it is necessary to merge feature matrices from several sources. This approach is called fusion.

This paper presents a review of the different image fusion approaches and steps used in image fusion, which include pre-processing, decomposition, image fusion rules, reconstruction, and in addition, a performance parameter evaluation was also presented. The spatial intensity hue saturation (IHS) image fusion on white flower images (indoor and outdoor) was tested, and it was discovered that the best results are obtained after fusing the images instead of using the single images. The remaining sections of the paper are arranged as follows: section 2 explains the methodology employed in this paper for image fusion. In section 3, the experimental results are discussed, tabulated and the output images are depicted. This is followed by the concluding remarks and future work in section 4.

2. METHODOLOGY

With the rapid advancement of imaging techniques, a variety of approaches in the field of ImF are being used in recent times. Image pre-processing (image normalization and image registration) [30], image decomposition [6], several ImF rules [31], image reconstruction, and quality evaluation parameters [32]-[34] are all included in ImF. Images are normalized at the same level, rotated into small sub-images, and then ImF rules are used to coalesce the various features of the sub-images at various resolutions during pre-processing. Fused images are reconstructed using several reconstruction techniques, and then evaluation parameters are calculated to check the image quality. Image pre-processing, image decomposition and reconstruction, fusion rules, and image quality measure parameters are all part of our proposed methodology's workflow.

In this approach, Image normalization and image registration is used for pre-processing of images. The images have different characteristics like dynamic range and contrast range. Normalization was performed by calculating the standard deviation (σ) and global mean (m) for each image. Every pixel (i, j) was normalized using (1),

$$p_0(i,j) = \frac{D}{2} + \left(\frac{2^n}{2n_0}\right)\left[\frac{p_i(i,j)-m}{\sigma}\right] \quad (1)$$

where p_0 is the output, p_i is the input, n is the desired number of bits of dynamic range and D is the maximum range of the data. After pre-processing, implementation of fusion methods was performed. The different decomposition algorithms are used to divide the image into sub-images. ImF methods are classified into different categories consisting of transform domain fusion (TDF) and spatial domain fusion (SDF) [35], [36]. High pass filtering, averaging, brovey method, PCA, and intensity hue saturation (IHS) methods are part of SDF. TDF can be further divided into the pyramid method and wavelet transform method. More recently, several papers have proposed different Pyramid methods such as the Laplacian pyramid, Gaussian pyramid, morphological pyramid, gradient pyramid, and ratio to low pass pyramid. Different wavelet methods have also been proposed such as DT-CWT, QWT, DWT, Shearlet transform (ST), directional contrast fuzzy transform (DC-FTR), red black wavelet transform (WT), counter let transform, curvelet transform [37]. Based on the review of ImF methods using different transform techniques, Table 1 presents the advantages and disadvantages of the existing approaches.

Table 1. Merits and demerits of existing approaches

Approaches	Author's	Merits	Demerits
DWT with Entropy concepts	[38]	Fused images are noise-free and contain better quality information, incorporating multimodality, and help in deriving useful information	Single modality can't give much useful information
NSCT with local energy match, NSPFB, and NSDFB	[20]	Uses low-frequency sub-bands to high-frequency sub-bands (directional vector), and obtains a better directional decomposition	Not able to employ noticeable information present in the low-frequency sub-bands
Contourlet Transform directional windows	[30]	Captures directional information of natural images	
Hybrid techniques	[39]	Computations are easy	
PCNN model employing Shearlet Domain	[21]	Provides multi-scale sub division and direction localization	
Gaussian Process	[28]	Used for non-deterministic, nonlinear and non-stationary images	
PCA and Red Black Wavelet	[29]	Enhances Image performance. Decomposition of diverse features can be done by this method	

In this paper, discrete wavelet transform and discrete cosine transform has been used to fuse two images. In the fusion process, different multiple images are combined to form one image with improved resolution. There are three different components for image fusion: coefficient grouping, activity-level measurement, and consistency verification. Coefficient grouping: This method is based on scale grouping. There are different types of scales: multi-scale, single scale, and no scale. If the grouping is done using multi-scale, it is known as a multi-scale grouping (MSG). MSG describes the coefficient of different images of multiple scales using the same method. Likewise, we have single-scale grouping and no scale grouping.

Activity-level measurement (ALM): As the name suggests, this type of method is used on a different activity like windows, coefficients, or regions. In this approach, when different windows are fused it is called window based. Also, if different coefficients are fused, it is called coefficient based and if different regions are fused then it is called region-based. Different coefficients of images, I_1 and I_2 at the i^{th} level are expressed using C_i^1 and C_i^2 respectively. There are various coefficient combination (CC) methods which include average rules (AR), maximum rules (MR), and weighted average rules (WAR). The generally combined coefficient (C_F) is expressed by (2).

$$C_F = \begin{cases} C_i^1 if C_i^1 > C_i^2 \\ C_i^2 if C_i^1 < C_i^2 \end{cases} \quad (2)$$

The common coefficient for AR is expressed by (3).

$$C_F = \frac{1}{2}(C_i^1 + C_i^2) \tag{3}$$

In WAR, the different weights, w_i^1 and w_i^2 of an image are considered and the common coefficient of WAR is represented by (4).

$$C_F = \frac{1}{2}(w_i^1 \times C_i^1 + w_i^2 \times C_i^2) \tag{4}$$

Consistency verification: In this technique, the same rules are used for fusing coefficients present in the neighborhood. Image fusion is achieved with different processing levels like feature level (FL), signal level (SL), pixel/data level (PL), and decision level (DL) [32], [33] as shown in Figure 1. The various performance evaluation parameters used in various research works are depicted in Figure 2 [34].

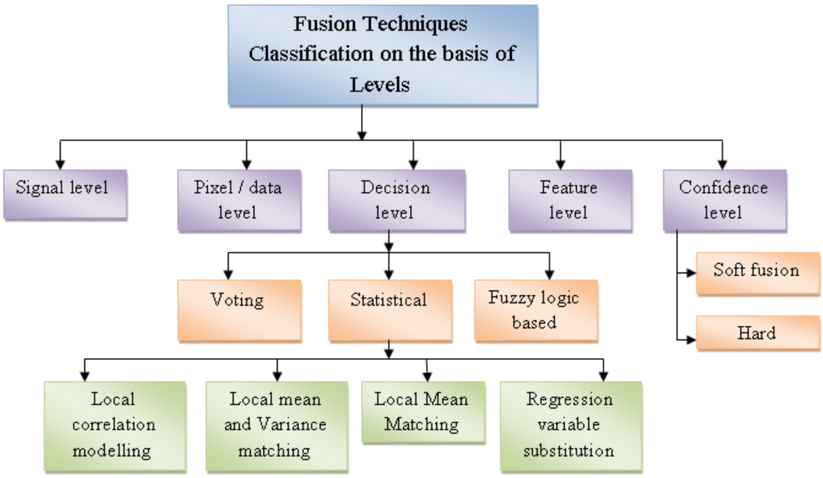

Figure 1. Different fusion techniques based on various processing levels

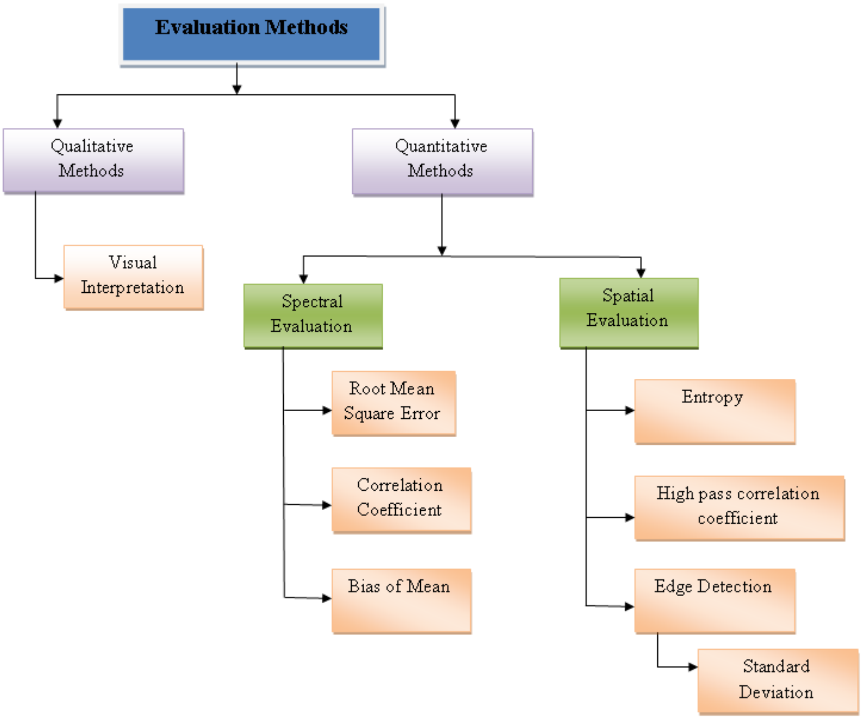

Figure 2. Various performance evaluation parameters

For spectral evaluation, the mean square error (MSE) characterizes gray level noise of an image lesser than the value of MSE and lower than the noise content. Peak signal to noise ratio (PSNR) is the ratio of original to compressed image and is used to compute the peak SNR of the fused image. If the value of PSNR is high, the quality of the reconstructed image is better and noise is less. The average gradient (AG) explains the spatial resolution of an image, while the spectral discrepancy (SD) explains the spectral quality of the amalgamated image.

3. RESULTS AND DISCUSSION

For experimentation, authors have used the indoor and outdoor images of white flowers. All the simulations were carried out using Python language on an i7-10700 CPU@2.90 GHz, with a 64-bit operating system. The various steps adopted in this paper are shown in Figure 3. The different images of the same object (white flower) at different places: outdoor and indoor are considered. Figure 4(a) represents the outdoor white flower image and Figure 4(b) shows the indoor white flower image. The images were normalized.

In this paper, spatial IHS transform-based image fusion was considered. All the pictures which are taken from a different device are regenerated into the same format. The red, green, blue (RGB) and IHS value was calculated for both indoor and outdoor images and the results are tabulated in Table 2 and Table 3 respectively. Considering feature level fusion, features of the indoor and outdoor images are fused to form one image. Figure 5 shows the fused image using a sample of the indoor and outdoor flower image.

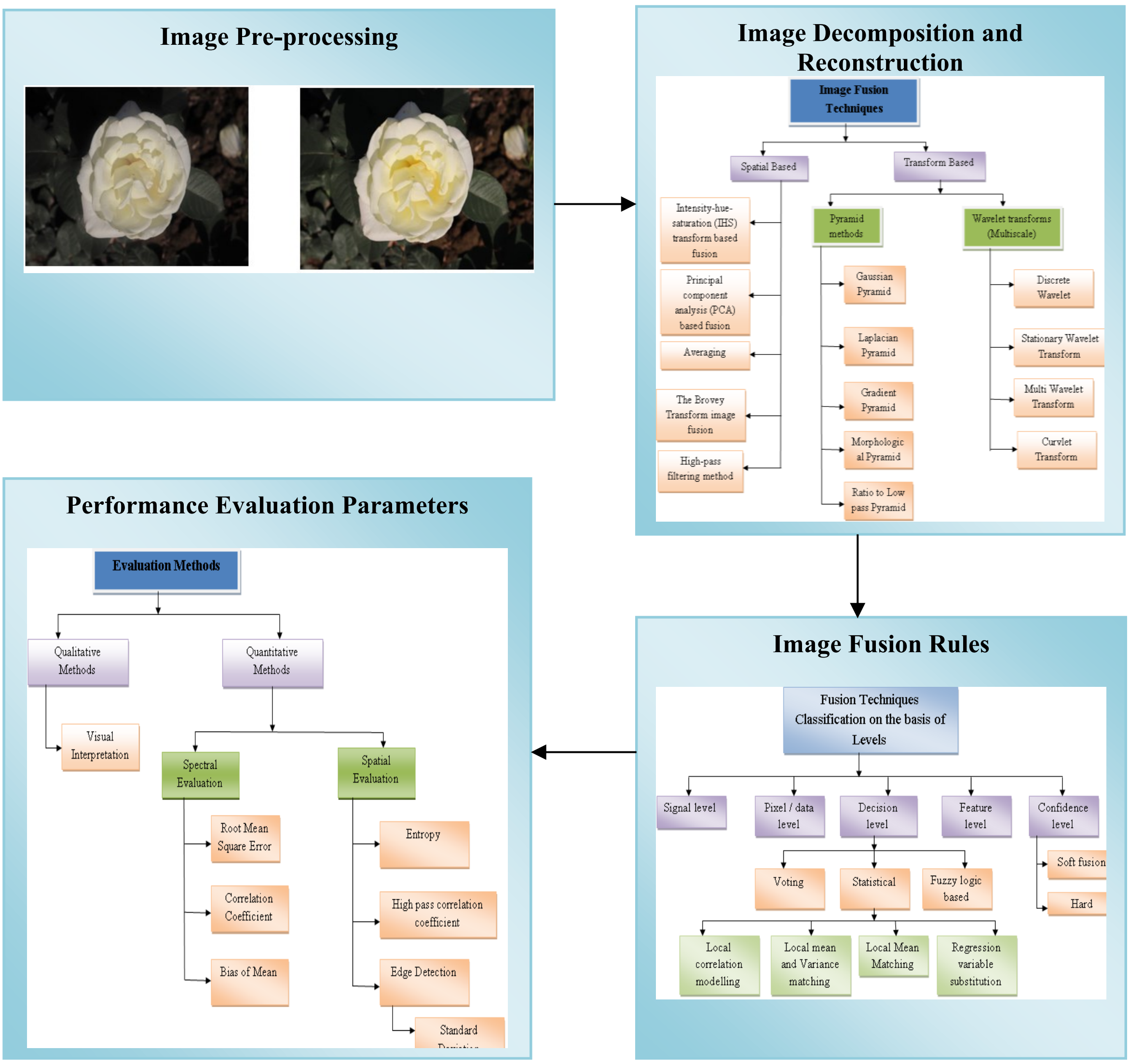

Figure 3. Different steps used for image fusion

(a)

(b)

Figure 4. White flower (a) outdoor image (b) indoor image

Table 2. RGB scale of indoor and outdoor white flower

RGB component	Indoor white flower	Outdoor white flower
R	173	205
G	164	190
B	142	151

Table 3. IHS scale of indoor and outdoor white flower

IHS component	Indoor white flower	Outdoor white flower
Normalized I	42%	43%
Normalized H	135%	35%
Normalized S	61%	69%

Figure 5. Fused image of indoor and outdoor white flower

Finally, after image fusion, images are reconstructed, and the evaluation of IHS and RGB values of the fused images were obtained and tabulated in Table 4. The results presented in Table 4 shows that the fused image gives a remarkable performance considering the RGB and IHS component of indoor and outdoor images. The experimental results illustrates that the designed framework attains an excellent recognition rate. Table 5 shows the results of the performance parameters using DWT and DCT fusion techniques.

In Table 5, PSNR 1 and SNR 1 give the experimental results between source image 1 and the corresponding fused image, and likewise for PSNR2 and SNR2. SNR is a metric used to determine the information-to-noise ratio of a fused image. The higher the value, the more identical the reference and fused images are, whereas, in the case of PSNR, it's a common metric that is calculated by dividing the number of grey levels in the image by the pixel values in the source and fused image. The fused and reference images are identical when the value is high.

Table 4. Performance parameters in terms of RGB and IHS

RGB	IHS
190 (R)	43% (I)
178 (G)	24% (H)
147 (B)	66% (S)

Table 5. Results of the performance parameters obtained from different fusion algorithms

Performance Metric (dB)	DCT	DWT
PSNR 1	114.04	113.32
PSNR 2	114.04	112.29
SNR 1	114.00	113.28
SNR 2	114.01	112.26

4. CONCLUSION

In this paper, a critical review of various image fusion approaches was presented. In addition, two methods were proposed discrete wavelet transform (DWT) method and discrete cosine transform (DCT) method) for fusing images. The results show that high spatial resolution is obtained with traditional ImF techniques which results in image blurring problems. Various ImF strategies have been presented by various researchers to tackle these issues in literature. Image pre-processing (image normalization and image registration), image decomposition, ImF rules, image reconstruction, and image quality evaluation criteria are among the approaches used to fuse images. Later in this paper, two different images were fused by utilizing a spatial IHS transform-based approach. The results show that the fused image produces better outcomes than using individual images for both methods used.

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