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A Review on Digital Image Fusion Techniques

Gaurav Choudhary[1], Dr. Avnesh Verma[2]

[1]*Deptt. of Electronics, Govt. Polytechnic College Rajsamand, India*
[2] *Dept . of Instrumentation (USIC), Kurukshetra University Kurukshetra-136119, India.*

Abstract: Digital Image Fusion is characterized as the way towards joining at least two distinct images into another single image holding critical highlights from each image with expanded information content. The consequence of this is the another image which is more reasonable for human and machine observation or for further image processing requirements such as image segmentation, feature recognition, and object recognition. In this paper, a review related to the techniques in digital image fusion which are already adopted has been given. The examination of every one of these techniques explains that every single technique has its own particular favorable position and disadvantage whether the operation is in spatial domain or transform domain.

Keywords - Image Fusion; Principal Component Analysis; Discrete Wavelet Transform.

1. Introduction

Image fusion process involves the merging of images for additional information, obtained by different or same sensors of several wavelengths simultaneously viewing of the same or different background, to form a single high resolution fused image. The fused image is formed to improve the content of the image for additional information and to make it easier for the user or observer for further processing [1]. In general, image fusion is an important area in digital image processing which involves improvement of image resolution using multiple images of different angles which are either partially focused or obtained from different sources or sensors, which is basically does not obtained by a single source or sensor [1]. Therefore, image fusion is an efficient and important method for proper utilization of huge volume of images obtained from multiple sources. The techniques related to image fusion have been used in various applications such as computer vision, remote sensing, medical imaging, and satellite imaging, etc. [1]-[5].

In the recent years, several image fusion algorithms have been proposed depending upon the requirement or application specific [6]-[36]. In general, image fusion algorithms have been attempted in two domains named as spatial domain and transform domain. The spatial domain approach is based on the operation of nearby task or local operation for an

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image and due to this, these methods have certain benefits such as ease of implementation, preserving original information from source images than the transform domain methods and also in transform domain methods, the fused image is obtained globally which sometimes results in deterioration due to misregistration of images which is generally not found in spatial domain algorithms [1]-[9]. However, the techniques related to spatial domain also have ill effects like reduced contrast and blurring effect etc. [10]-[34], while in case of transform domain methods the fused image obtained has the high signal to noise ratio and high spectral content [10]-[34]. Simple averaging method, Principal Component Analysis (PCA) method, empirical mode decomposition (EMD) etc. are some of the common techniques that have been attempted in spatial domain [1]-[9] while in case of transform domain, Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT), and other commonly related transform techniques have been proposed [10]-[34].

In this paper, the techniques adopted in this area have been explained and reviewed accordingly. The comparison of these techniques which are applied in image fusion states that in most of the cases, the fusion rule is dependent on the type of the image which is obtained from the source/sensor. The rest of the paper is organized in the following manner. In section II, the description regarding the methodologies for image fusion is given. In section III, the observation results with the commonly used performance metrics for image comparison are given and finally in section IV, conclusion following the references is given.

Digital Image Fusion Techniques

Image fusion from the past years has been attempted in two domains namely spatial domain and transform domain.

Spatial Domain Techniques

The spatial domain techniques are based on the direct pixel based operation or in other words it can be said that these techniques are based on local operation approach. Some of the commonly used techniques in spatial domain are explained as:

Averaging Method- This technique is one of the least complex techniques in spatial domain based image fusion algorithms in which average is taken by taking the comparing pixel of the sample images [6]. This technique is additionally named as pixel level strategy [6].

Let U and V are the two input images and F be the fused image. Then according to the averaging rule in spatial domain, the fused image is calculated as [6]

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$$F(i,j) = \frac{U(i,j)+V(i,j)}{2}, \tag{2}$$

where, i and j represent the corresponding row and column for a particular pixel. The main advantages of this method are that this method is simple and easy to implement as it is pixel by pixel approach, but it does not guarantee to have a clear fused image from a given set of input images [6].

a) **Intensity-Hue-Saturation (IHS) based image fusion method** - In this type of image fusion method, the intensity component (I_0) in HSI color space is replaced by a gray level image (I_{new}) having higher spatial resolution and transformed back into the original RGB space with the original H and S components as described in [7]. That is,

$$\begin{bmatrix} I_0 \\ H \\ S \end{bmatrix} = \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ -\sqrt{2}/6 & -\sqrt{2}/6 & 2\sqrt{2}/6 \\ 1/\sqrt{2} & -1/\sqrt{2} & 0 \end{bmatrix} \begin{bmatrix} R_0 \\ G_0 \\ B_0 \end{bmatrix}. \tag{3}$$

Now, after replacing I_0 by I_{new}, the new value of RGB components in RGB color space is calculated as [7]

$$\begin{bmatrix} R_{new} \\ B_{new} \\ G_{new} \end{bmatrix} = \begin{bmatrix} 1 & -1/\sqrt{2} & 1/\sqrt{2} \\ 1 & -1/\sqrt{2} & 1/\sqrt{2} \\ 1 & \sqrt{2} & 0 \end{bmatrix} \begin{bmatrix} I_{new} \\ H \\ S \end{bmatrix}, \tag{4}$$

where, R_0, G_0, B_0, I_0, H, and S represent the corresponding values for the resized original image. R_{new}, B_{new}, and G_{new} are the corresponding values of the high resolution fused image [6], [7].

A problem with this method (and also for similar types of other existing image fusion methods) [6], [7] is color balancing. In other words, the color of the image may be changed during fusion. This problem is called as color distortion problem [6], [7]. The other details can be seen in [6], [7].

b) **Principal component analysis (PCA) based image fusion method** - This image fusion technique is also known as the Karhunen-Loeve transform

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technique, which is basically a decorrelation scheme used for various mapping and information extraction in remote sensing area [6].

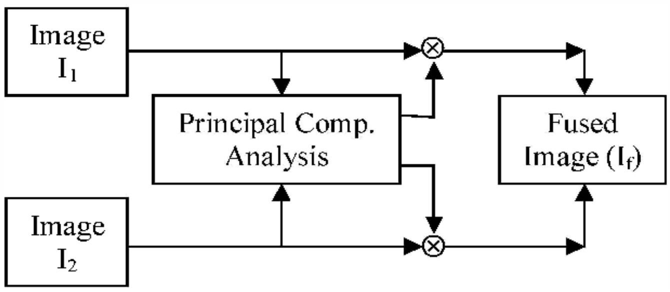

Fig.1. Image Fusion Process using PCA

An orthogonal color coordinate system for PCA can be derived, which is given as [6]

$$\begin{bmatrix} PC_1 \\ PC_2 \\ PC_3 \end{bmatrix} = \begin{bmatrix} \varphi_{11} & \varphi_{12} & \varphi_{13} \\ \varphi_{21} & \varphi_{22} & \varphi_{23} \\ \varphi_{31} & \varphi_{32} & \varphi_{33} \end{bmatrix} \begin{bmatrix} R_0 \\ G_0 \\ B_0 \end{bmatrix}, \tag{5}$$

$$H = \tan^{-1}\left(\frac{PC_3}{PC_2}\right), \tag{6}$$

$$S = \sqrt{PC_2^2 + PC_3^2}. \tag{7}$$

The hue and saturation in the above equations are different from the IHS system [6]. The transformation matrix φ consisting of the term φ_{ij}, consists of the eigen vectors of the covariance matrix of the RGB color space vectors. Let R denotes the covariance matrix with general terms r_{ij} , then the transformation matrix satisfies the following relationship which is defined in [6] as

$$\varphi R \varphi^T = \Lambda, \tag{8}$$

where, $\Lambda = diag(\Lambda_1, \Lambda_2, \Lambda_3)$ are the eigen values of φ matrix in descending order. The steps to merge the RGB image and the Pan image using the PCA method are similar to that of the IHS method of [6]. That is, the first component (PC_1) of the PCA space is replaced by the Pan image and retransformed back into the original RGB color space [6].

c) **Singular value decomposition (SVD) based image fusion methods** - The singular value decomposition (SVD) is a method of decomposition of either a real matrix or complex matrix, and is a useful technique in many signal/image processing applications [6]. The SVD of a real or complex matrix U, whose size is $L \times M$ can be expressed as [6]

$$U = ASB^{*}, \tag{9}$$

where, A is the $L \times L$ real or complex unitary matrix, S is a $L \times M$ diagonal matrix having non-negative diagonal values and B^{*} (the conjugate transpose of B) whose size is $M \times M$ is the real or complex unitary matrix [6].

d) **Empirical mode decomposition (EMD) based image fusion methods** - Empirical mode decomposition (EMD) is an adaptive technique in the area of signal/digital image processing, which decomposes a signal into a finite set of components called as intrinsic mode functions (IMF_S) by means of an algorithm called as sifting algorithm [8]. The EMD decomposes a signal $f(t)$ in [8] as

$$f(t) = \sum_{i=1}^{N} C_i(t) + C_r(t), \tag{10}$$

where, $C_i(t)$, $i = 1, 2, \ldots\ldots, M$, are the corresponding IMF_s and $C_r(t)$ is the residue. The rest details for EMD can be seen in [8].

Besides EMD, the bivariate EMD has also been introduced in [8], [9] and the corresponding IMF_s obtained from the bivariate EMD can be used in image fusion [8]-[9], whose operation is similar to EMD [8], [9]. Thus, the IMF_s obtained from the bivariate EMD have been attempted in both spatial and transform domains in image fusion [8], [9], for example multiscale image fusion using complex extension of EMD in [9].

1.1. Transform Domain Techniques

Transform based methods for image fusion have also been proposed using different transforms, e.g., the pyramid decomposition [10]-[12], discrete wavelet transform (DWT) [13]-[16], stationary wavelet transform (SWT) [17], [18], dual-tree complex wavelet transform (DTCWT) [19]-[22], curvelet transform (CVT) [23]-[27],

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contourlet transform (CT) [28]-[30], non-subsampled contourlet transform (NSCT) [31]-[33], and discrete cosine transform (DCT) based Laplacian pyramid (DCT-LP) [34] etc. The brief descriptions of some of the commonly used image fusion algorithms in transform domain are as follows with ready references.

a) **Discrete wavelet transform (DWT) based image fusion methods** - The 2-D discrete wavelet transform is a mathematical tool and it is used when digital images are to be processed at multiple resolutions [13]-[16]. The 2-D DWT provides powerful insight into an image's frequency characteristics [13]-[16]. The kernels can be represented as three separable 2-D wavelets, which are called as horizontal, vertical, and diagonal wavelets and one separable 2-D scaling function respectively [13]-[16].The other details can be seen in [13].

   On the basis of above description, several image fusion methods using the DWT have been proposed [13]-[16], for e.g., multisensor image fusion using the wavelet transforms [13], multiscale-decomposition based image fusion scheme [14], etc.

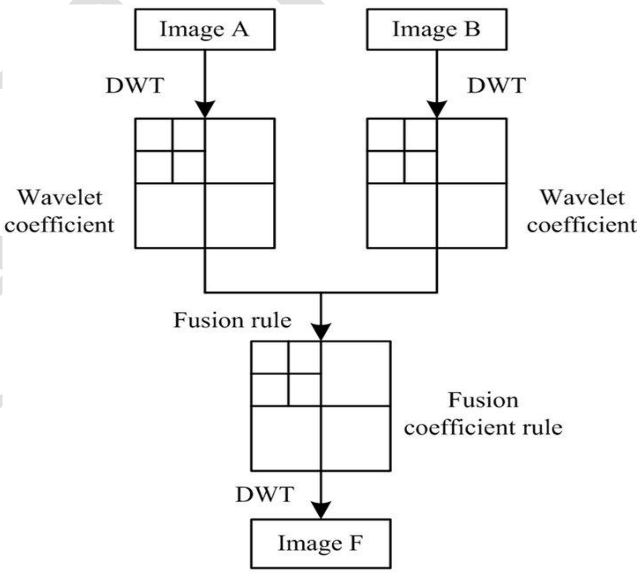

Fig. 3. Image Fusion Steps using 2-D DWT

b) **Dual-tree complex wavelet transform (DTCWT) based image fusion methods** - The DTCWT is an enhanced version of the DWT with some

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additional properties [19]-[22]. A comparative analysis between DWT and DTCWT is given in [19].

On the basis of DTCWT, some of the already existing techniques for image fusion are driven image fusion based on alpha-stable modeling of wavelet coefficients [20], complex wavelets for extended depth of microscopy images in image fusion [21], and dual tree discrete wavelet transform with application to image fusion [22].

c) **Curvelet transform (CVT) based image fusion methods** - Curvelet transform (CVT) is a non-adaptive technique in signal processing applications [23] and it is used for multi-scale object representation [23]. The CVT is also an extension of the DWT [23] and that is why the CVT is also used in various image processing applications [23]-[27].

Some of the commonly used image fusion methods using the CVT are remote sensing image fusion using the curvelet transform [26], and a novel image fusion method using curvelet transform based on linear dependency test [27] etc.

d) **Contourlet transform (CT) based image fusion methods** - The contourlet transform (CT) is based on Laplacian pyramid decomposition [28]-[30], followed by directional filter bank for each sub band to get the smooth contour of the images [28]-[30]. On the basis of the above definition of CT, several image fusion algorithms have been proposed such as multimodality medical image fusion based on multiscale geometric analysis of contourlet transforms [29], image fusion based on a new contourlet packet [30], etc.

e) **Stationary wavelet transform (SWT) based image fusion methods** - The stationary wavelet transform (SWT) is a wavelet transform which is basically designed to overcome the lack of translation-invariance of the DWT [17], [18]. Some of the common applications of the SWT are signal denoising, pattern recognition, and MR image classification etc., [17], [18]. The algorithms based on the SWT for image fusion are given in [17] and [18].

f) **Discrete cosine transform (DCT) based image fusion methods** - The discrete cosine transform gives a finite sum of cosine functions at different frequencies [34] and has been implemented in various applications of science and engineering such as lossy compression of audio (MP3), and JPEG images [34]. One of the recent image fusion algorithms has been proposed in which fusion rule is applied accordingly with the help of discrete cosine functions [34].

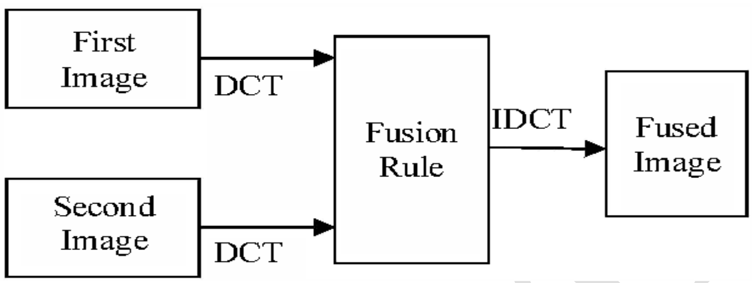

Fig. 4. Image Fusion Steps using DCT

2. Experiments and Analysis

In this section, the simulation results of some the existing techniques which are carried out in MATLAB are provided. The details of testing data and performance metrics with ready references are given below.

3.1 Mutual Information (MI)

The mutual information (MI) is basically a measure of mutual dependence of random variables. It can be calculated by using the joint distribution $p_{XY}(x,y)$ and the distribution associated with the complete independence $p_X(x)\ p_Y(y)$, by means of relative entropy in [35] as

$$I_{XY} = \sum_{x,y} p_{XY}(x,y) \log_2 \frac{p_{XY}(x,y)}{p_X(x)\, p_Y(y)}, \tag{11}$$

where, X and Y are the two discrete random variables.

Now, considering any two source images, say U and V, and the fused image F, the amount of information that F contains about U and V is calculated in [35] as

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$$I_{FU}=\sum_{f,u}p_{FU}(f,u)\log_2\frac{p_{FU}(f,u)}{p_F(f)\;p_U(u)}, \tag{12}$$

and

$$I_{FV}=\sum_{f,v}p_{FV}(f,v)\log_2\frac{p_{FV}(f,v)}{p_F(f)\;p_B(v)}. \tag{13}$$

By using the equations explained above, the mutual information can be calculated as [35]

$$MI=I_{FU}+I_{FV}. \tag{14}$$

3.2 Information Entropy (H)

The entropy $H(k)$ of a discrete random variable k is defined as [35]

$$H(k)=-\sum_{i=0}^{L-1}p_F(i)\log_2 p_F(i), \tag{15}$$

where, k, p_F, and L denote the gray-level index, the normalized histogram, and the number of bins in the histogram, respectively [35].

3.3 Xydeas and Petrovic metric

This performance metric is proposed by Xydeas and Petrovic, which basically measures the relative amount of edge information that is transformed from the source images U and V into the fused image, F [35], [36]. Sobel edge detector is used by this method in order to calculate the strength $g(m,n)$ and orientation $\alpha(m,n)$ information together at each pixel in both the inputs and output images. The relative orientation and the relative strength values of a input image U, with respect to the output (fused) image F, are defined in [35] as

$$G_{m,n}^{UF}=\frac{g_F(m,n)}{g_U(m,n)};\; g_U(m,n)>g_F(m,n)$$
$$\frac{g_U(m,n)}{g_F(m,n)};\; otherwise. \tag{16}$$

$$A_{m,n}^{UF}=1-\frac{\left|\alpha_U(m,n)-\alpha_F(m,n)\right|}{\pi/2}. \tag{17}$$

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Edge information preservation values are calculated as [36]

$$Q_{m,n}^{UF} = \Gamma_g \Gamma_\alpha \left(1+e^{K_g\left(G_{m,n}^{UF}-\sigma_g\right)}\right)^{-1}\left(1+e^{K_\alpha\left(A_{m,n}^{UF}-\sigma_\alpha\right)}\right)^{-1}, \tag{18}$$

where, the constants Γ_g, K_g, σ_g, and Γ_α, K_α, σ_α determine the shape of the sigmoid function orientation [35]. Now, having $Q_{m,n}^{UF}$ and $Q_{m,n}^{VF}$ for two $L \times M$ source images, a normalized weighted performance metric is obtained in [35] as

$$Q^{UV/F} = \frac{\sum_{m=1}^{M}\sum_{n=1}^{N} Q_{m,n}^{UF} w_{m,n}^{UF} + Q_{m,n}^{VF} w_{m,n}^{VF}}{\sum_{m=1}^{M}\sum_{n=1}^{N} w_{m,n}^{UF} + w_{m,n}^{VF}}, \tag{19}$$

where, $Q_{m,n}^{UF}$ and $Q_{m,n}^{VF}$ are the edge preservation values and are weighted by the values of $w_{m,n}^{UF}$ and $w_{m,n}^{VF}$, which are defined as $w_{m,n}^{UF} = \left[g_U(m,n)\right]^L$ and $w_{m,n}^{VF} = \left[g_U(m,n)\right]^L$, where L is a constant and $0 \le Q^{UV/F} \le 1$ [36].

3.4 Standard deviation (σ)

This metric is more efficient in absence of noise. It basically measures the contrast in the fused image. An image with high contrast would have high standard deviation [35]. The standard deviation of an image is calculated as [36]

$$\sigma = \sqrt{\sum_{i=0}^{L-1}(i-i')\,p_F(i)}, \tag{20}$$

and

$$i' = \sum_{i=0}^{L-1} i\, p_F(i), \tag{21}$$

where, $p_F(i)$ and i have the usual meaning as explained above in the information entropy (H).

The results obtained for 'watch' and 'PET & MRI' sample images [32], [5] are shown below.

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a *b* *c*

d *e* *f*

Fig. 5. Fusion results for 'watch' sample images[32]
a) 1st Input image
b) 2nd Input image
c)Averaging method in spatial domain

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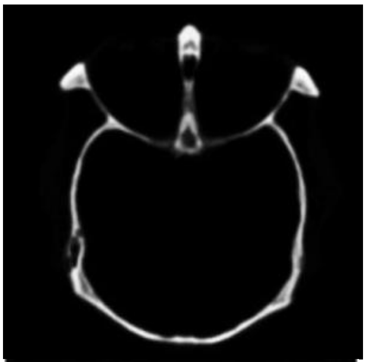
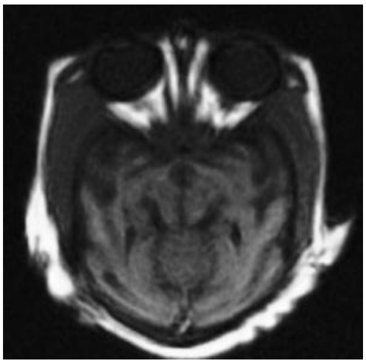
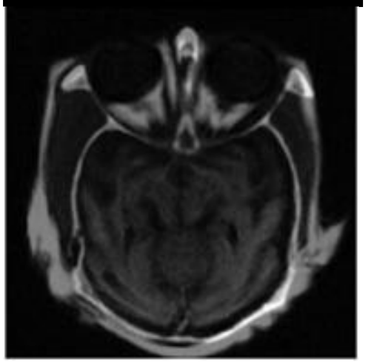
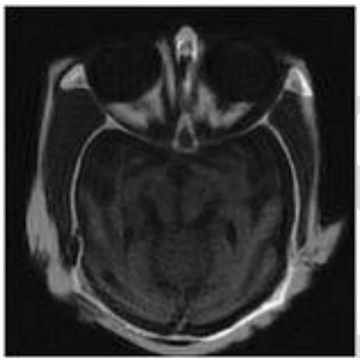
d)DCT-LP method
e)SWT-Level 1 method
f)SWT-Level 2 method

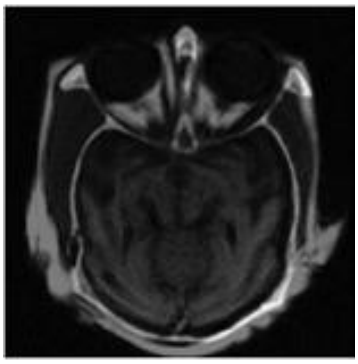


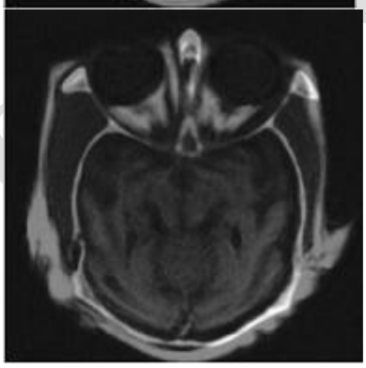




a ***b*** ***c***







e ***f*** ***g***

Fig. 6. Fusion results for 'PET and MRI' sample images[5]
a) 1st Input image
b)2nd Input image

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c)Averaging method in spatial domain
d)DCT-LP method
e)SWT-Level 1 method
f)SWT-Level 2 method

The various non-reference performance metrics calculated for the above images in MATLAB are shown in the following tables.

Watch	*MI (F, U)*	*MI (F, V)*	*Entropy (H)*	$Q^{UV/F}$	*Std. Deviation*
Averaging (Spatial Domain)	2.8693	2.9621	7.3736	0.5032	44.6292
DCT-LP	2.2954	2.6166	7.4500	0.5308	46.0964
SWT (Level 1)	2.7483	2.9560	7.4319	0.5649	45.6790
SWT (Level 2)	2.6942	2.9557	7.4399	0.5777	45.9242

Table 1. Comparison of Methods Using Performance Evaluation Metrics for Fig. 5.

PET+MRI	*MI (F, U)*	*MI (F, V)*	*Entropy (H)*	$Q^{UV/F}$	*Std. Deviation*
Averaging (Spatial Domain)	0.5885	4.4678	6.0158	0.4363	35.5772
DCT-LP	0.5249	2.5238	6.2238	0.4641	36.0867
SWT (Level 1)	0.5820	3.8613	6.0949	0.4654	35.6873
SWT (Level 2)	0.5774	3.7004	6.1024	0.4813	35.6873

Table 2. Comparison of Methods Using Performance Evaluation Metrics for Fig. 6.

3. Conclusion

In this paper, a review related to the techniques in digital image fusion which are already adopted has been given. The examination of every one of these techniques explains that every single technique has its own particular favourable position and disadvantage whether the operation is in spatial domain or transform domain.

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