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## Analysis of Fusion Techniques with Application to Biomedical Images: A Review

**Hamsalekha.R**

M.Tech Student, Department of ECE  
HKBK College of Engineering  
Bangalore, India  
hamsalekha20@gmail.com

**Dr. Rehna V. J**

Professor, Department of ECE  
HKBK College of Engineering  
Bangalore, India  
rehna\_vj@yahoo.co.in

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**Abstract:** *One of the major research fields in image processing is image fusion. Image fusion is a process of combining the relevant information from a set of images, into a single image, where in the resultant fused image obtained will have more complete information of the all the input images in a single image itself. Image fusion is defined as the integration of data and information from all input registered images without any loss of information and distortion. It is not possible to get an image with all relevant features in focus, so to get all the features in one image is by fusing images with different focus settings. This paper presents a review of different fusion techniques like primitive fusion methods which includes Average Method, Select Maximum And Select Minimum, Discrete Wavelet Transformation Based Fusion, Principal Component Analysis (PCA), Graph cut method etc. This paper also gives the details of different fusion techniques performance measures like Peak signal to noise ratio (PSNR), Normalized Cross Correlation (NCC), Entropy (EN), Mean Square Error (MSE), Structural Similarity Index Measure (SSIM), Laplacian Mean Square Error (LMSE), Structural Content (SC), Maximum Difference (MD), Normalized Absolute Error (NAE). Comparison and effective use of all techniques in quality of image assessment is also determined.*

**Keywords:** *Image fusion, discrete wavelet transform, graph cuts, image quality assessment parameter.*

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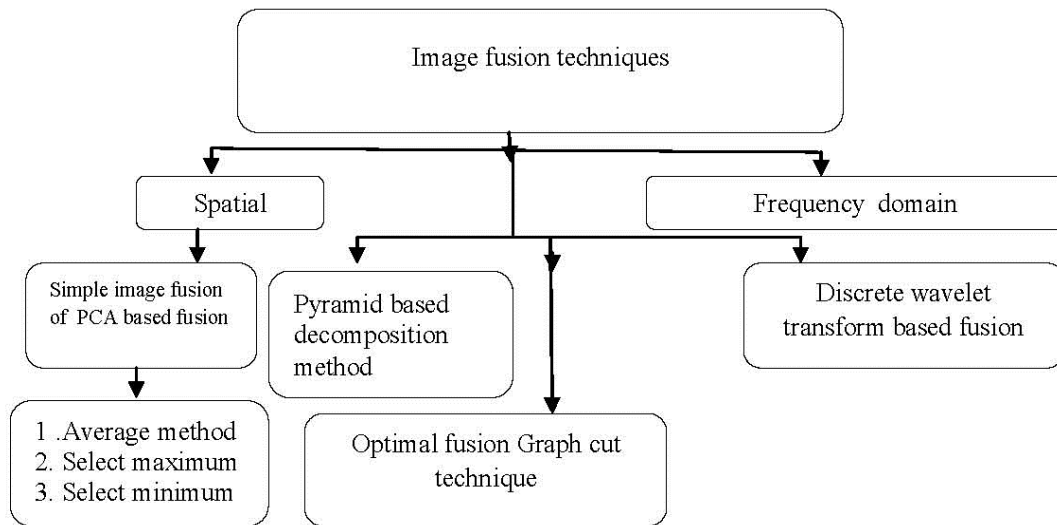
### 1. INTRODUCTION

Image fusion is the process of combining relevant information from a set of images of the same scene, into a single image, where in the resultant fused image obtained will have more complete information of the all the input images in a single image itself. The input image can be multi-modal, multifocal, multi sensor or multi temporal. Image fusion finds its application in navigation, medical diagnosis, object detection and recognition satellite imaging etc. Image fusion algorithms can be categorized into different levels like low, middle and high; or pixel, feature, and decision levels. The pixel level method works either in the spatial domain or in the transformation domain. Pixel level fusion works directly on the pixels obtained at imaging sensor outputs while feature level fusion algorithms operate on features extracted from the source images. Several fusion algorithms starting from simple pixel based to sophisticated wavelets and PCA based are available. Image fusion system has several advantages over single image source and resultant fused image should have higher signal to noise ratio, increased robustness and reliability in the event of sensor failure, extended parameter coverage and rendering a more complete picture at different of the system. The pixel based image fusion methods average pixel intensity values to the source images pixel by pixel which leads to undesired side effects in the resultant image. Recently researchers have recognized that it is more meaningful to combine objects or regions rather than pixels. The region based algorithm has many advantages over pixel based algorithm like it is less sensitive to noise, better contrast, less affected by mis-registration but at the cost of complexity. Section 2 describes different image fusion techniques, section 3 presents the various performance measures. During the study we have observed various issues which are summarised in section 4 and finally conclusion is presented in section 5.

### 2. IMAGE FUSION TECHNIQUES

Image fusion techniques can enhance a digital image without spoiling it. The enhancement methods are of two types namely spatial domain methods and frequency domain methods. Spatial domain method directly deal with pixels of input images pixels. The fusion methods such as simple maximum, simple minimum, averaging, principal component analysis (PCA), and IHS based methods fall under spatial domain approaches. In transformation domain method image is first transferred in to frequency

domain. The fusion method such as DWT fall under transform domain method. The figure 2.1 shows the classification of different image fusion techniques.



**Fig2.1.** Classification of image fusion techniques

**2.1. Simple Maximum Method**

In this image fusion method, the resultant fused image is obtained by selecting the maximum intensity of corresponding pixels from both the input image.

$$F(i,j)=\sum_{i=0}^m \sum_{j=0}^n \max A(i, j)B(i, j)$$

A (i,j), B(i,j) are input images and F(i,j) is fused image.

**2.2. Simple Minimum Method**

In this image fusion method, the resultant fused image is obtained by selecting the minimum intensity of corresponding pixels from both the input image.

$$F (i,j)=\sum_{i=0}^m \sum_{j=0}^n \min A(i, j)B(i, j)$$

A (i,j), B(i,j) are input images and F(i,j) is fused image.

**2.3. Simple Average Method**

In this image fusion method the resultant fused image is obtained by taking the average intensity of corresponding pixels from both the input image.

$$F (i,j)=A(i, j) + B(i, j)2$$

A(i,j), B(i,j) are input images and F(i,j) is fused image.

**2.4. Weighted Average Method**

In this image fusion method the resultant fused image is obtained by taking the weighted average intensity of corresponding pixels from both the input image.

$$F (i,j)=\sum_{i=0}^m \sum_{j=0}^n W A(i, j) + (1 - w)B(i, j)$$

A (i,j), B(i,j) are input images and F(i,j) is fused image and W is weight factor.

**2.5. Principal Component Analysis (PCA)**

PCA is defined as a mathematical tool which transforms a number of correlated variables into a number of uncorrelated variables. The PCA is used extensively in image compression and image classification. The PCA involves a mathematical procedure that transforms a number of correlated variables into a number of uncorrelated variables called principal components. It computes a compact and optimal description of the data set. The first principal component accounts for as much of the variance in the data as possible and each succeeding component accounts for as much of the remaining variance as possible. First principal component is taken to be along the direction with the

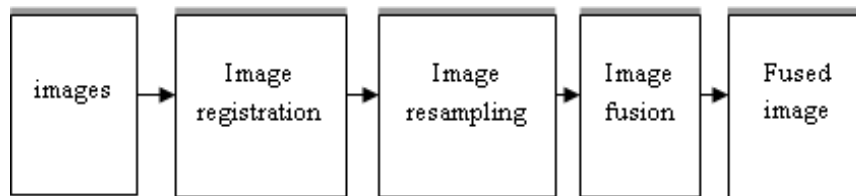
maximum variance. The second principal component is constrained to lie in the subspace perpendicular of the first. Within this Subspace, this component points the direction of maximum variance. The third principal component is taken in the maximum variance direction in the subspace perpendicular to the first two and so on. The PCA is also called as Karhunen-Loève transform or the Hotelling transform. The PCA does not have a fixed set of basis vectors like FFT, DCT etc.

**2.6. Discrete Wavelet Transform Method (DWT)**

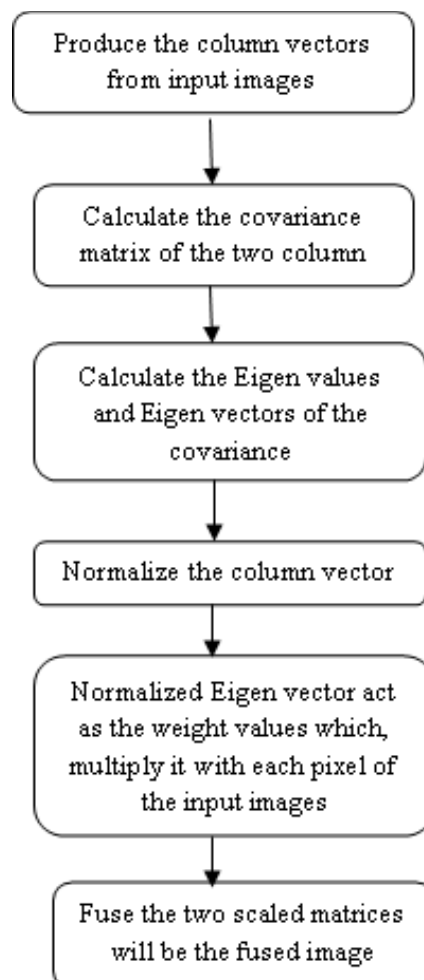
Wavelets are defined as the finite duration oscillatory functions with zero average value with finite energy. They are suited for transient signal analysis. The irregularity and good localization properties make them better basis for analysis of signals with discontinuities. Wavelets can be described by using two functions they are the scaling function  $f(t)$ , also known as “father wavelet” and the wavelet function or “mother wavelet”. Mother wavelet  $(t)$  undergoes translation and scaling operations to give self similar wavelet families as given by Equation:

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}} \left( \frac{t-b}{a} \right), (a, b \in R)$$

The wavelet transform decomposes the image into low-high, high-low, high-high spatial frequency bands at different scales and the low-low band at the coarsest scale which is shown in fig: 2.3 The L-L band contains the average image information whereas the other bands contain directional information due to spatial orientation. Higher absolute values of wavelet coefficients in the high bands correspond to salient features such as edges or lines the basic steps performed in image fusion given Figure 2.2.



Stepwise procedure for PCA method is given below



The wavelets-based approach is appropriate for performing fusion tasks for the following reasons:-

- It is a multi-resolution approach well suited to manage the different image resolutions. Useful in a number of image processing applications including the image fusion
- The discrete wavelets transform allows the image decomposition in different kinds of coefficients preserving the image information. Such coefficients coming from different images can be appropriately combined to obtain new coefficients so that the information in the original images is collected appropriately
- Once the coefficients are merged the final fused image is achieved through the inverse discrete wavelets transform (IDWT), where the information in the merged coefficients is also preserved,

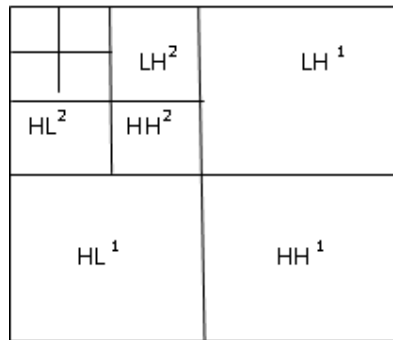


Fig2.3. wavelet decomposition

H-----High frequency bands

L-----low frequency bands

1,2,3-----decomposition levels

### 2.7. Orthogonal Wavelet Decomposition Based Image Fusion

The orthogonal wavelet decomposition (OWD) is a method used for fusing multi-sensor images which is very popular. The OWD allows the decomposition of an image with a wavelet basis according to a pyramid scheme. The resolution is reduced by one-half at each level by sub sampling data by two. The complete decomposition produces the same number of pixels as the original image. Four plans are produced at each resolution level corresponding to one approximation image (low resolution content) and three detail images (horizontal, vertical and diagonal detail images). The use of the OWD for image fusion allows improving the quality of the fused image compared to the Laplacian pyramid. However, some limitations can be evoked:

- The OWD is implemented for discrete images with sizes that are powers of two because the resolution is reduced by two at each level. From this fact, it is not possible to fuse images of any sizes.
- The analysis pixel by pixel is not possible since data are reduced at each resolution; it is then not possible to follow the evolution of a dominant feature through levels.
- The OWD does not permit to distinguish easily the dominant features of the image. Finally, there is presently no satisfactory rule allowing good quality of the fusion with an orthogonal decomposition.

### 2.8. Curvelet Transform Based Image Fusion

The wavelet fusion technique is employed in both satellite, remote and medical image applications. The basic limitation of wavelet fusion algorithm is in the fusion of curved shapes. Thus, there is a need for another technique that can handle curved shapes efficiently. So, the applications of the curvelet transform result in better fusion efficiency. A few attempts of curvelet fusion have been made in the fusion of satellite images but no attempts have been made in the fusion of medical images. The main objective of medical imaging is to obtain a high resolution image with as much details as possible for the sake of diagnosis. There are several medical imaging techniques such as the MR and the CT techniques. Both techniques give Special sophisticated characteristics of the organ the MR and the CT images of the same organ would result in an integrated image of much more details.

Researchers have made few attempts for the fusion of the MR and the CT images. Most of this attempt the application of the wavelet transform for this purpose. Due to the limited ability of the wavelet transform to deal with images having curved shapes, the application of the curvelet transform for MR and T image fusion is presented in this work. The algorithm of the curvelet transform of an image  $P$  can be summarized in the following steps:

- The image  $P$  is split up into three sub-bands  $\Delta_1$ ,  $\Delta_2$  and  $P_3$  using the additive wavelet transform.
- Tiling is performed on the sub-bands  $\Delta_1$  and  $\Delta_2$ .
- The Discrete Ridgelet transform is performed on each tile of the sub-bands  $\Delta_1$  and  $\Delta_2$ .

### 2.8.1. Sub Band Filtering

It is used to decompose the image into additive components; each of which is a sub band of that image. This step isolates the different frequency components of the image into different planes without down.

### 2.8.2. Sampling as in the Traditional Wavelet Transform

Tiling: Tiling is the process by which the image is divided into overlapping tiles. These tiles are small in dimensions to transform curved lines into small straight lines in the sub bands  $\Delta_1$  and  $\Delta_2$ . The tiling improves the ability of the curve-let transform to handle curved edges.

### 2.8.3. Ridgelet Transform

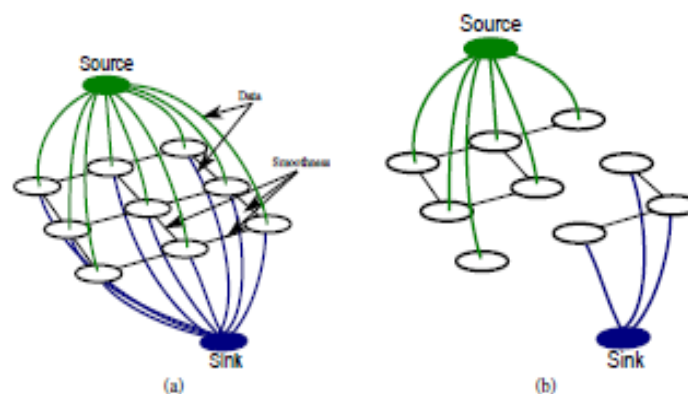
The Ridgelet transform belongs to the family of discrete transforms employing basis functions. To facilitate its mathematical representation, it can be viewed as a wavelet analysis in the Radon domain. The Radon transform itself is a tool of shape detection. So, the Ridgelet transform is primarily a tool to detection shape of the objects in Image.

## 2.9. Graph Cut Optimization Technique

Exactly one label is given to each pixel in the image, with associated data and smoothness costs assigned to the links in the graph. To formulate this optimization let  $G = (V, E)$  be a weighted graph, with  $V$  a set of nodes and  $E$  a set of weighted edges.  $V$  contains a node for each pixel in  $\Omega$  and for each label in  $L_\alpha$ . There is an edge  $e\{p,q\}$  between every pair of nodes  $p, q$ . A cut  $C \subset E$  is a set of edges that separates all the label nodes from each other, thereby, creating a sub-graph for each label. The minimum-cut problem consists of finding a cut  $C$  with the lowest cost. The cost of this minimum cut, denoted  $|C|$ , equals the sum of the edge weights in  $C$  properly setting the weights of the graph, one can use a series of swap moves from combinatorial optimization to efficiently compute the minimum-cost cuts corresponding to a minimum of Functional  $E$ .

## 3. IMAGE QUALITY METRICS

It is not possible to get an image that contains all relevant objects in focus because of limited focus depth of the optical lens.



**Fig2.6.** An illustration of the graph-cut problem: a) A binary graph showing the data cost of assigning a label to the sink/source and smoothness cost of assigning a labelling to adjacent pixel locations, b) the end result of the labelling of the graph.

Image Quality is a characteristic of an image that measures the perceived image degradation. Imaging systems like the fusion algorithm may introduce some amounts of distortion or artefacts in the signal, so the quality assessment is an important problem. Image Quality assessment methods can be broadly classified into two categories: Full Reference Methods (FR) and No Reference Method (NR). In FR, the quality of an image is measure in comparison with a reference image which is assumed to be perfect in quality .NR methods do not employ a reference image. The image qualities metrics considered and implemented here fall in the FR category. In the following sections, the SSIM and some other image quality metrics implemented to assess the quality of our fused are analysed with their performance measures.

### 3.1. Structural Similarity Index Measure (SSIM )

It is defined as a measure of structural information change can provide a good approximation to perceived image distortion. The SSIM compares local patterns of pixel intensities that have been normalized such as luminance and contrast. It is an improved version of traditional methods like PSNR and MSE. The SSIM index is a decimal value between 0 and 1. A value of 0 would mean zero correlation with the original image, and 1 means the exact same image

1. Symmetry:  $S(x, y) = S(y, x)$
2. Boundedness:  $S(x, y) \leq 1$
3. Unique maximum:  $S(x, y) = 1$  if and only if  $x = y$  (in discrete representations  $x_i = y_i$  , for all  $i = 1, 2, \dots, N$ )

SSIM can be calculated using SSIM

$$MEAN = \left( \frac{(2\mu_1\mu_2 + c_1)(2\sigma_{12} + C_2)}{(\mu_1^2 + \mu_2^2 + c_1)(\sigma_1^2 + \sigma_2^2 + c_1)} \right)$$

$$\sigma_1^2 = (A_{ij}^2 \cdot G) - \mu_1^2$$

$$\sigma_2^2 = (A_{ij}^2 \cdot G) - \mu_2^2$$

$$\sigma_{12}^2 = (A_{ij}^2 \cdot B_{ij} \cdot G) - \mu_1 \cdot \mu_2$$

$$\mu_1 = A \cdot G \text{ where } G \text{ being Gaussian filter window, } \mu_2 = B \cdot G$$

$$c_1 = (K_1 \cdot L)^2$$

$$c_2 = (K_2 \cdot L)^2 \text{ where } L=255, K=[0.01 \text{ to } 0.03]$$

### 3.2. Laplacian Mean Squared Error (LMSE)

Laplacian mean square error, error is calculated based on the Laplacian value of the expected and obtained data is given by LMSE is given by

$$LMSE = \frac{\sum_{i=1}^m \sum_{j=1}^n (\nabla^2 A - \nabla^2 B)^2}{\sum_{i=1}^m \sum_{j=1}^n (\nabla^2 A)^2}$$

For an ideal situation, the fused and perfect image being identical, the LMSE value is supposed to be 0. The error value which would exist otherwise would range from 0 to 1.

### 3.3. Mean Squared Error (MSE)

Mean square error is a measure of image quality index. The large value of mean square means that image is a poor quality. Mean square error between the reference image and the fused image is

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

Where  $A_{i, j}$  and  $B_{i, j}$  are the image pixel value of reference image.

### 3.4. Peak signal to Noise Ratio (PSNR)

The ratio between maximum possible powers of the signal to the power of the corrupting noise that creates distortion of image. The peak signal to noise ratio can be represented as

$$PSNR (db) = 20 \log \frac{255\sqrt{3mn}}{\sqrt{\sum_{i=1}^m \sum_{j=1}^n (A_{ij} - B_{ij})^2}}$$

Where A- fused image, B – perfect image, i – pixel power index, j – pixel column index, M, N – Number of rows and columns respectively.

### 3.5. Entropy (EN)

Entropy is used to evaluate the information quantity contained in an image. The higher value of entropy implies that the fused image is better than the reference image. Entropy is defined as

$$E = -\sum_{i=0}^{L-1} p_i \log_2 p_i$$

Where L = total of grey labels,

P = {p<sub>0</sub>, p<sub>1</sub>, p<sub>L-1</sub>} is the probability distribution of each labels

### 3.6. Structural Content (SC)

The structural content measure used to compare two images in a number of small image patches the images have in common. The patches to be compared are chosen using 2D continuous wavelet which acts as a low level corner detector. The large value of structural content SC means that image is poor quality

$$SC = \frac{\sum_{i=1}^m \sum_{j=1}^n (A_{ij})^2}{\sum_{i=1}^m \sum_{j=1}^n (B_{ij})^2}$$

### 3.7. Normalized Cross Correlation (NCC)

Normalized cross correlation is a measure of similarity of two waveforms as a function of the time lag applied to one of them. The cross correlation is similar in nature to the convolution of two functions.

$$NCC = \frac{\sum_{i=1}^m \sum_{j=1}^n (A_{ij} * B_{ij})}{A^2_{ij}}$$

### 3.8. Maximum Difference (MID)

Difference between any two pixels such that the larger pixel appears after the smallest pixel. The large value of Maximum difference means that image is poor in quality.

$$MD = \text{Max} (|A_{ij} - B|), i = 1, 2, \dots, m; j = 1, 2, \dots, n$$

#### I. Normalized Absolute Error

The large value of normalized absolute error means that image is poor quality. NAE is defined as follows

$$NAE = \frac{\sum_{i=1}^m \sum_{j=1}^n (|A_{ij} - B_{ij}|)}{\sum_{i=1}^m \sum_{j=1}^n (A_{ij})}$$

## 4. CONCLUSION

This paper provides a review of different image fusion techniques. Spatial domain provides high spatial resolution.

But in spatial domain spectral distortion is the main drawback therefore transform domain image fusion is done. Based on the analysis done on various transform domain techniques such as, wavelet transform, discrete wavelet transform, curvelet transform and graph cut techniques. It has been concluded that each technique it meant for specific application and one technique has an edge over the other in terms of particular application. Finally the image quality assessment parameters have been reviewed and determine the role of individual image quality assessment parameter to determine the quality of the fused image.

### 4.1. Comparative Study of Various Image Fusion Techniques

Based on the of the study, few comparisons between the different existing fusion techniques have been made and are analysed along with their performance measures theoretically which are shown in Table 1 as below.

S.NO	Fusion Technique /Algorithm	Domain	Measuring parameter	Advantages	Disadvantages
1	Simple Average	Spatial	PSNR-25.48 EN-7.22	Simplest and best method of image fusion	The main disadvantage of Pixel level method is that this method does not give guarantee to have a clear objects from the set of images.
2	Simple Maximum	Spatial	PSNR-26.86 EN-7.20	Resulting in highly focused image output obtained from the input image as compared to average method	Pixel level method are affected by blurring effect which directly affect on the contrast of the image
3	PCA	Transform	PSNR-76.44 NC-0.998	PCA is a tools which transforms number of correlated variable into number of uncorrelated variables, this property can be used in image fusion,	Spectral degradation is present
4	DWT	Transform	PSNR-76.44 NC-0.998	It provides better signal to noise ratio than pixel based approach	less spatial resolution
5	Combine DWT,PCA	Transform	PSNR-76.44 NC-0.998	Multi level fusion where the image undergoes fusion twice using efficient fusion technique provide improved result output image contained both high spatial resolution with high quality spectral content	This method is complex in fusion algorithm. Required good fusion technique for better result
6	Combination of Pixel & Energy Fusion rule	Transform	PSNR-77 NC-0.99	Preserves boundary information and structural details without introducing any other inconsistencies to the image.	Complexity of method increases.
7	Orthogonal wavelet decomposition method	Transform	PSNR-77 EN-0.999	Improves the quality of the fused image	Analysis of pixel by pixel is not possible
8	Curvelet transform based image fusion	Transform	SSIM-0.22 ±0.30(Bone) SSIM-0.12 ±0.08(Tissue)	Helps in shape detection of the fused image	Limited availability of wavelet transform leads to curved shapes of the fused image.
9	Graph cut techniques	pixel	SSIM-0.52 ±0.33Bone) SSIM-0.12 ±0.12(Tissue)	Eliminates pixilation artifacts effect and less complex	Poor ability to discriminate between tissue and bone details

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