

# Implementation of Image Fusion Algorithms for Clinical Diagnosis

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## Abstract

Image Fusion is a process of combining common features of a set of images to get an output image with superior content in terms of subjective as well as objective analysis point of view. Main aim of this work is to present a review on some of the Image Fusion Techniques. A comparison of all techniques are done fusing MRI and CT images and analysis is conducted using various quality measures such as entropy, MSE, PSNR, SSIM and BRISQUE. CT modalities provide information on denser tissues whereas MRI provides information on soft tissues. For medical applications CT and MRI images are fused for diagnostic purposes.

**Keywords:** DWT, HIS, Image Fusion, Medical Diagnosis, PCA, Performance Evaluation

## 1. Introduction

Image Fusion objective is to combine information of number of images and the resultant image one which is more informative and of better quality.

The Fused image is then more suitable for human/machine perception and for further image processing tasks such as segmentation, feature extraction and object recognition<sup>1</sup>.

Medical image fusion techniques has been used to derive useful information from multimodality medical image data. The idea behind this is to improve the image content by fusing images like Computer Tomography (CT) and Magnetic Resonance Imaging (MRI) images, so as to provide more information to the doctor and clinical treatment planning system<sup>2</sup>.

The main principles of image fusion are the redundancy, the complementary, the time-limit and low cost<sup>3</sup>.

Image 1  
+ Image 2  
Output Fused image

**Figure 1.** Image fusion process.

### 1.1 Image Fusion Types

#### 1.1.1 Multimodal Images

Multimodal fusion is applied to images from different modalities such as the visible and infrared CT, NMR. The main aim is to decrease the amount of data.

#### 1.1.2 Multifocus Images

When using digital cameras all subjects at a distance are not sharply focussed. To solve this image fusion is done by acquiring series of images with different focus setting and then fuse them into a single image.

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### 1.1.3 Multiview Images

Here a set of images are taken by same sensor but at different view points and then fused to get a single image.

### 1.1.4 Multitemporal Images

In this images are taken at different times in order to detect changes between images and fuse them to a single image.

## 1.2 Image Fusion Classification

Image fusion can be performed at different levels: signal, pixel, feature and symbol levels. Almost all image fusion algorithms developed to date fall into pixel level.

Pixel level fusion gives an output image in which information content associated with each pixel is determined from a set of pixels in source images. Fusion at this level can be performed either in spatial or in frequency domain. However, pixel level fusion may conduct to contrast reduction<sup>1</sup>.

Feature level fusion requires the extraction of important features which are depending on their environment such as pixel intensities, edges or textures. These similar features from the input images are fused. This fusion level can be used as a means of getting additional composite features. The fused image can also be used for classification or detection<sup>4</sup>.

Decision level is a higher level of fusion. Input images are processed individually for information extraction. The got information is then combined by applying certain decision rules to reinforce common interpretation<sup>5</sup>.

Image Fusion types are broadly classified into 2 groups;

### 1.2.1 Spatial Domain

Spatial domain fusion method is performed directly on the source images. Weighted average is the simplest spatial domain method, which needn't any transformation or decomposition on the original images. The merit of this method is simple and fit for real-time processing, but simple addition will reduce the signal-to-noise of the result image<sup>6</sup>.

### 1.2.2 Transform Domain

Image is first transformed to frequency domain. In frequency domain methods, the input images are decomposed into multiscale coefficients initially. Various fusion rules

are used in the selection or manipulation of these coefficients and synthesized via inverse transforms to form the fused image. This type method can avoid blocking effects. However, many of these approaches, such as Discrete Wavelet Transform (DWT), Wavelet Packet Transform (WPT) and Curvelet transform are shift-variant<sup>6</sup>.

## 2. Implementation of Different Fusion Algorithms

In this work different image fusions such as simple averaging, PCA, IHS, wavelet transform, curvelet transform is implemented.

### 2.1 Simple Averaging

Image Fusion by Simple Averaging is a basic and straight forward technique and fusion could be achieved by simple averaging corresponding pixels in each input image. The value of pixel  $p(i,j)$  of each image is taken and added. This sum is divided by 2 to get the average. This will be repeated for all pixels.

$K(i,j) = (X(i,j) + Y(i,j))/2$  where  $X(i,j)$  and  $Y(i,j)$  represents the 2 input images<sup>7</sup>.

### 2.2 IHS Method

This method is mainly used for sharpening. In IHS technique the color image is converted to IHS space. In the IHS space spatial information is mostly reflected in hue and saturation. The intensity component of IHS is replaced by high resolution components and then again transformed to RGB. This proves to have better visual effects but also carries distortion.

### 2.3 PCA

Principal Component Analysis (PCA) is a statistical technique which transforms a number of correlated variables into a number of uncorrelated variables. It computes a compact and optimal description of the data set. 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. The third principal component is taken in the maximum variance direction in the subspace perpendicular to the first two and so on. The PCA does not have a fixed set of basis vectors like FFT, DCT and wavelet etc. Its basis vectors depend on the data set. The input images (images to be fused)  $I_1(X,Y)$  and  $I_2(X,Y)$  are arranged in two

column vectors and their empirical means are subtracted. The resulting vector has a dimension of  $n \times 2$ , where  $n$  is length of the each image vector. The eigenvector and Eigen values for this resulting vector are computed and the eigenvectors corresponding to the larger Eigen value achieved. The normalized components P1 and P2 (i.e.,  $P1 + P2 = 1$ ) are computed from the obtained eigenvector. The fusion is achieved by weighted average of images to be fused. The weights for each source image are obtained from the eigenvector corresponding to the largest Eigen value of the covariance matrices of each source<sup>8</sup>.

## 2.4 Wavelet Transform

This is common form of transform fusion. The basic idea is to perform decomposition on each input image and getting the low and high frequency components. The level of decomposition is chosen accordingly. At each level 2 sets of coefficients are got. First perform the DWT in the vertical direction, followed by the DWT in the horizontal direction. After the first level of decomposition, there are 4 sub-bands: LL1, LH1, HL1 and HH1. For each successive level of decomposition, the LL sub band of the previous level is used as the input. The approximation and detailed coefficients of both images are combined using fusion rules. The fusion rule used here is simply averages the approximate coefficients and picks detailed coefficients in each sub band with the highest magnitude.

## 2.5 Curvelet Transform

Medical images have several objects and curved structures. One good way to enhance spatial resolution is to enhance the edges. It is expected that the curvelet transform would be better in their fusion. Curvelet-based

image fusion method provides richer information in the spatial and spectral domains simultaneously.

The curvelet transform is based on the segmentation of the whole image into small overlapping tiles and thereon each tile is subjected to ridgelet transform. The idea of segmentation is to approximate curved lines by straight lines. As with the wavelet transform, the curvelet transform is a multi-resolution transform with frame elements indexed by scale and location parameters. Unlike the wavelet transform, however, the curvelet transform has directional parameters and the curvelet pyramid contains elements with a high degree of directional specificity. In addition, the curvelet transform is based on a special anisotropic scaling principle that is quite different from the isotropic scaling of wavelets. The elements obey a special scaling law, in which the length of the support of frame elements and the width of the support are linked by the relation  $\text{width} = \text{length}^2$ .

In order to achieve a higher level of efficiency, curvelet transform is usually implemented in the frequency domain. This means that a 2D FFT is applied to the image. For each scale and orientation, a product of  $U_j, l$  "wedge" is obtained; the result is then wrapped around the origin and 2D IFFT is then applied resulting in discrete curvelet coefficients<sup>9</sup>.

Curvelet transform = IFFT {FFT (Curvelet)  $\times$  FFT\_ Image}.

## 3. Results and Discussion

### 3.1 Metric Analysis

Metric analysis includes both reference analysis and non reference analysis. Under reference analysis MSE, PSNR,

**Table 1.** Parameter Estimation for Different Fusion Methods

		IMAGE SET 1				
		Simple Averaging	PCA	IHS	Wavelet Transform	Curvelet Transform
ENTROPY		7.4	7.50	7.09	7.28	7.72
MSE	IMAGE 1	0.04	0.02	98.50	0.24	0.03
	IMAGE 2	0.060	0.04	176.7	0.09	0.12
PSNR	IMAGE 1	13.87	16.68	10.17	18.41	62.22
	IMAGE 2	12.17	13.74	6.12	10.62	57.22
SSIM	IMAGE 1	0.38	0.38	0.52	0.356	0.262
	IMAGE 2	0.18	0.16	0.27	0.109	0.105
BRISQUE		117.5	100.5	114.1	112.01	104.33

		IMAGE SET 2				
		Simple Averaging	PCA	IHS	Wavelet Transform	Curvelet Transform
ENTROPY		7.19	7.50	7.56	7.6	7.31
MSE	IMAGE1	0.02	0.44	98.06	0.02	0.05
	IMAGE2	0.03	0.05	244.1	0.14	0.20
PSNR	IMAGE1	15.59	13.49	7.19	16.39	60.63
	IMAGE2	14.68	12.48	4.86	8.47	55.01
SSIM	IMAGE1	0.362	0.389	0.47	0.40	0.26
	IMAGE2	0.169	0.18	0.03	0.13	0.113
BRISQUE		101.9	117.26	113.4	113.21	122.65

		IMAGE SET 3				
		Simple Averaging	PCA	IHS	Wavelet Transform	Curvelet Transform
ENTROPY		7.43	7.50	7.44	7.50	7.53
MSE	IMAGE1	0.04	0.03	254.7	0.04	0.07
	IMAGE2	0.04	0.04	250.5	0.07	0.11
PSNR	IMAGE1	13.8	14.03	6.834	13.6	59.48
	IMAGE2	13.6	13.5	5.57	11.07	57.54
SSIM	IMAGE1	0.29	0.30	0.007	0.30	0.21
	IMAGE2	0.37	0.37	0.005	0.29	0.25
BRISQUE		107.2	107.87	114.6	100.59	123.80

		IMAGE SET 4				
		Simple Averaging	PCA	IHS	Wavelet Transform	Curvelet Transform
ENTROPY		7.65	7.5	7.4	7.5	7.16
MSE	IMAGE 1	0.03	0.03	147.9	0.44	0.02
	IMAGE 2	0.04	0.04	252.8	0.20	0.17
PSNR	IMAGE 1	14.23	14.3	6.97	18.6	63.37
	IMAGE 2	13.24	13.2	3.52	8.94	55.64
SSIM	IMAGE 1	0.48	0.48	0.28	0.47	0.39
	IMAGE 2	0.23	0.23	0.04	0.75	0.14
BRISQUE		100.8	100.4	112.0	106.17	114.47



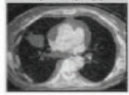


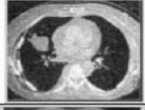

SSIM were calculated and under non reference analysis Entropy and BRISQUE was evaluated.

### 3.2 Visual Analysis

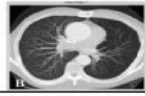

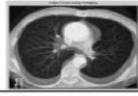
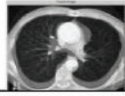
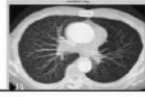

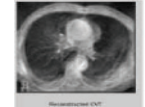
For visual evaluation following criterion was considered such as appearance, brightness, contrast and enhancement.

## 4. Conclusion





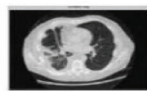


The simulation results show the comparison in identification of more tumor regions in different fusion algorithms in the fusion of CT and MR images from both the visual quality and the quantitative analysis points of view.

IMAGE SET 1	Input image 1	Input image 2
		
Simple avg. fusion		
PCA fusion		
IHS fusion		
Wavelet fusion		
Curvelet fusion		

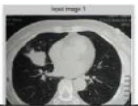
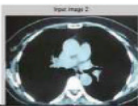

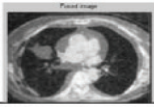
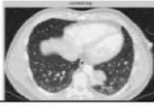
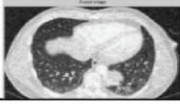
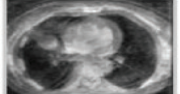
(a)

IMAGE SET 3	Input image 1	Input image 2
		
Simple avg. fusion		
PCA fusion		
IHS fusion		
Wavelet fusion		
Curvelet fusion		

(c)

IMAGE SET 2	Input image 1	Input image 2
		
Simple avg. fusion		
PCA fusion		
IHS fusion		
Wavelet fusion		
Curvelet fusion		

(b)

IMAGE SET 4	Input image 1	Input image 2
		
Simple avg. fusion		
PCA fusion		
IHS fusion		
Wavelet fusion		
Curvelet fusion		

(d)

Figure 1. Visual analysis of (a) Image set 1, (b) Image set 2, (c) Image set 3 and (d) Image set 4.

## 5. References

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