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# Multimodal image fusion using multiresolution techniques

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**ABSTRACT**

Multimodal Image Fusion techniques combine information from different sensors together to produce a more accurate and efficient representation which is more useful for further analysis. A Multi resolution based Multimodal Image Fusion Algorithm is this paper, an automatic algorithm based on multi resolution technique for fusing multimodal images is proposed. The multimodal images are decomposed using the Dual Tree Complex Wavelet Transform and Contourlet Transform and they are fused using some efficient and robust fusion rules. Finally, they are reconstructed using the Inverse transform and a new fused image with more information content is obtained. The basic idea of all multiresolution fusion schemes is motivated by the human visual system being primarily sensitive to local contrast changes, e.g. the edges or corners. These techniques also provide better directional information. The DT-CWT and Contourlet Transform methods are good at faithfully retaining the salient structural information present in both the multimodal images.



## Introduction

The goal of image fusion is to integrate complementary information from various modalities, so that the new image should be more suitable for the purpose of human visual perception and further analysis. Image fusion has become a common term used within medical diagnostics and treatment. The term fusion is used when multiple patient images are registered and overlaid or merged to provide additional information. Fused images may be created from multiple images of the same imaging modality, or by combining information from multiple modalities, such as Magnetic Resonanace Image (MRI), Computed Tomography (CT), Positron Emission Tomography (PET), and Single Photon Emission Computed Tomography (SPECT). In radiology, these images serve different medical purposes. For this reason, the radiologists prefer integrating multiple imaging modalities to obtain more details from input images. Commonly, a successful fusion should extract complete information from the source images, and should form the resulting image without introducing any artifacts or inconsistencies.

## Overview of Image Fusion

The medical image fusion mainly uses pixel based fusion techniques. Usually, the pixel level fusion is broadly classified into three main categories.

1. Spatial Domain Techniques: (PCA, Averaging, etc.)
2. Optimization Approach: (Bayesian Approach)
3. Transform Domain Approach: (Multi-resolution Techniques)

Initially, the fusion techniques are based on spatial domain techniques. The basic techniques which were used are Principal Component Analysis (PCA), Averaging, Weighted Averaging, etc. the main advantage of this spatial domain technique is, they are easy to implement. But there are few drawbacks in these methods. This technique produces spatial distortion in images. Also, some of the image details will not be present in the final fused image with respect to the input images. The second one is Bayesian approach, which suffers from the problem of computational complexity. The third one is based on transform domain approach .based on redundant multi resolution decomposition techniques capable of preserving structural characteristics. The transform decomposes the image into several components and the various components are fused based on their structural and functional importance and finally using an inverse transform the fused image is reconstructed. It provides more information for further analysis and diagnosis of various diseases.. The different multi scale transform domain techniques are wavelet, curvelet, contourlet, etc.

## Proposed methods

There are some major drawbacks in the wavelet transform. First, it doesn't provide shift invariance, and it does not capture the edges properly. Another major drawback in the wavelet transform is, it provides limited information along the horizontal, vertical and diagonal direction.

## Dual Tree Complex Wavelet Transform

The above said drawbacks are removed using the proposed technique. In the proposed technique Multimodal images are decomposed using Dual Tree Complex Wavelet transform (DT-CWT). 2D – DT-CWT is the combination of two 1-D transforms. In wavelet transform, it has 1-D real filters. But in dual tree, there are two trees containing complementary filter values, one tree corresponds to real values and the other one is imaginary. Designing complex filters is not an easy task, but it makes the process more efficient. Also this Dual tree complex wavelet transform produces Approximate Shift invariance and it also provides limited directional information when compared to the wavelet transform. Also this technique captures more edge information when compared to wavelet transform.

## Contourlet Transform

The Contourlet transform is used to decompose the image at different scales and orientations. Contourlet transform is an extension of wavelet transform and it uses directional filte

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banks. The multiscale decomposition is done by the laplacian pyramid. This Contourlet transform not only comprises all the features corresponding to a wavelet transform but also it provides better directional information. Contourlet transform captures smooth contours as well as edges at all orientations. Contourlet transform consists of a double filter bank structure and it is implemented by the pyramidal directional filter bank (PDFB) which decomposes images into directional subbands at multiple scales.

**Fusion Rules:**

**Method 1:**

In this method, the fused high frequency coefficients are formed by using their Maximum Absolute values and the low frequency coefficients are fused using the Averging method.

**Method 2:**

In this technique, the fused high frequency coefficients are formed by using their Maximum coefficient values and the low frequency coefficients are fused based on the Averaging method.

**Method 3:**

Here, both the high frequency and low frequency coefficients are fused based on their Maximum coefficient values.

**Method 4:**

In this method, the high frequency coefficients are fused based on their Maximum Absolute values and the low frequency values are fused based on their Maximum coefficient values.

**Method 5:**

In this technique, both the high frequency and low frequency coefficients are fused based on their Maximum Absolute Values.

**Image Fusion Process**

Here in this method structural image from two modalities, viz, CT and MRI are considered. First the input images are decomposed using the above transforms and the corresponding high frequency and low frequency coefficients of both the input images are obtained. Now the high frequency and low frequency coefficients of both the images are fused based on the above fusion rules..

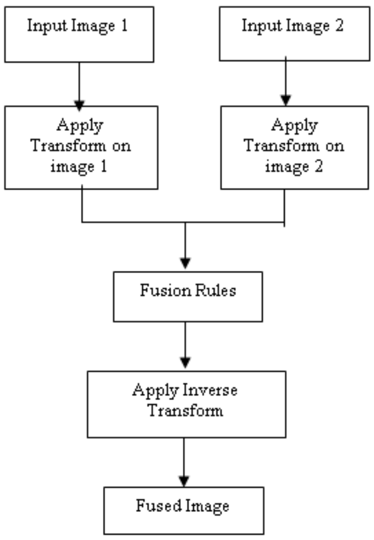


**Figure 1. Proposed method for DT-CWT and Contourlet Transform based Image Fusion.**

A new fused image with maximum information content is obtained by taking inverse transform of the fused coefficients. This resulting image will provide more information when compared to input images. The above flow diagram shows the image fusion process

The quality of the fused image is determined using the following performance measures.

**Coefficient Correlation: (CC)**

This shows the small similarities between the fused image and the input images. This can be calculated using the following formula;

$$CC(F,d)=\frac{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(F(i,j)-\bar{F})(d(i,j)-\bar{d})}{\sqrt{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(F(i,j)-\bar{F})^2\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(d(i,j)-\bar{d})^2}}$$

Here $\bar{d}$ and $\bar{F}$ denotes the mean values of reference image and fused image respectively. .

**Standard Deviation:**

`This denotes the information capability of images. Greater value of standard deviation refers to better quality of the image.

$$STD=\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(f(i,j)-\hat{\mu})^2/MN}$$

f(i,j) is the values of the fused image and μ refers to the mean value of the image.

**Image Quality Index(IQI):**

The value of IQI varies from [-1,1]. If the value of 1 is achieved, then F=R, where F is the fused image and R is the Reference image.

$$IQI=\frac{\sigma_{FR}}{\sigma_F\sigma_R}\cdot\frac{2\overline{F}\overline{R}}{(\overline{F})^2+(\overline{R})^2}\cdot\frac{2\sigma_F\sigma_R}{\sigma_F^2+\sigma_R^2}$$

**Entropy:**

Image Entropy refers to the richness of the image information. It represents the property of combination of the two input images.

$$H=-\sum_{i=0}^{L-1}p_i\log p_i$$

$P_i$ is the probability of the gray level i and L is the overall gray scale of the image.

**Results and Discussion**

**Results:**

The following are the input images of two different modalities (CT and MRI).

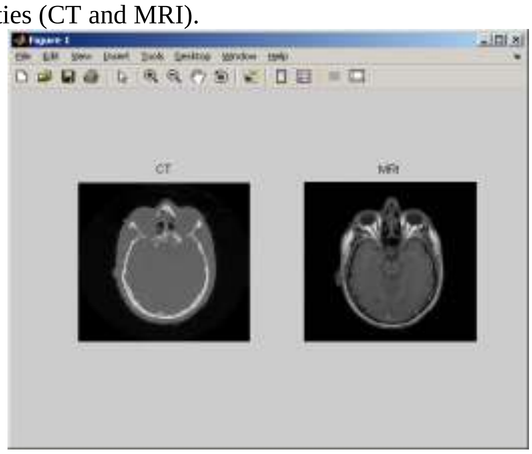


**Figure 2. Input Images**

The fused images based on various fusion rules using Dual Tree Complex Wavelet Transform are as follows;

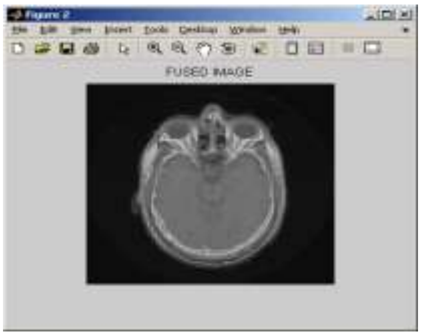


**Figure 3. Fused Image (Method 1)**


**Figure 4. Fused Image (Method 2)**


**Figure 5. Fused Image (Method 3)**


**Figure 6. Fused Image (Method 4)**

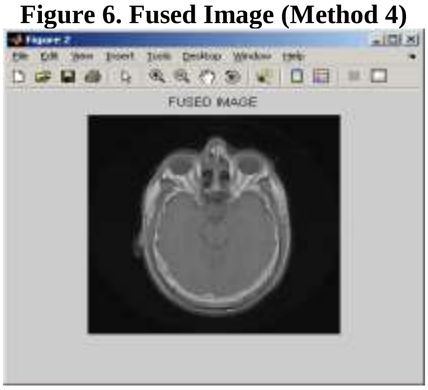


**Figure 7. Fused Image (Method 5)**

The fused images based on various fusion rules using Contourlet transform are as follows;

**Figure 8. Fused Image (Method 1)**

**Figure 9. Fused Image (Method 2)**

**Figure 10. Fused Image (Method 3)**

**Figure 11. Fused Image (Method 4)**

**Figure 12. Fused Image (Method 5)**

The following tabular columns shows the comparison between Dual Tree Complex Wavelet Transform and Contourlet Transform based on various methods of fusion rules. Standard Deviation values obtained for various methods of Fusion:

| | DT-CWT | Contourlet |
|---|---|---|
| Method 1 | 37.3901 | 37.3411 |
| Method 2 | 37.3295 | 37.3101 |
| Method 3 | 45.5371 | 45.8595 |
| Method 4 | 45.5664 | 45.8749 |
| Method 5 | 45.5667 | 45.8749 |

**Table 1. Standard Deviation Values**

Coefficient Correlation values obtained for various methods of Fusion:

| | DT-CWT | Contourlet |
|---|---|---|
| Method 1 | 0.9315 | 0.9296 |
| Method 2 | 0.9441 | 0.9426 |
| Method 3 | 0.8862 | 0.8777 |
| Method 4 | 0.8769 | 0.8754 |
| Method 5 | 0.8769 | 0.8754 |

**Table 2. Coefficient Correlation Values**

Image Quality Index values obtained for various methods of Fusion:

| | DT-CWT | Contourlet |
|---|---|---|
| Method 1 | 0.9080 | 0.9153 |
| Method 2 | 0.9441 | 0.9197 |
| Method 3 | 0.9375 | 0.9310 |
| Method 4 | 0.9263 | 0.9274 |
| Method 5 | 0.9264 | 0.9274 |

**Table 3. Image Quality Index Values**

Entropy values obtained for various methods of Fusion:

| | DT-CWT | Contourlet |
|---|---|---|
| Method 1 | 2.1104 | 2.2520 |
| Method 2 | 1.9862 | 2.1956 |
| Method 3 | 1.1492 | 1.3183 |
| Method 4 | 1.2469 | 1.3966 |
| Method 5 | 1.2579 | 1.4006 |

**Table 4. Entropy values**

**Discussions:**

The above tabular column shows the performance measures based on various Fusion rules. Here, the Standard Deviation, Coefficient Correlation, Image Quality Index and Entropy are calculated and comparisons are made on both dual tree complex wavelet and contourlet transforms. From the above tabulations it is shown that Contourlet Transform is better than Dual Tree Complex Wavelet Transform. Also Method 4 is better when compared to all other methods used for fusion of multimodal images.

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