# A Method For Measuring The Accuracy Of Multi-Modal Medical Image Fusion Using Non-Subsampled Contour Transform And Pulse Couple Neural Network

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**Abstract:** *The multimodal medical images fusion is useful in the field of medical sciences. The main aim is to obtain the applicable information from the medical image sources and fuse them together to provide a single output which forms as an important system in the medical diagnosis. The fusion criterion is to minimize different error between the fused image and the input images. With respect to the medical diagnosis, the edges and outlines of the interested objects is more important than other information. Therefore, how to preserve the edge-like features is worthy of investigating for medical image fusion. In term of this view, the project proposed a new medical image fusion scheme based on discrete contourlet transformation and pulse couple neural network , which is useful to provide more details about edges at curves. It is used to improve the edge information of fused image by reducing the distortion. The pixel and decision level fusion rule will be applied selected for low frequency and high frequency. The fused contourlet coefficients are reconstructed by inverse NS contourlet transformation. The goal of image fusion is to obtain useful complementary information from CT/MRI multimodality images. By this method we can get more complementary information.*

**Keyword:** Multimodal medical image fusion, Pulse-Coupled Neural Network, Multiscale Geometric analysis, NSCT

## 1. Introduction

Medical image fusion paly very important role in the field of medical diagnosis. For the doctor medical image is major source to diagnose the diseases. The medical imaging has its own kinds of imaging techniques like X-ray, computed tomography (CT), magnetic resonance imaging (MRI). X-ray and CT can provide images as dense like structure with which the physiological changes could not be detected whereas in MRI images even the soft pathological tissues can be visualized better. As a result the anatomical and functional medical images are needed to be combined for better visualization and for accurate diagnosis. To serve this purpose the multimodal medical image fusion is an effective way to provide solution to generate information from medical image fusion. This fusion technique not only provides accurate diagnosis and analysis but also helps in reducing the storage cost by reducing storage to a single fused image [1].

Various image fusion techniques have been discovered and implemented so far. These techniques are generally categorized three stages. They include pixel level, feature level and decision level fusion. Most medical image fusion goes with the pixel level fusion. Pixel level fusion has the advantages of retaining the original measured quantities and found to be computationally efficient [1]. The well-known pixel level fusion are based on principal component analysis (PCA), independent component analysis (ICA), contrast pyramid (CP), gradient pyramid (GP) filtering, etc. Since, the image features are sensitive to the human visual system exists in different scales [2].

For the development of multiscale decomposition, wavelet transform has been identified ideal method for image fusion. However, it is argued that wavelet decomposition is good at isolated discontinuities, but not good at edges and textured region. Further, it captures limited directional information along vertical, horizontal and diagonal direction [3]. These

issues are rectified in a recent multiscale decomposition contourlet, and its non-subsampled version.

Image Fusion is a process of combining the relevant information from a set of images of the same scene into a single image and the resultant fused image will be more informative and complete than any of the input images. Input images could be multi sensor, multimodal, multifocus or multi temporal. There are some important requirements for the image fusion process. Multi-modal medical image fusion algorithms and devices have shown notable achievements in improving clinical accuracy of decisions based on medical images. Medical image fusion encompasses a broad range of techniques from image fusion and general information fusion to address medical issues reflected through images of human body, organs, and cells. In addition, the use of multi-sensor and multi-source image fusion methods offer a greater diversity of the features used for the medical analysis applications [4].

## 2. Image Fusion Algorithms

Image fusion method can be divided into two groups– 1.Spatial domain fusion method 2.Transform domain fusion. Spatial domain fusion method directly deals with pixels of input images. The fusion methods such as simple maximum, simple minimum, averaging, principal component analysis (PCA) and HIS. In transform domain method image is first transferred in to frequency domain. The fusion method such as DWT.

Pixel-level algorithms are as below:

**2.1 Simple Maximum Method:** The resultant fused image is obtained by selecting the maximum intensity of corresponding pixels from both the input image.

$$F(i,j) = \sum_{i=0}^{m} \sum_{j=0}^{n} maxA(i,j)B(i,j) \qquad (1)$$

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

**2.2 Simple Minimum Method:** In this method, the resultant fused image is obtained by selecting the minimum intensity of corresponding pixels from both the input image.

$$F(i,j) = \sum_{i=0}^{m} \sum_{j=0}^{n} minA(i,j)B(i,j) \qquad (2)$$

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

**2.3  Simple Average 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 (3)

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

**2.4 Weighted Average Method:** The resultant fused image is obtained by taking the weighted average intensity of corresponding pixels from both the input image.

$$F(i,j) = \sum_{i=0}^{m} \sum_{j=0}^{n} WA(i,j) + (1 - w)B(i,j) \qquad (4)$$

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) method:** Principal Component Analysis is a sub space method, which reduces the multidimensional data sets into lower dimensions for analysis. This method determines the weights for each source. Image using the eigenvector corresponding to the largest eigen value of the covariance matrix of each source image [5].

**2.6  Discrete Wavelet Transform Method:** Wavelet transforms are multi-resolution image decomposition tool that provide a variety of channels representing the image feature by different frequency subbands at multi-scale. It is a famous technique in analyzing signals. When decomposition is performed, the approximation and detail component can be separated 2-D Discrete Wavelet Transformation (DWT) converts the image from the spatial domain to frequency domain. The image is divided by vertical and horizontal lines and represents the first-order of DWT, and the image can be separated with four parts those are LL1, LH1, HL1 and HH1 [6].
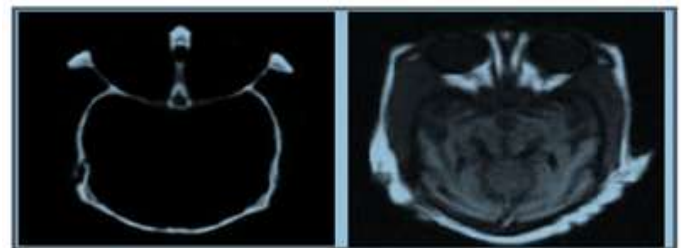
| LL$^3$ | LH$^3$ | LH$^1$ | |
|--------|--------|--------|---|
| HL$^3$ | HH$^3$ | | |
| HL$^1$ | | HH$^1$ | |

1, 2, 3 ---- Decomposition Levels

H---------- High Frequency Bands
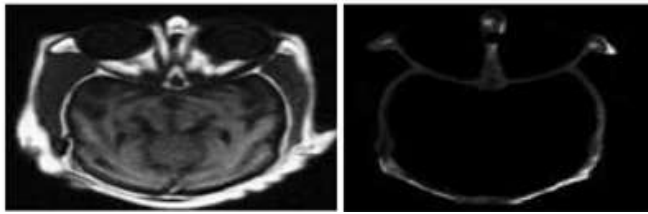
L---------- Low Frequency Bands

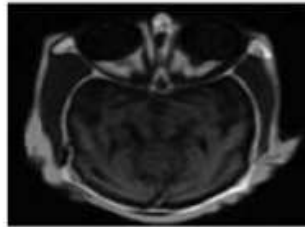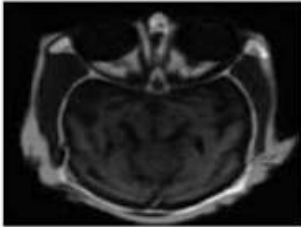**Figure 1**: Wavelet Decomposition

Sources images
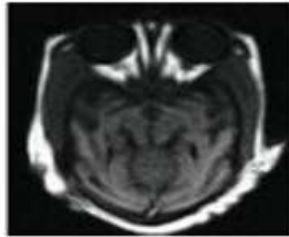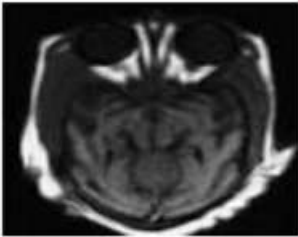
a) CT image            b) MRI image

c) Simple average  d) Simple minimum



e) Simple maximum  f) Simple weight average



g) PCA  h) DWT

**Figure 2:** Resultant Fused Images [7]

## 3. The Non-Subsampled Contourlet Transforms

The main purpose of image fusion algorithm is to serve fuse image from multimodal images and the fused image as output. Some image fusion techniques are described as above. The Wavelet decompositions waitrons good for discontinuities those are isolated in images but it has limit at edge and texture region. it detentions limited information from the images such as the horizontal, vertical and diagonal directions only. To overcome this problem, a new multiscale decomposition technique established known as the NSCT decomposition technique. It is very important for the medical experts to diagnose the health issues of a person. Wavelet transforms perform the image compression and denoising efficiently.

The main property of NSCT is providing a multidirectional, multiscale, shift invariant image decomposition that can be efficiently implemented by means of the fusion techniques or algorithms.

### 3.1 Non-Subsampled Pyramid Structure (NSP)
The main multiscale property of nonsubsampled contourlet transforms is conserved by NSP. It is assembled by

combining the directional filter banks and laplacian pyramid. The pyramidal filter bank structure plays important roles in the compression applications as a result of production of very little redundancy by the pyramidal filter bank with the contourlet transform. Two channel non-subsampled 2D filter banks can be used to achieve the multiscale property in the NSCT domain.

### 3.2 Non-Subsampled Directional Filter Bank (NSDFB)
The upsamplers and the downsamplers are disregarded from the directional filter bank to contain the non-subsampled directional filter bank. The nonsubsampled directional filter bank produces a tree structured filter bank.

### 3.3 Combination of NSDFB And NSP
The NSCT is the mixture of both NSP and NSDFB.NSCT is fabricated very carefully such that it does not disturb the upper stages of the pyramid because applying directional response at lower and higher frequencies may cause aliasing due to the tree structured format of the NSDFB.

### 3.4 Directive Contrast
The directive contrast is useful for fusion of high frequency coefficients of the input images. For the better interpretation of the image selection of high frequency coefficients are necessary. The bright and sharp regions of the image are generally symbolized by the high frequency coefficients of an image. Directive contrast is also produce accurate result.

### 3.5 Phase Congruency
The phase congruency is useful for fusion of low frequency coefficients of input images. It yields the contrast and brightness invariant representation of the low frequency coefficients of the image.

It conveys the luminance and contrast invariant feature extraction in the low frequency coefficients of the image. It is also beneficial for selecting and combining the brightness and the contrast invariant of the low frequency coefficients of the image.

The main useful of the phase congruency is in feature perception of the image based on local energy model, which postulates the important features of the image at points of pixels.
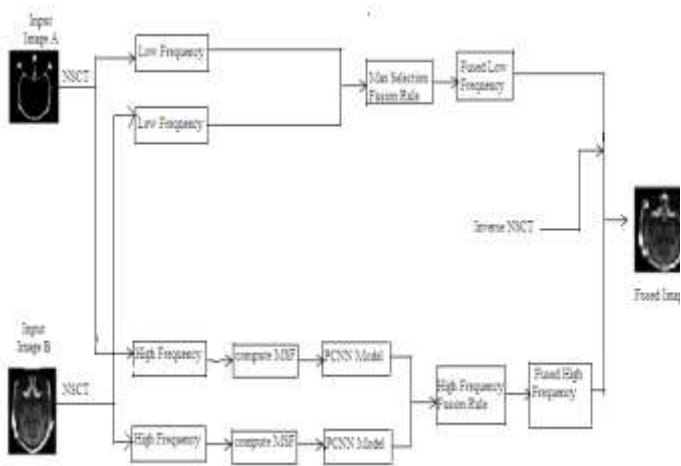
## 4. Proposed System

**Figure 3:** Block diagram of proposed multimodal image fusion for medical application

Proposed Methodology as follow:
A. NSCT based Multiscale decomposition
B. PCNN Model.
C. Fusion of Low Frequency sub bands.
D. Fusion of High Frequency Sub bands.
E. Performance Analysis

## 4.1 NSCT Based Multiscale Decomposition

NSCT is a fully shift-invariant, multiscale, and multidirectional expansion with fast implementability [8]. NSCT achieves the shift-invariance property by using the nonsubsampled pyramid filter bank (NSP)
and the nonsubsampled directional filter bank (NSDFB).As compared to other multiresolution based algorithms, NSCT perform better result. NSCT is an multi-scale geometric analysis tool which utilizes the geometric regularity in the image and provide a asymptotic optimal representation in the terms of better localization, multi-direction and shift invariance [2]. If the NSCT based methods have been compared then it can be observed that the performance of the proposed method is better than existing NSCT based methods [9] [10].

Multimodal medical images such as CT, MRI, PET taken as input images. The input images are decomposed by means of non-subsampled pyramid decomposition which is of three stages represented in figure 4.
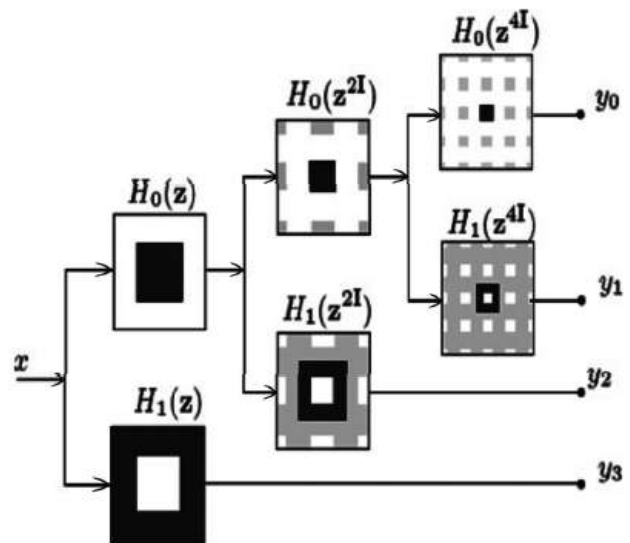


**Figure 4:** Three stage pyramid decomposition

The three stage pyramid decomposition is used to decompose the images. It ensures the Multiscale property of the images by using the two channel nonsubsampled filter bank with which one low frequency image and one high frequency image are produces at the end of each non-subsampled pyramid (NSP) decomposition level.

NSCT read CT and MRI images and then decomposing the image by the filter banks and pyramid decomposition. After that fusing the low and high frequency image, then finally fused image is obtained by inverse NSCT.

## 4.2 Pulse Coupled Neural Network

PCNN is a single layered, two-dimensional, laterally connected neural network of pulse coupled neurons. The structure of PCNN as shown in figure 5.
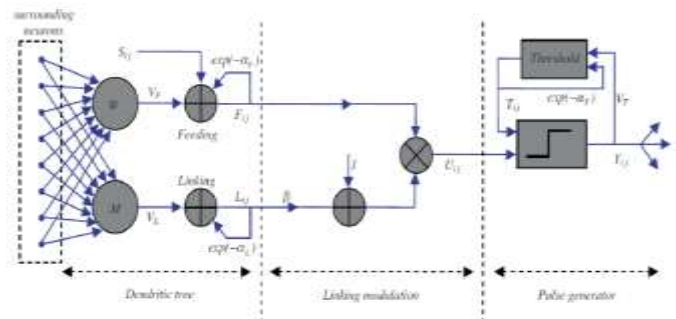


**Figure 5:** Structure of PCNN.

The neuron consists of an input part (dendritic tree), linking part and a pulse generator. The neuron receives the input signals from feeding and linking inputs. Feeding input is the primary input from the neurons receptive area. The neuron receptive area consists of the neighboring pixels of corresponding pixel in the input image. Linking input is the secondary input of lateral connections with neighboring neurons. The difference between these inputs is that the

feeding connections have a slower characteristic response time constant than the linking connections.

## 4.3 Fusion of Low Frequency sub bands

The LFSs coefficients are fused using 'max selection' rule. According to this fusion rule, select the frequency coefficients from $L_G^A$ or $L_G^B$ with greater absolute value as the fused coefficients.

## 4.4 Fusion of High Frequency Sub band

The HFSs of the source images are fused using PCNN. As humans are sensitive to features such as edges, contours etc., so instead of using PCNN in NSCT domain directly, modified spatial frequency (MSF) in NSCT domain is considered as the image feature to motivate the PCNN.

## 4.5 Performance Analyses

Performance Analysis is used to calculate the quality of the fused image. For performance analysis following parameters into considerations:

**4.5.1 Image quality index:** (IQI) measures the similarity between two images (I1 & I2) and its value ranges from -1 to 1. IQI is equal to 1 if both images are identical. IQI measure is given by

$$IQI \quad = \frac{m_{ab}2xy2m_am_b}{m_am_bx^2+y^2m_a^2+m_b^2} \qquad (5)$$

Where x and y denote the mean values of images I1 and I2.

**4.5.2 Fusion Factor:** If there is two images like as image A and image B and their fused image F, then fusion factor is given by

$$FF = IAF+IBF \qquad (6)$$

Where IAF and IBF are the MIM values between input images and fused image.

**4.5.3 Fusion Symmetry:** Fusion symmetry (FS) is an indication of the degree of symmetry in the information content from both the images.

$$FS = \quad abs\left(\frac{I_{AF}}{I_{AF}+I_{BF}} - 0.5\right) \qquad (7)$$

4.5.4 Fusion Index: It is parameter from the factors Fusion symmetry and Fusion factor. This is defined as
$$FI = IAF/IBF \qquad (8)$$

Where IAF is the mutual information index between multispectral image and fused image and IBF is the mutual information index between panchromatic image and fused image.

**4.5.5 Root Mean Square Error:** The root mean square error (RMSE) measures the amount of change per pixel due to the processing. The RMSE between a reference image R and the fused image F is given by

$$RMSE = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(R(i,j)-F(i,j))} \qquad (9)$$

**4.5.6 Peak Signal to Noise Ratio**: Peak signal to noise ratio (PSNR) can be calculated by using the formula

$$PSNR = 20log_{10}\left(\frac{L^2}{MSE}\right) \qquad (10)$$

**4.5.7 Entropy:** The entropy is a measure of information content. It is the average number of bits needed to quantize the intensities in the image. It is defined as

$$E = \quad -\sum (P * log_2 (P)) \qquad (11)$$

## 4.6 Algorithm for proposed system

The medical images to be fused must be registered to assure that the corresponding pixels are aligned. The steps for proposed system as follow:

1. Decompose the registered input medical images *A* and *B* by NSCT to get the LFSs and HFSs.
2. Fused the coefficients of LFSs using the 'max selection' rule.
3. Compute the MSF using overlapping window on the coefficients in HFSs.
4. Input MSF of each HFS to motivate the PCNN and generate pulse of neurons.
5. If n = N, then iteration stops.
6. Apply inverse NSCT (INSCT) on the fused LFS and HFSs to get the final fused medical image.
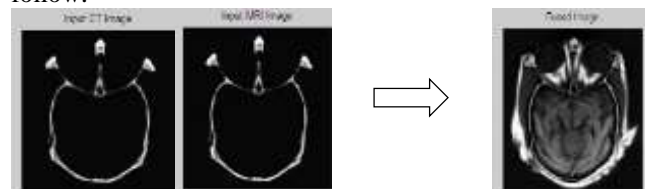
## 5. Result
### 5.1 Experimental Setup
The proposed system implemented in MATLAB. The experiments were carried out on a PC with 2.50 GHz CPU and 4 GB RAM and system type is 32 bit operating system. Parameters of PCNN were set as
$K \times l = 3 \times 3$ $\alpha_T = 0.2$ and $V_T = 20$ ,W = [0.7071 1 0.7071;1 0 1; 0.7071 1 0.7071] ,N =200.

### 5.2 Experiments on CT/MRI Image Fusion
To evaluate the performance of the proposed image fusion approach, different datasets of human brain are considered as follow:



Input Images         Fused Image
**Figure 6:** Result of proposed system

**5.3 Performance Measurement**

**Table 1:** Performance measurement

| Sr.No. | Different images | RMSE | PSNR(dB) |
|---|---|---|---|
| 1 | CT Image | 0.2820 | 19.13 |
| 2 | MRI Image | 0.7004 | 11.22 |

## 5. Conclusion

A novel image fusion framework is proposed for multi-modal medical images, which is based on non-subsampled contourlet transform and Pulse Couple Neural Network. For fusion, two different rules are used by which more information can be preserved in the fused image with improved quality. The use of modified spatial frequency along with the use of different fusion rules for different subbands produces fused images with higher spatial resolution and less unwanted degradations with less difference to the source images. The visual and statistical comparisons demonstrate that the proposed algorithm can enhance the details of the fused image, and can improve the visual effect with much less information distortion than its competitors.

## Acknowledgment

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