

Multimodality Medical Image Fusion Using NSCT

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Abstract

Image fusion plays an important role in medical diagnosis. Multimodal image Fusion is, acquiring medical images from various imaging modalities like CT, MRI,PET,SPECT etc. and the images are combined together(fuse) using NSCT algorithm followed by combining low- and high-frequency components. Here two different fusion rules based on phase congruency and directive contrast are proposed and used to fuse low- and high-frequency coefficients. Finally, the fused image is constructed by the inverse NSCT. The output contains relevant information which is compared with the results obtained from the wavelet fusion algorithm. Here, parameters like RMSE, PSNR (Peak Signal Noise Ratio), are measured, which result in the accurate analysis of the multimodality imaging.

Index Terms—Multimodal medical image fusion, non-subsampled contourlet transform, phase congruency, directive contrast.

1. INTRODUCTION:

Multimodal medical image fusion not only helps in diagnosing diseases, but it also used to reduces the storage cost by reducing storage to a single fused image instead of multiple-source images. The image fusion technique have been Categorized into three categories. These include pixel level, feature level and decision level fusion where Multimodal medical image fusion usually employs the pixel level fusion due to the advantage of containing the original measured quantities. To perform NSCT on the source images followed by the fusion of low- and high-frequency coefficients. The phase congruency and directive contourlet contrast feature are unified as the fusion rules for low- and high-frequency coefficients. The phase congruency provides a contrast and brightness-invariant representation of low-frequency coefficients whereas directive contrast efficiently which determines the frequency coefficients from the clear parts in the high-frequency. The combinations of these two can preserve more details in source images and further improve the quality of fused image.

2. Non-Subsampled Contourlet Transform (NSCT)

The non-subsampled contourlet transform (NSCT) is a fully shift-invariant, multi-scale, and multi-direction. It achieves similar sub band decomposition as that of contourlets, but without down samplers and up samplers in it. Because of its redundancy, the filter design problem of the NSCT is much less constrained than that of contourlets. The Non-subsampled Pyramid (NSP): What gives the multi-scale property of the NSCT is a shift invariant filtering structure that achieves a sub band decomposition similar to that of the Laplacian pyramid.

Our solution is obtained by using two-channel non-subsampled 2-D filter banks. Figure 2, illustrates the proposed NSP decomposition with $J = 3$ stages. As a result, NSP can result in sub-images, which consists of one low- and high-frequency images having the same size as the source image where denotes the number of decomposition levels.

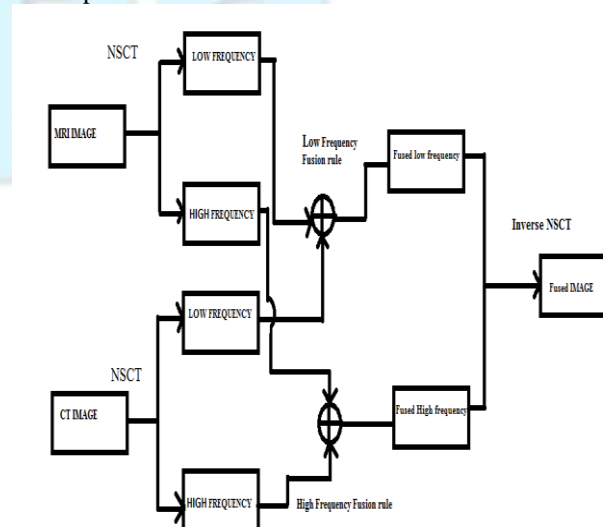


Figure 1 :The Block diagram of proposed multimodal medical image fusion

2.1. Phase Congruency:

Phase congruency is a measure of feature perception in the images which provides a illumination and contrast invariant feature extraction method . This approach is based on the Local Energy Model, which postulates that significant features can be found at points in an image where the Fourier components are maximally in phase. Furthermore, the angle at which phase congruency occurs signifies the feature type. The phase congruency approach to feature perception has been used for detection. First, logarithmic Gabor filter banks at different discrete orientations are applied to the image and the local amplitude and phase at a point are obtained. The phase congruency, is then calculated for each orientation as how in

$$P_{x,y}^o = \frac{\sum_n W_{x,y}^o [A_{x,y}^{o,n} (\cos(\phi_{x,y}^{o,n} - \delta_{x,y}^{o,n}) - |\sin(\phi_{x,y}^{o,n} - \delta_{x,y}^{o,n})|) - T] + \xi}{\sum_n A_{x,y}^{o,n} + \xi}$$

where is the $W_{x,y}^o$ weight factor based on the frequency spread, $A_{x,y}^{o,n}$ and $\phi_{x,y}^{o,n}$ are the respective amplitude and phase for the scale n, $\delta_{x,y}^{o,n}$ is the weighted mean phase is a noise threshold constant and is a small constant to avoid divisions by zero.

2.2 Directive Contrast in NSCT Domain

The contrast feature measures the difference of the intensity value at some pixel from the neighbouring pixels. The human visual system is highly sensitive to the intensity contrast rather than the intensity value itself. Generally, the same intensity value looks like a different intensity value depending on intensity values of neighbouring pixels. Therefore, local contrast is developed and is defined as

$$C = L_H / L_B$$

Where L is the local luminance and L_B is the luminance of the local background. Generally, is regarded as local low-frequency and hence,

$L - L_B = L_H$ is treated as local high-frequency.

$$D_{l,\theta}(i,j) = \begin{cases} \frac{SML_{l,\theta}(i,j)}{I_L(i,j)}, & \text{if } I_L(i,j) \neq 0 \\ SML_{l,\theta}(i,j), & \text{if } I_L(i,j) = 0 \end{cases}$$



FIGURE 2.,(a) CT AND (b)MRI IMAGE OF THE BRAIN

3. Proposed fusion framework :

Fusion of Low-frequency Sub-images:

The coefficients in the low-frequency sub-images represent the approximation component of the source images. The simplest way is to use the conventional averaging methods to produce the composite bands. However, it cannot give the fused low-frequency component of high quality for medical image because it leads to the reduced contrast in the fused images. Therefore, a new criterion is proposed here based on the phase congruency.

Fuse the low-frequency sub-images as

$$C_l^F(x, y) = \begin{cases} C_l^A(x, y), & \text{if } PC_l^A(x, y) > PC_l^B(x, y) \\ C_l^B(x, y), & \text{if } PC_l^A(x, y) < PC_l^B(x, y) \\ \frac{\sum_{k \in A, B} C_l^k(x, y)}{2}, & \text{if } PC_l^A(x, y) = PC_l^B(x, y) \end{cases}$$



Figure 3: Low Frequency Fused image

Fusion of High-frequency Sub-images:

The coefficients in the high-frequency sub-images usually include details component of the source image. It is noteworthy that the noise is also related to high-frequencies and may cause miscalculation of sharpness value and therefore effect the fusion performance.

Therefore, a new criterion is proposed here based on directive contrast

Fuse the high-frequency sub-images as

$$C_{l,\theta}^F(x, y) = \begin{cases} C_{l,\theta}^A(x, y), & \text{if } Dc_{l,\theta}^A(x, y) \geq Dc_{l,\theta}^B(x, y) \\ Dc_{l,\theta}^A(x, y), & \text{if } Dc_{l,\theta}^A(x, y) < Dc_{l,\theta}^B(x, y) \end{cases}$$

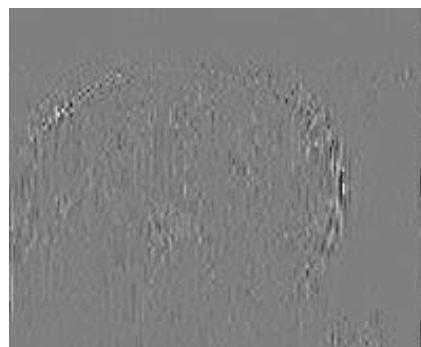


Figure 4: High Frequency Fused image

4. EXPERIMENTAL RESULTS

The proposed algorithm for the fusion of MRI and CT images is tested and compared to the traditional wavelet fusion algorithm.

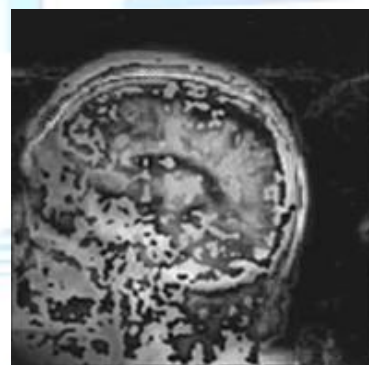


Figure 5: Fused output image

The root mean square error of the fusion result is given by

$$RMSE = \sqrt{\frac{\sum_{i=1}^M \sum_{j=1}^N [R(i, j) - F(i, j)]^2}{M, N}}$$

where $R(i, j)$ is either the MR or the CT image and $F(i, j)$ is the fusion result. M and N are the dimensions of the images to be fused. The smaller the value of the RMSE, the better the performance of the fusion algorithm

. The PSNR of the fusion result is defined as follows

$$\text{PSNR} = 10 \times \log((f_{\max})^2 / \text{RMSE}^2)$$

where f_{\max} is the maximum gray scale value of the pixels in the fused image. The higher the value of the PSNR is the better the performance of the fusion algorithm.

Method	Parameters
Directive contrast based on NSCT	RMSE= 0.0344 Fused image with MRI image. RMSE = 0.1013 Fused image with CT image.
	PSNR= 37.39 Fused image with MRI image. PSNR= 29.08 image with CT image.

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4. Conclusion:

In this paper, a novel image fusion framework is proposed for multi-modal medical images, which is based on non-subsampling contourlet transform and directive contrast. For fusion, two different rules are used by which more information can be preserved in the fused image with improved quality. The low frequency bands are fused by considering phase congruency whereas directive contrast is adopted as the fusion measurement for high-frequency bands.

FUTURE WORK:

The simulation results show the superiority of the NSCT and future going to compare the result with the wavelet transform or curvelet transform. The higher the value of the PSNR and RMSE, is the better performance of the fusion algorithm.