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Multi Model Medical Image Fusion under Non Subsampled Contour let Transform Domain

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Abstract

The Project presents the multi modal medical image fusion technique based on discrete non subsampled contourlet transform and pixel level fusion rule. 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. As we know, the image with higher contrast contains more edge-like features. In term of this view, the project proposed a new medical image fusion scheme based on discrete contourlet transformation, 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. This transformation will decompose the image into finer and coarser details and finest details will be decomposed into different resolution in different orientation. The pixel and decision level fusion rule will be applied selected for low frequency and high frequency and in these rule we are following image averaging, Gabor filter bank and gradient based fusion algorithm. The fused contourlet coefficients are reconstructed by inverse NS contourlet transformation. The visual experiments and quantitative assessments demonstrate the effectiveness of this method compared to present image fusion schemes, especially for medical diagnosis.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 and also satisfactory Entropy, Better correlation coefficient, PSNR (Peak- Signal-to-Noise Ratio) and less MSE (Mean square error).

Keywords: CT and MRI image, Non Subsampled contourlettransform, filter bank(Gabor and parallelogram filter bank)..

Introduction

Medical image fusion has been also a popular research topic. Generally, medical image fusion means the matching and fusion between two or more images of the same lesion area from different medical imaging equipment, and aims to obtain complementary information and increase the amount of information. Medical image fusion technique is to combine the information of a variety of images with computer-based image processing method. It is being used for medical image fusion so as to get a better image which is clearer and contains more information. In the clinical diagnosis and treatment, the use of fused images can provide more useful information. It isimportant for lesion location, diagnosis, making treatment and pathological study.

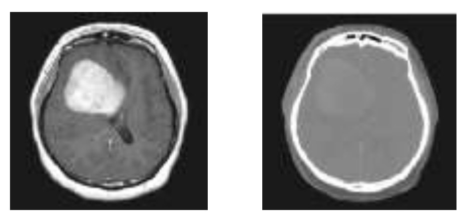

Fig: 1 CT and MRI image

In the medical imaging field, we can get different images of the same part of the same patient with different imaging devices, and the information provided by a variety of imaging modes is often complementary. Fig 1 shows the CT and MRI images.In the medical images, CT can clearly reflect the anatomical structure of bone tissues. Oppositely, MRI can clearly reflect the anatomical structure of soft tissues, organs and blood vessels. CT, MRI and other modes of medical images reflect the human information from various angles. In the clinical

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diagnosis and treatment, the problems about the comparison and synthesis between image CT and MRI were frequently encountered. With the development of new imaging sensors arises the need of a meaningful combination of all employed imaging sources. The actual fusion process can take place at different levels of information representation; a generic categorization is to consider the different levels as, sorted in ascending order of abstraction: signal, pixel, feature and symbolic level. This site focuses on the so-called pixel level fusion process, where a composite image has to be built of several input images. To date, the result of pixel level image fusion is considered primarily to be presented to the human observer, especially in image sequence fusion (where the input data consists of image sequences). A possible application is the fusion of forward looking infrared (FLIR) and low light visible images (LLTV) obtained by an airborne sensor platform to aid a pilot navigate in poor weather conditions or darkness. In pixel-level image fusion, some generic requirements can be imposed on the fusion result. The fusion process should preserve all relevant information of the input imagery in the composite image (pattern conservation) The fusion scheme should not introduce any artifacts or inconsistencies which would distract the human observer or following processing stages .The fusion process should be shift and rotational invariant, i.e. the fusion result should not depend on the location or orientation of an object the input imagery .In case of image sequence fusion arises the additional problem of temporal stability and consistency of the fused image sequence. The human visual system is primarily sensitive to moving light stimuli, so moving artifacts or time depended contrast changes introduced by the fusion process are highly distracting to the human observer. So, in case of image sequence fusion the two additional requirements apply. Temporal stability: The fused image sequence should be temporal stable, i.e. gray level changes in the fused sequence must only be caused by gray level changes in the input sequences, they must not be introduced by the fusion scheme itself; Temporal consistency: Gray level changes occurring in the input sequences must be present in the fused sequence without any delay or contrast change.

Algoithm for Non Subsampled Contourlet Transform

A.System Architecture*:* Various image fusion techniques have been proposed to meet the requirements of different applications, such as concealed weapon detection, remote sensing, and medical imaging. Combining two or more images of the same scene usually produces a better application-wise visible image. The fusion of different images can reduce the uncertainty related to a single image. Furthermore, image fusion should include techniques that can implement the geometric alignment of several images acquired by different sensors. Such techniques are called a multi-sensor image fusion. The output fused images are usually efficiently used in many military and security applications, such as target detection, object tracking, weapon detection, night vision, etc. The Brovey Transform (BT), Intensity Hue Saturation (IHS) transforms, and Principal Component Analysis (PCA) provide the basis for many commonly used image fusion techniques. Some of these techniques improve the spatial resolution while distorting the original chromaticity of the input images, which is a major drawback. Recently, great interest has arisen on the new transform techniques that utilize the multi-resolution analysis, such as Wavelet Transform (WT). The multi-resolution decomposition schemes decompose the input image into different scales or levels of frequencies. Wavelet based image fusion techniques are implemented by replacing the detail components (high frequency coefficients) from a colored input image with the details components from another gray-scale input image. However, the Wavelet based fusion techniques are not optimal in capturing two-dimensional singularities from the input images. The two-dimensional wavelets, which are obtained by a tensor-product of one-dimensional wavelets, are good in detecting the discontinuities at edge points. However, the 2-D Wavelets exhibit limited capabilities in detecting the smoothness along the contours. Moreover, the singularity in some objects is due to the discontinuity points located at the edges. These points are located along smooth curves rendering smooth boundaries of objects. Do and Vetterli introduced the new two-dimensional Contourlet transform. This transform is more suitable for constructing a multi-resolution and multi-directional expansions using non-separable Pyramid Directional Filter Banks (PDFB) with small redundancy factor.

B. NSCT Decomposition*:* Image fusion is the combination of two or more different images to form a new image by using a certain algorithm. The combination of sensory data from multiple sensors can provide more reliable and accurate information. It forms a rapidly developing area of research in remote sensing and computer vision. Most of fusion

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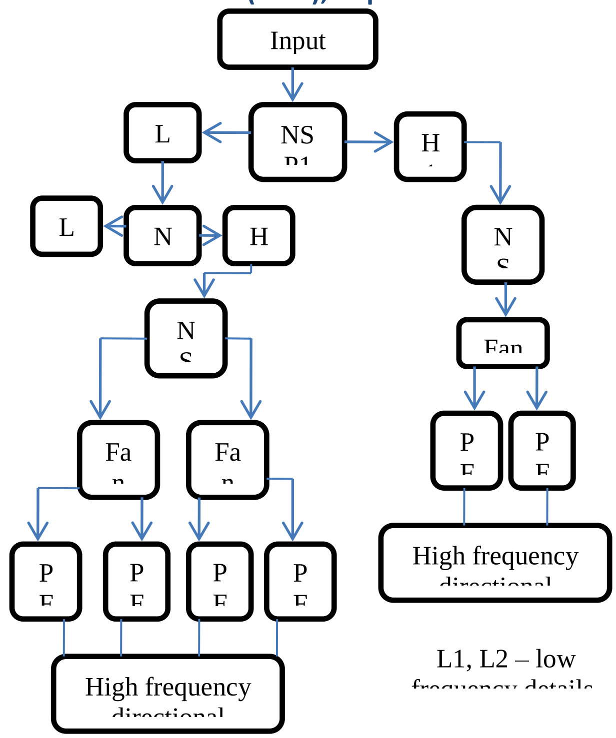
approaches were based on combining the multi-scale decompositions (MSD's) of the source images. MSD-based fusion schemes provide much better performance than the simple methods studied previously. Due to joint information representation at the spatial-spectral domain, the wavelet transform becomes the most popular approximation in image fusion. However, wavelet will not "see" the smoothness along the contours and separable wavelets can capture only limited directional information. Contourlet transform was recently pioneered by Minh N. Do and Martin Vetterli .It is a "true" two-dimensional transform that can capture the intrinsic geometrical structure, which is key in visual information. Compared with wavelet, contourlet provides different and flexible number of directions at each scale. It has been successfully employed in image enhancement, denoising and fusion. Unfortunately, due to down samplers and upsamplers presented in both the laplacian pyramid and the directional filter banks (DFB), the foremost contourlet transform is not shift-invariant, which causes pseudo-Gibbs phenomena around singularitiesNSCT decomposition is to compute the multi scale and different direction components of the discrete images. It involves the two stages such as non-sub sampled pyramid(NSP) and non-sub sampled directional filter bank(NSDFB) to extract the texture, contours and detailed coefficients. NSP decomposes the image into low and high frequency subbands at each decomposition level and it produces n+1 sub images if decomposition level is n.NSDFB extracts the detailed coefficients from direction decomposition of high frequency subbands obtained from NSP. It generates m power of 2 direction sub images if number of stages be m .The decomposition flow is shown in fig a.



Fig; a.Decomposition flow

C. The Principle of Contourlet Transform

The wavelet transform is good at isolating the discontinuities at object edges, but cannot detect the smoothness along the edges. Moreover, it can capture limited directional information. The contourlet transform can effectively overcome the disadvantages of wavelet; contourlet transform is a multi-scale and multi-direction framework of discrete image. In this transform, the multi-scale analysis and the multi-direction analysis are separated in a serial way. The Laplacian pyramid (LP) [6] is first used to capture the point discontinuities, then followed by a directional filter bank (DFB) [7] to link point discontinuities into linear structures. The overall result is an image expansion using basic elements like contour segments. The framework of contourlet transform is shown in Figure 1.

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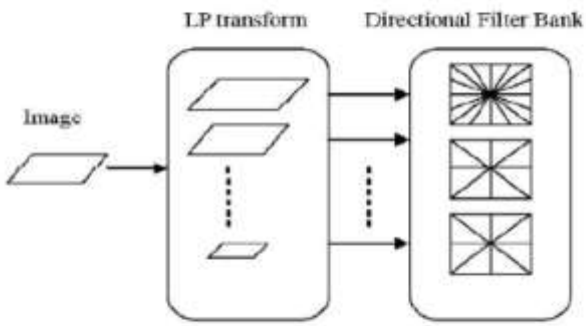

Figure 1: The contourlet transform framework

Figure 2 shows the contourlet filter bank. First, multi scale decomposition by the Laplacian pyramid, and then a directional filter bank is applied to each band pass channel.Contourlet expansion of images consists of basis images oriented at various directions in multiple scales with flexible aspect ratio. In addition to retaining the multi-scale and time-frequency localization properties of wavelets, the contourlet transform offer high degree of directionality. Contourlet transform adopts no separable basis functions, which makes it capable of capturing the geometrical smoothness of the contour along any possible direction. Compared with traditional image expansions, contourlet can capture 2-D geometrical structure in natural images much more efficiently [8]. Furthermore, for image enhancement, one needs to improve the visual quality of an image with minimal image distortion. Wavelet-based methods present some limitations because they are not well adapted to the detection of highly anisotropic elements such as alignments in an image.

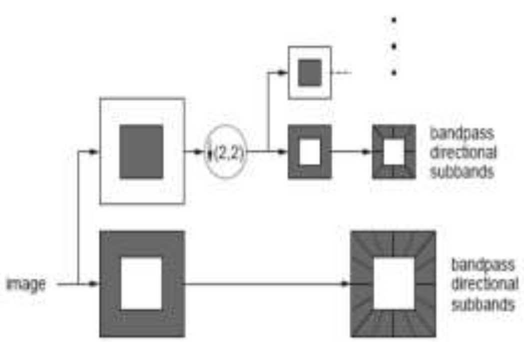

Figure 2: Contourlet filter bank

Contourlet transform has better performance in representing the image salient features such as edges, lines, curves and contours than wavelet transform because of its anisotropy and directionality. Therefore, it is well-suited for multi-scale edge based image enhancement. To highlight the difference betweenthe wavelet and contourlet transform, Figure 3 shows a few wavelet and contourlet basis images. It is possible to see that contourlet offer a much richer set of directions and shapes, and thus they are more effective in capturing smooth contours and geometric structures in images.

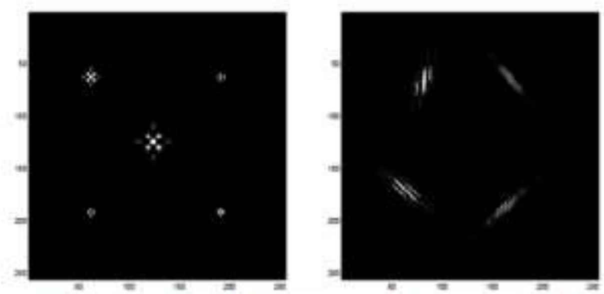

Figure 3: Comparison between actual 2-D wavelets (left) and contourlets (right) [5]

D. Finer and Coarsest Scale*:*As a hot topic in the sparse representation of images, coefficients characteristics of contourlet also have been studied. There are three relationships in contourlet coefficients, which are shown in Fig.4.

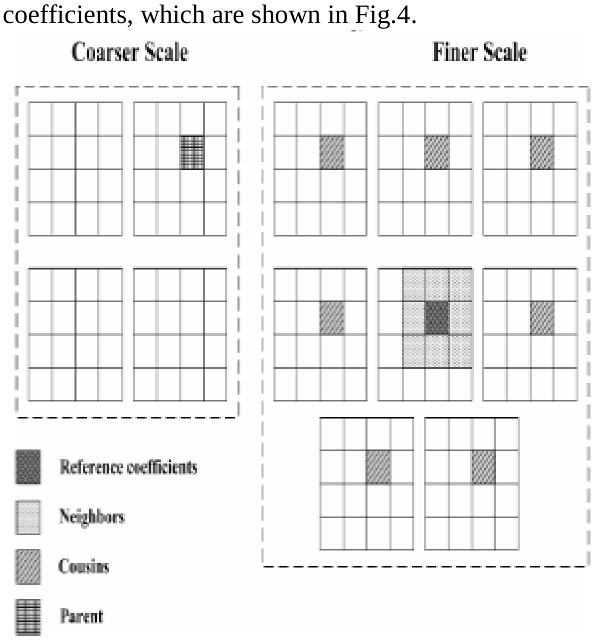

Figure: 4. Contourlet coefficient relationships

The reference coefficient has eight neighbors (NX) in the same subband, parent (PX) at the same spatial location in the immediately coarser scale and cousins (CX) at the same scale and spatial location but in directional subbands. In, mutual

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information is utilized as a measure of dependencies to study the joint statistics of contourlet coefficients. Suppose I (X;Y) stands for the mutual information between two random variables X and Y. Estimation results in show that at fine scales I (X;NX) is higher than I (X;CX) , which is higher than I (X;PX) .It indicates that the eight neighbor coefficients contain the most information about the coefficients, less information is contained in cousins and the least information is contained in the parent coefficients. Inspired by the estimation results, salience measure, based on region energy of neighborhood coefficients and correlation of cousin coefficients, is defined to combine the coefficients of source images in the fusion process in NSCT-based Fusion Algorithm

Image Fusion

A. Pixel Level Fusion

The subband images of two source images obtained from NSCT are utilized for morphing process to get the enhanced information to diagnose the brain diseases.Here, the pixel level fusion method is approached for this process. It will be implemented based on Gabor filter bank and gradient detection for coefficient selection.The low frequency subbands of two source images will be fused by Gabor coefficients selection and high frequency subbands will be fused by gradient measurement to select desired coefficients.Finally, fused two different frequency subbands are inverse transformed to reconstruct the fused image and parameters will be evaluated between input and fused image

.

B.Gabor Filter Approach

The low frequency subbands of two source images are fused based on selection of appropriate coefficients using Gabor filtering. It is useful to discriminate and characterize the texture of an image through frequency and orientation representation. It uses the Gaussian kernel function modulated by sinusoidal wave to evaluate the filter coefficients for convolving with an image. The complex Gabor in space domain, here is the formula of a complex Gabor function in space domain

g(x, y) = s(x, y) wr(x, y)

Where s(x; y) is a complex sinusoidal, known as the carrier, and wr(x; y) is a 2-D,Gaussian-shaped function, known as the envelop

The complex sinusoidal is denotes as follows,

s(x, y) = exp (j (2*pi(u0 x + v0 y) + P))

Where (u0, v0) and P denotes the spatial frequency and the phase of the sinusoidal respectively.

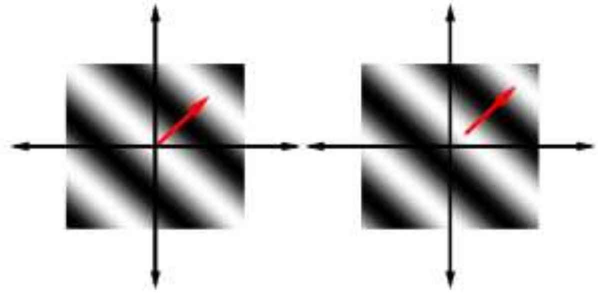

Figure 5: The real and imaginary parts of a complex sinusoidal .The images are128 X128 pixels. The parameters are: u0 = v0 = 1=80 cycles/pixel; P = 0 deg.The real part and the imaginary part of this sinusoidal are

Re (s(x, y)) = cos (2*pi*(u0 x + v0 y) + P)

Im (s(x, y)) = sin (2*pi*(u0 x + v0 y) + P)

The parameters u0 and v0 denotes the spatial frequency of the sinusoidal in Cartesian coordinates. This spatial frequency can also be expressed in polar coordinates as magnitude F0 and direction w0:

$$F_0 = \sqrt{u_0{}^2 + v_0{}^2}$$
$$\omega_0 = \tan^{-1}\left(\frac{v_0}{u_0}\right)$$

$$u_0 = F_0 \cos \omega_0$$
$$v_0 = F_0 \sin \omega_0$$

i.e.,

Using this representation, the complex sinusoidal is

$$s(x,y) = \exp\left(j\left(2\pi F_0\left(x\cos\omega_0 + y\sin\omega_0\right) + P\right)\right)$$

The Gaussian envelop looks as follows

$$w_r(x,y) = K\exp\left(-\pi\left(a^2\left(x-x_0\right)_r{}^2 + b^2\left(y-y_0\right)_r{}^2\right)\right)$$

Where (x0; y0) is the peak of the function, a and b are scaling parameters of theGaussian, and the r subscript stands for a rotation operation3 such that

$$(x-x_0)_r = (x-x_0)\cos\theta + (y-y_0)\sin\theta$$
$$(y-y_0)_r = -(x-x_0)\sin\theta + (y-y_0)\cos\theta$$

C. Fusion Process Flow:Fusion of high-frequency coefficient:

High-frequency coefficients always contain edge and texture features. In order to make full use of information in the neighborhood and cousin coefficients in the NSCT domain, a salience measure, as a combination of region energy ofNSCT

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coefficients and correlation of the cousin coefficients, is proposed for the first time.We define region energy by computing the sum of the coefficients'square in the local window. Suppose C_l^k (x y) is,the high-frequency CT coefficients, whose location is (x,y) in the subband of k-th direction at l-th decomposition scaleThe region energy is defined as follows

$$E_l^k(x,y) = \sum_{m,n \in S_{M\times N}} \left(C_l^k(x+m, y+n)\right)^2$$

where $S_{M\times N}$ denotes the regional window and its size is M × N (typically 3×3).Region energy, rather than single pixel value, will be more reasonable to extract features of source images by utilizing neighbors' information. Large region energy means important image information. Note that size of region energy map is equal to size of each subband.

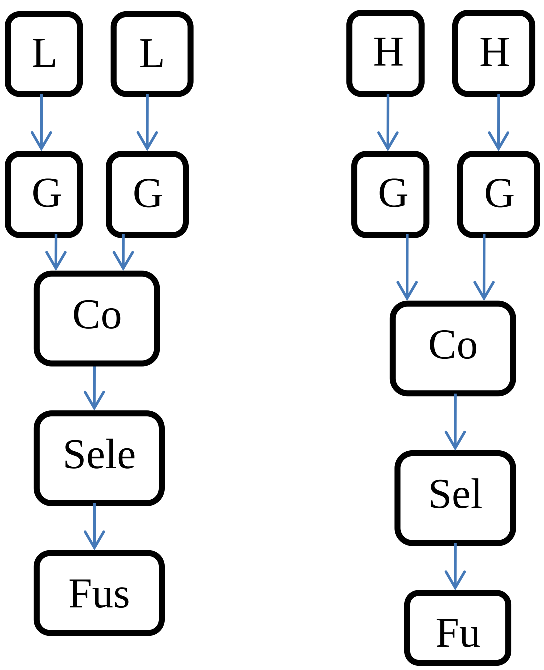


Fig: 6: block diagram in high frequency coefficients.

The high frequency coefficients are also fused by evaluating the gradient of the each subband coefficients. The gradient of an image will be defined as,

G = Sqrt (dzdx. ^2 + dydx. ^2).

Where, the dzdx and dydx are the y derivatives and x derivatives obtained by the sobel edge operators.

Then these coefficients are fused based on the searching maximum gradient of these two using decision rule.

D. Parameter Evaluation

Peak –signal-to noise ratio and Mean square error(Peak Signal to Noise Ratio) is defined in equation as follows:

PSNR = 10*log10 (255*255/MSE)

Where, MSE (Mean Square Error) stands for the mean-squared difference between the cover-image and the stego-image. The mathematical definition for MSE is defined in equation as follows:

$$MSE = 1/(M*N) \sum_{i=1}^{M} \sum_{j=1}^{N} (a_{ij}-b_{ij})^2$$

In this above equation a_{ij}means the pixel value at position (i,j) in the input image and b_{ij} is the pixel value at the same position in the output image.The calculated PSNR usually adopts dB value for quality judgment. The larger PSNR is, the higher the image quality is (which means there is only little difference between the input-image and the fused-image). On the contrary, a small dB value of PSNR means there is great distortion between the input-image and the fused-image.

E. Correlation Coefficient

It gives similarity in the small structures between the original and reconstructed images. Higher value of correlation means that more information is preserved. Coefficient correlation in the space domain is defined by:

Correlation = sum (sum (B.*A))/Sqrt (sum (sum (B.*A))*sum (sum (A.*A)));

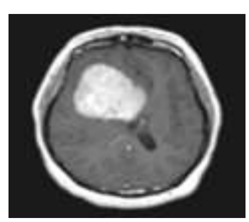
Where, B is difference between fused image and its overall mean value. A is difference between source image and its overall mean value

Simulated Results

a) NST Decomposition

NST Decomposition is given below

Non subsampled Contourlet coefficients level 1



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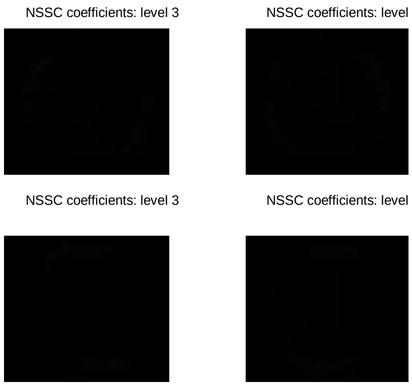
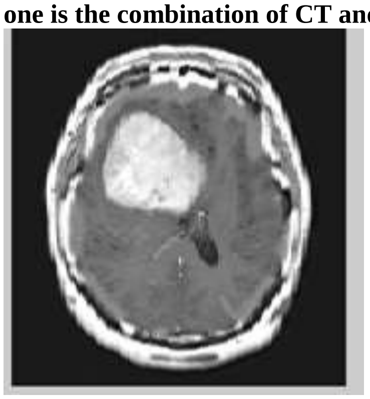


b).Fused Image

The output fused image is given below, this one is the combination of CT and MRI image



Percentage Residual Difference: 0.2196
Root Mean Square Error: 0.0137
Peak Signal to Noise Ratio (in dB): 66.7640

Conclusion

The project presented that multi modal medical images such as MRI and CT images were fused effectively based on NSCT and pixel level fusion. NSCT was helped to represent an image with better contour edges in different directions. The pixel level fusion was performed to fuse relevant details from low and high frequency using texture descriptors such as Gabor and gradient features analysis. The fused image contains significant information of both MRI and CT brain tissues details. It's medical imaging based on fusion is used for further analysis of brain structure to identify the conditions. Finally the fusion performance will be measured with parametric such as Peak signal to Noise ratio, Correlation and Entropy.

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