MULTIMODAL MEDICAL IMAGE FUSION BASED ON HYBRID FUSION METHOD

Sinija.T.S

MTECH, Department of computer science

Mohandas College of Engineering

Karthik.M

Assistant professor in CSE

Mohandas College of Engineering

***Abstract*---The importance of information offered by the medical images for diagnosis support can be increased by combining images from different compactable medical devices. Medical image fusion has been used to derive useful information from multimodality medical image data. Fused image will be represented in format capable for computer processing. The source medical images undergo a three level fusion process. 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 subjected to another combined fusion using Centralization Method. Experimental results and comparative study show that the proposed fusion framework provides an effective way to enable more accurate analysis of multimodality images. Further, the applicability of the proposed framework is carried out by the three clinical examples of persons affected with Alzheimer, subacute stroke and recurrent tumor.**

***Keywords*---**Multimodal medical imaging, Phase congruency, Directive contrast, NSCT.

1. INTRODUCTION

Processing the image and gathering the hidden information from a noised or blurred image can be carried out by various methods. Various techniques such as image fusion and super resolution enhance the image quality to show hidden information in processing the image. Fusion of two or more images of the same scene to form a single image is known as image fusion. Several fusion algorithms have been evolved such as pyramid based, wavelet based, curvelet based, HSI (Hue Saturation Intensity), color model, PCA (Principal Component Analysis) method. All of them lack in one criteria or the other [1]. Fusion of medical images should be taken carefully as the whole diagnosis process depends on it. Medical images should be of high resolution with maximum possible details [2]. The medical images should represent all important characteristics of the organ to be imaged so the integrated image should present maximum possible details. Therefore our aim is to adopt the best method of image fusion so that the diagnosis must be accurate and perfect.

Medical imaging has become increasingly important in medical diagnosis, which enabled radiologists to quickly acquire images of human body and its internal structures with effective resolution. Different medical imaging techniques such as X-rays, computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET) provide different perspectives on human body. For example, CT scans provide dense structures like bones and implants with less distortion, MRI scans provide normal and pathological soft tissue within the body while PET scans provide better information on blood flow and flood activity with low spatial resolution. Therefore, an improved understanding of a patient condition can be achieved through the use of different imaging modalities.

A powerful technique used in medical imaging analysis is medical image fusion, where streams of information from medical images of different modalities are combined into a single fused image. Medical image fusion plays important role in clinical applications such as image-guided surgery, image-guided radiotherapy, noninvasive diagnosis, and treatment planning .A single modality of medical image cannot provide comprehensive and accurate information. Combining anatomical and functional medical images provide more useful information through image fusion. The new fused image generated contains more accurate description of the scene than any of the individual source image and is more suitable for human visual and machine

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perception or further image processing and analysis tasks.

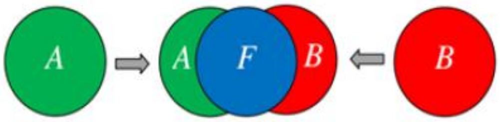


Figure 1.1: Image Fusion

Two images, image A and image B of same or different modalities are taken and by applying the various fusion methods, final fused image F is obtained which is more informative than single image. 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. There are some important requirements for the image fusion process [1].

- The fused image should preserve all relevant information from the input images.
- The image fusion should not introduce artifacts which can lead to a wrong diagnosis.

Recently, with 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 [21]. These issues are rectified in a recent multiscale decomposition Contourlet, and its non-subsampled version. Contourlet is a true 2-D sparse representation for 2-D signals like images where sparse expansion is expressed by contour segments.

The objective of the multimodality image fusion is to combine the complementary and redundant information from multiple images and generate one image which contains all the information which is present in all the source images so the resultant fused image has a better description than any other individual image. All the complementary information which is not present simultaneously in the single image can be observed in one image simultaneously which is a fused image using our proposed algorithm. The motivation behind fusing multimodality, multi-resolution images is to create a single enhanced image with improved interpretability and more suitable for the purpose of human visual perception, object detection and target recognition.

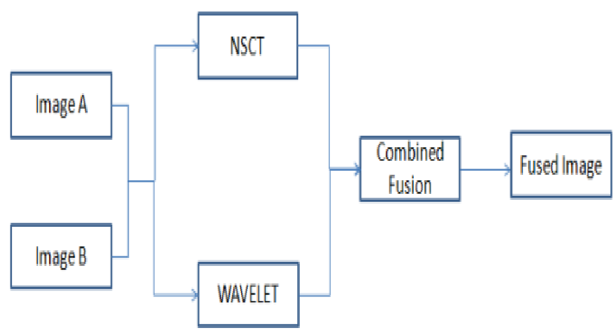
In proposed method the source medical images undergo a three level fusion process. The source medical images are first transformed by Non sub sampled Contourlet transform (NSCT) followed by fusion of low frequency and high frequency components. Two different fusion rules based on phase congruency and Directive contrast are used to fuse low and high frequency coefficients. In second level, the source images are again transformed using wavelet transform. In third level the results of first and second level are fused together using another fusion rule, centralization method. This new fusion significantly reduces the amount of distortion and the loss of contrast information usually observed in fused images.

3. PROPOSED SYSTEM

The Proposed method consists of three levels of fusion. First level fusion done with the NSCT Transform same as the existing method, then the source images undergone wavelet transform. The two outputs of transforms are fused together using a combined fusion method.

There are mainly three steps involved in proposed algorithm.

- Image fusion in NSCT domain
- Image fusion in wavelet domain
- Fusion of above results



3.1 Basic Concepts

3.1.1 Non-Subsampled Contourlet Transform

NSCT, based on the theory of CT, is a kind of multi-scale and multi-direction computation framework of the discrete images . It can be divided into two stages including non-subsampled pyramid (NSP) and non subsampled directional filter bank (NSDFB). The former stage ensures the multiscale property by using two-channel non-subsampled filter

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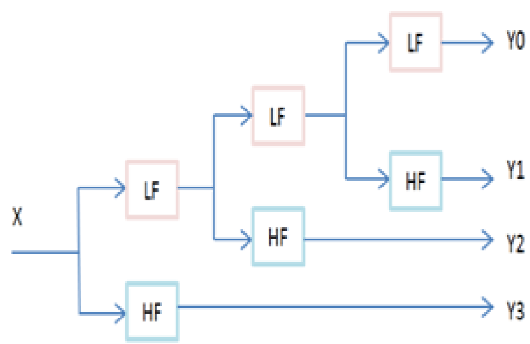
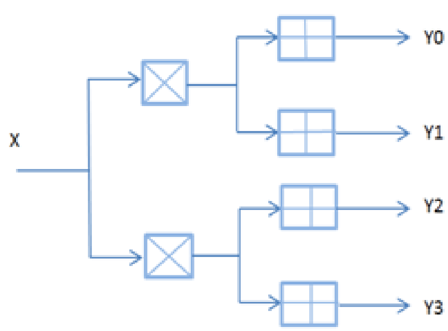
bank, and one low-frequency image and one high-frequency image can be produced at each NSP decomposition level. The subsequent NSP decomposition stages are carried out to decompose the low frequency component available iteratively to capture the singularities in the image. As a result, NSP can result 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. The NSDFB is two-channel





non-subsampled filter banks which are constructed by combining the directional fan filter banks. NSDFB allows the direction decomposition with stages in high-frequency images from NSP at each scale and produces directional sub-images with the same size as the source image. Therefore, the NSDFB offers the NSCT with the multi-direction property and provides us with more precise directional details information.

The NSDFB is two-channel non-subsampled filter banks which are constructed by combining the directional fan filter banks. NSDFB allows the direction decomposition with stages in high-frequency images from NSP at each scale and produces directional sub-images with the same size as the source image. Therefore, the NSDFB offers more precise directional details information.

3.1.2 Phase Congruency

Phase congruency is a measure of feature perception in the images which provides an 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 feature detection. First, logarithmic Gabor filter banks at different discrete orientations are applied to the image and the local amplitude and phase at a point(x,y) are obtained. The main properties, which acted as the motivation to use phase congruency for multimodal fusion, are as follows.

- The phase congruency is invariant to different pixel intensity mappings. The images captured with different modalities have significantly different pixel mappings,even if the object is same. Therefore, a feature that is free from pixel mapping must be preferred.
- The phase congruency feature is invariant to illumination and contrast changes. The capturing environment of different modalities varies and resulted in the changeof illumination and contrast. Therefore, multimodal fusion can be benefitted by an illumination and contrast invariant feature.
- The edges and corners in the images are identified by collecting frequency components of the image that are in phase. As we know, phase congruency gives the Fourier components that are maximally in phase. Therefore, phase congruency provides the improved localization of the image features, which lead to efficient fusion.

3.1.4 Wavelet Transform

Wavelet Transforms are based on small wavelets with limited duration. The power of a signal concentrates more likely in the low frequency components. Power of $\emptyset(t)$ is more compact at low frequencies while the power of $\varphi(t)$ concentrates at relatively high frequencies. In formal $\emptyset(t)$ is called scaling function to do approximation and $\varphi(t)$ is called wavelet function to find the details. Fusion steps

- Transform is applied on registered images
- This operation generates coefficient for images.
- A fusion rule has to be established and applied on these coefficients.

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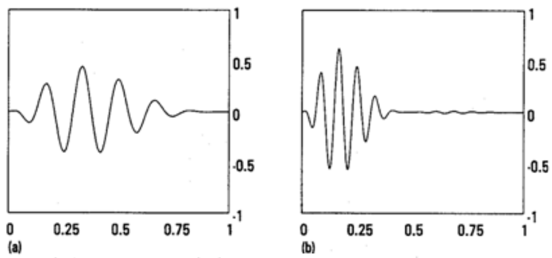
- The fused image is obtained using inverse transform.

We transform input images say A and B using wavelet Transform. It decomposes a signal into a set of basis function(wavelets). Wavelets are functions defined over a finite interval. Magnitudes of fluctuations are often smaller than those of original signal.So for the detailed vision of information it is better to prefer Haar Wavelet Transform. Haar Wavelet Transform which decompose signal into two sub signals of half of its length ie, into two sub signals of half of its length Running average and Running difference. so each minute fluctuations in the image can be identified.



(a) Signal, (b) Haar transform, 1-level

Figure , Haar Wavelet Transform

3.1.4 Proposed Algorithm

Consider two perfectly registered images.

Step 1: Input two source images A and B.

Step 2: Images undergo some preprocessing steps,

- Image De-noising, using wiener filter
- Image Enhancement, using Adaptive histogram

This step results images with better visual effect.

Step 3: Perform NSCT Transform on the source images A and B, to obtain one low frequency and a series of high frequency images

- Fusion of low frequency
- Fusion of high frequency
- Perform inverse NSCT transform on fused low and high frequency

Store the result in variable F.

Step 4: Perform wavelet transform of the source image A and B then the fused image is stored on variable C.

Step 5: Combined fusion using centralization method which makes the mean and standard deviation of the two transformed images, common.

Using the equation,

$$C = \frac{C}{\mu 2C}\sigma 2C$$

$$F = \frac{F}{\mu 2F}\sigma 2F$$

$$\mathrm{D} = \begin{cases} C & \text{if } C \text{ is greater than F} \\ F & \text{otherwise} \end{cases}$$

Thus get the final fused image in D.

4. SYSTEM TESTING AND EXPERIMENTAL RESULTS

Some general requirements for fusion algorithm are:

- It should be able to extract complimentary features from input images.
- It must not introduce artifacts or inconsistencies according to Human Visual System.
- It should be robust and reliable.

Generally, these can be evaluated subjectively or objectively. The former relies on human visual characteristics and the specialized knowledge of the observer, hence vague, time-consuming and poor-repeatable but are typically accurate if performed correctly. The other one is relatively formal and easily realized by the computer algorithms, which generally evaluate the similarity between the fused and source images. However, selecting a proper consistent criterion with the subjective assessment of the image quality is rigorous. Hence, there is a need to create an evaluation system. Therefore, first an evaluation index system is established to evaluate the proposed fusion algorithm. These indices are determined according to the statistical parameters.

5.1 Performance

Results of some clinical examples

5.1.1 Experiment with data set 1: Alzheimer

Results of fusion of scan images of Brain affected Alzheimer. He had become lost on several occasions, and had difficulty orienting himself in unfamiliar circumstances. This man is affected by the diseases namely Alzheimer. In Figure the first two column in image shows the input images, Image A and B, third column shows the fusion result using previous method NSCT and fourth Hybrid method.

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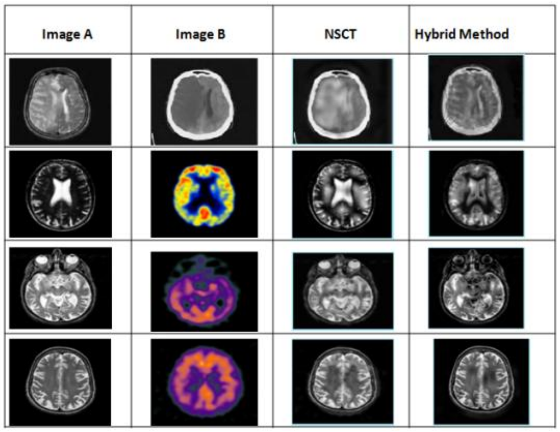

Figure 5.1: Fused images of MRI and SPECT images of Brain affected Alzheimer.

5.1.2 Experiment with data set 2: Stroke

Results of fusion of scan images of Brain affected Stroke. Stroke is due to blood clot in blood vessels or due to high Blood pressure and blood vessels may rupture.MRI scan is used to find the type of stroke. In Figure the first two column in image shows the input images, Image A and B, third column shows the fusion result using previous method NSCT and fourth column shows the fused result using proposed Hybrid method.

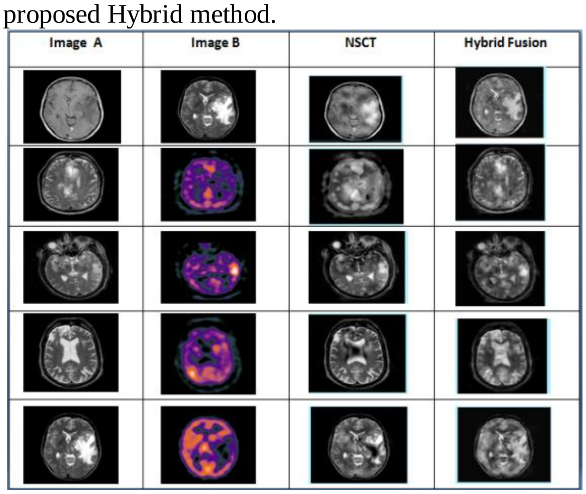

Figure 5.2: Fused images of MRI and SPECT images of Brain affected stroke.

5.1.3 Experiment with data set 3: Tumor

Tumor occurs due to undefined growth of cells as it results in loss of visual effects and hemiparesis. Through MRI scan ,the presence of active tumor can be found. SPECT scan aggressive growth and possibility of spreading can be found. In Figure the first two column in image shows the input images, Image A and B, third column shows the fusion result using previous method NSCT and fourth column shows the fused result using proposed Hybrid method.

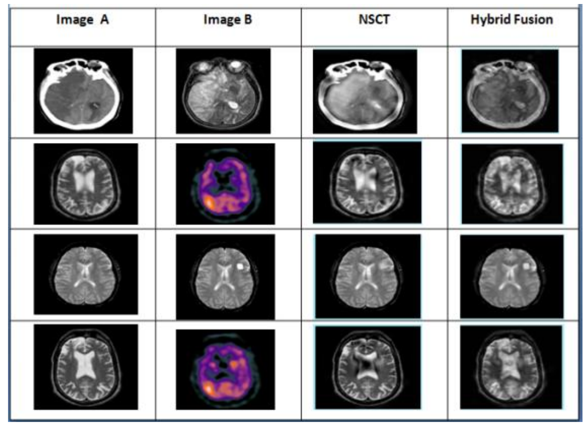

Figure 5.3: Fused images of MRI and SPECT images of Brain affected tumor

5.1.4 Experiment with data set 4:Glioblastoma

Glioblastoma is a Type of serious cancerous Tumor. In Figure the first two column in image shows the input images, Image A and B,third column shows the fusion result using previous method NSCT and fourth column shows the fused result using proposed Hybrid method. From the comparison of fused image using NSCT and Hybrid method it is clear that the hybrid method provide better visual effect and information content.

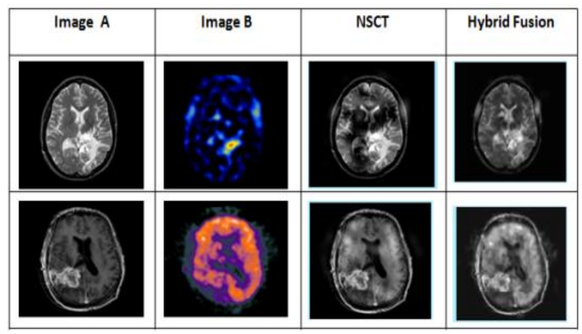

Figure 5.4: Fused Scan images of Brain affected Glioblastoma.

5.2 Evaluation Index System

5.2.1 Structural Similarity Based Metrix:

It is designed by modeling any image distortion as the combination of loss of correlation and contrast distortion.

$$SSIM(U,V) = \frac{\sigma_U V}{\sigma_U}\frac{2\mu_U \mu_V}{\mu_U^2+\mu_V^2}\frac{2\sigma_U \sigma_V}{\sigma_U^2+\sigma_V^2}$$

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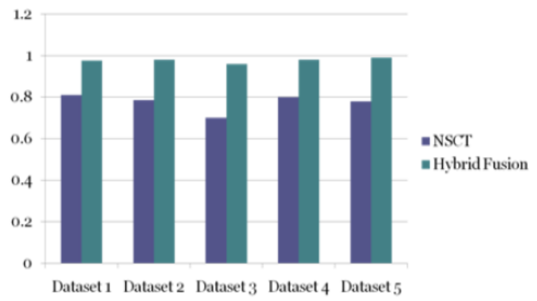
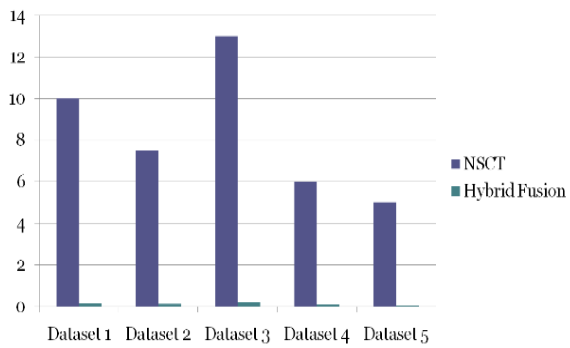


5.2.2 Mean Square Error

The mathematical equation of MSE is given by the following equation,

$$MSE = \frac{1}{mn}\Sigma_{i=1}^{m}\Sigma_{j=1}^{n}(A_{ij} - B_{ij})^2$$

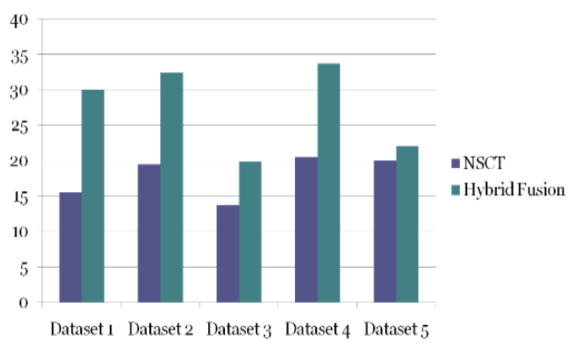
Low value of MSE provides better information.



5.2.3 Peak Signal to Noise Ratio

Ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation.

$$PSNR(dB) = 20log\frac{255}{\Sigma_{i=1}^{m}\Sigma_{j=1}^{n}(A_{ij} - B_{ij})^2}$$

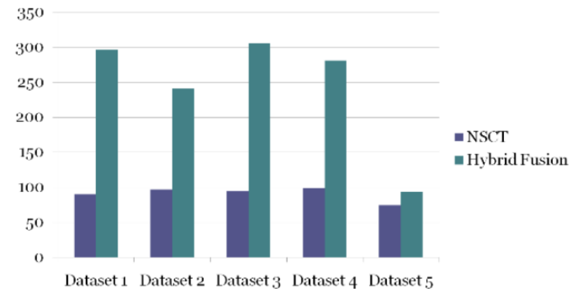


High PSNR value show better quality of image.

5.2.4 Normalized Cross Correlation

NCC are used to find out similarities between fused image and original image

$$NCC = \frac{\Sigma_{i=1}^{m}\Sigma_{j=1}^{n}(A_{ij} * B_{ij})^2}{\Sigma_{i=1}^{m}\Sigma_{j=1}^{n}(A_{ij})^2}$$



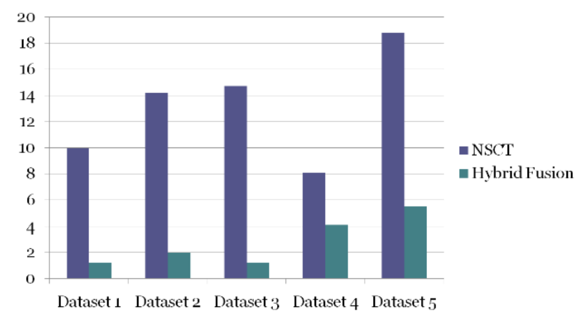
High value of NCC provides useful information for diagnosis purpose.

5.2.5 Maximum Difference

Difference of pixels between original and fused image

$$MD = max|A_(ij) - B_(ij)|$$

Low MD value provides better image details.



	Dataset1		Dataset2		Dataset3		Dataset4		Dataset5	
	NSCT	Hybrid	NSCT	Hybrid	NSCT	Hybrid	NSCT	Hybrid	NSCT	Hybrid
SSIM	0.81	0.97	0.78	0.98	0.70	0.96	0.98	0.99	0.78	0.99
MSE	10.6	0.14	7.05	0.11	13	0.2	6.1	0.90	5.1	0.5
PSNR	15.57	30	19.5	32.5	13.71	19.91	20.5	33.7	20.01	22.05
NCC	90	297	9.7	241	94	306	98.7	281.4	74.4	93.7
MD	10	1.2	14.2	2.0	14.7	1.2	8.5	4.1	18.8	5.5

Table 5.1: Performance Evaluation Table

The bar charts of SSIM, MSE, PSNR, NCC and MD are based on the measured values of five datasets shown in table. From the bar charts and table it is clear that the performance of the proposed Hybrid method provide better results than the previous NSCT method.

5. CONCLUSION

In this paper, an image fusion framework is proposed for multi-modal medical images, which is based on Three Level Fusion Method. For this fusion, Centralization method is 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

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high-frequency bands. 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. Further, in order to show the practical applicability of the proposed method, three clinical example are also considered which includes analysis of diseased person's brain with alzheimer, subacute stroke and recurrent tumor.

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