THREE LEVEL MULTIMODAL MEDICAL IMAGE FUSION

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***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

There are different types of imaging techniques such as X-ray, computed tomography (CT), magnetic resonance imaging (MRI), magnetic resonance angiography (MRA), etc., provide limited information where some information is common, and some are unique.

For example, X-ray and computed tomography (CT) can provide dense structures like bones and implants with less distortion, but it cannot detect physiological changes. Similarly, normal and pathological soft tissue can be better visualized by MRI image whereas PET can be used to provide better information on blood flow and flood activity with low spatial resolution. As a result, the anatomical and functional medical images are needed to be combined for a compendious view. For this purpose, the multimodal medical image fusion has been identified as solution which aims to integrating information from multiple modality images to obtain a more complete and accurate description of the same object.

Multimodal medical image fusion not only helps in diagnosing diseases, but it also reduces the storage cost by reducing storage to a single fused image instead of multiple-source images. The technique for medical image fusion have been categorized into three categories according to merging stage. These include pixel level, feature level and decision level fusion where medical image fusion usually employs the pixel level fusion due to the advantage of containing the original measured quantities, easy implementation and computationally efficiency. Hence, in this paper, mainly concentrate to pixel level fusion, and the terms image fusion or fusion are intently used for pixel level fusion. The well-known pixel level fusion is 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. Therefore, these are not the highly suitable for medical image fusion. Recently, with the development of multiscale decomposition, wavelet transform has been identified ideal method for image fusion.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. As a result, it can capture 2-D geometrical structures in visual information much more effectively than traditional multiscale methods .

2. LITERATURE REVIEW

GuihongQu, Dali Zhang, 2001,"Medical image fusion by wavelet transform modulus maxima"[6]. Here proposed a novel method for multimodality medical image fusion. Using wavelet transform, we achieved a fusion scheme. A fusion rule is proposed and used for calculating the wavelet transformation modulus maxima of input images at different bandwidths and levels. To evaluate the fusion result, a metric based on mutual information (MI) is presented for measuring fusion effect. The performances of other two methods of image fusion based on wavelet transform are briefly described for comparison. The experiment results demonstrate the effectiveness of the fusion scheme.

LigiaChiorean, Mircea-Florin Vaida, 2008"Medical Image Fusion Based on Discrete Wavelet Transform"[7]. The fusion process allows combination of salient feature of these images. In this paper we present different techniques of image fusion, our work for medical image fusion based on discrete wavelet transform and how we understand to integrate this process into a distributed application. The dedicated application considers Java technology for using its facilities as a future development, regarding a remote access mechanism .

F. E. Ali, I. M. El-Dokany, A. A. Saad,"Curvelet Fusion of MR and CT Images"[8].This paper presents a curvelet based approach for the fusion of magnetic resonance (MR) and computed tomography (CT) images. The objective of the fusion of an MR image and a CT image of the same organ is to obtain a single image containing as much information as possible about that organ for diagnosis. Some attempts have been proposed for the fusion of MR and CT images using the wavelet transform. Since medical images have several objects and curved shapes, it is expected that the curvelet transform would be better in their fusion. The simulation results show the superiority of the curvelet transform to the wavelet transform in the fusion of MR and CT images from both the visual quality and the peak signal to noise ratio (PSNR) points of view. Curvelet Transform is based on the segmentation of whole image into small overlapping tiles and then the ridgelet transform is applied to each tile. The segmentation process is to approximate curved lines by small straight lines. The overlapping of tiles aims at avoiding edge effects. The curvelet transform was proposed for image de-noising.

S. Das, M. Chowdhury, and M. K. Kundu,'Medical image on Ripplet Transform Type-1' [10] The motivation behind fusing multimodality, multi-resolution images is to create a single image with improved interpretability. In this paper, we propose a novel multimodality Medical Image Fusion (MIF) method, based on Ripplet Transform Type-I (RT) for spatially registered, multi-sensor, multi-resolution medical images. RT is a new Multi-scale Geometric Analysis (MGA) tool, capable of resolving two dimensional (2*D*) singularities and representing image edges more efficiently. The source medical images are first transformed by discrete RT (DRT). Different fusion rules are applied to the different subbands of the transformed images. Then inverse DRT (IDRT) is applied to the fused coefficients to get the fused image. The performance of the proposed scheme is evaluated by various quantitative measures like Mutual Information (MI), Spatial Frequency (SF), and Entropy (EN) etc. Visual and quantitative analysis shows, that the proposed technique performs better compared to fusion scheme based on Contourlet Transform (CNT).

GauravBhatnagar and Balasubramanian Raman, 'A NewImage Fusion Technique Based on Directive Contrast' [11].For making an image, which is more suitable for segmentation, feature extraction, object recognition, and Human Visual System, image fusion is frequently used technique. It combines complimentary information from different images of the same scene in a single image. In this paper, a simple but efficient algorithm is presented for image fusion employed in wavelet packet domain. For fusion, all the source images are decomposed into low and high frequency sub-bands and then fusion of high frequency sub-bands is done by the means of Directive Contrast while for low frequency median values is used. To reconstruct the fused image, inverse wavelet packet transform is performed. The performance of the algorithm is carried out by the experimental evaluation and the comparison is carried out with the existing algorithms.

3. EXISTING SYSTEM

Directive Contrast Based Multimodal Medical Image Fusion in NSCT Domain

The framework is based on some concepts.

3.1. 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 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.

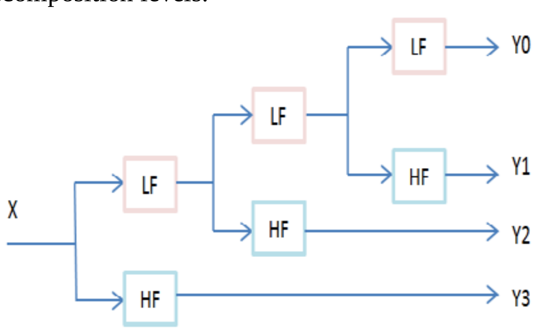


Fig.3.1 NSP decomposition

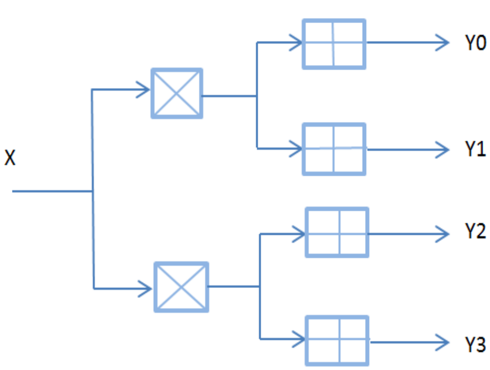


Fig.3.2. Four-channel non-subsampled directional filter bank.

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.

3.2. Fusion Framework

Considering, two perfectly registered source images and the proposed image fusion approach consists of the following steps:

1. Perform -level NSCT on the source images to obtain one low-frequency and a series of high-frequency sub-images at each level and direction ∅ , i.e.,
$$A:\{C_\ell^A, C_{l,\theta}^A\} \text{ and } B:\{C_\ell^B, C_{l,\theta}^B\}$$
where C_ℓ^* are the low-frequency sub-images and $C_{l,\theta}^*$ represents the high-frequency sub-images at level l ∈ [1,l] in the orientation .

2. *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. The complete process is described as follows.

- First, the features are extracted from low-frequency sub-images using the phase congruency extractor denoted by $P_{C_\ell^A}$ and $P_{C_\ell^B}$ respectively.
- Fuse the low-frequency sub-images as

$$C_\ell^F(x,y) = \begin{cases} C_\ell^A(x,y), & \text{if } P_{C_\ell^A}(x,y) > P_{C_\ell^B}(x,y) \\ C_\ell^B(x,y), & \text{if } P_{C_\ell^A}(x,y) < P_{C_\ell^B}(x,y) \\ \dfrac{\sum_{k\in A,B} C_\ell^k(x,y)}{2}, & \text{if } P_{C_\ell^A}(x,y) = P_{C_\ell^B}(x,y) \end{cases}$$

3. *Fusion of High-frequency Sub-images:*

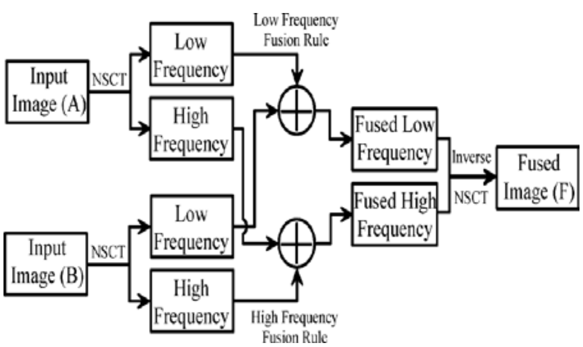
The coefficients in the high-frequency sub-images usually include details component of the source image. It is noteworthy that the noise is also related to high-frequencies and may cause miscalculation of sharpness value and therefore effect the fusion performance. Therefore, a new criterion is proposed here based on directive contrast. The whole process is described as follows.

- First, the directive contrast for NSCT high-frequency sub-images at each scale andorientation and is denoted by $D_{C^A_{l,\theta}}$ an $D_{C^B_{l,\theta}}$ at each level l ∈ [1,l] in the direction ∅ .

Fuse the high-frequency sub-images as

$$C^F_{l,\theta}(x,y) = \begin{cases} C^A_{l,\theta}(x,y), & \text{if } D_{C^A_{l,\theta}}(x,y) \geq D_{C^B_{l,\theta}}(x,y) \\ C^A_{l,\theta}(x,y), & \text{if } D_{C^A_{l,\theta}}(x,y) < D_{C^B_{l,\theta}}(x,y) \end{cases}$$

4. Perform -level inverse NSCT on the fused low-frequency (C^F_ℓ) and high-frequency $(C^F_{l,\theta})$ sub images, to get the fused image.



4. PROPOSED SYSTEM

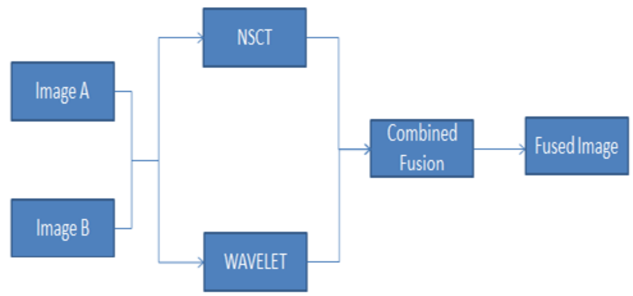
4.1 Three level Multimodal medical Image Fusion

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

A three level fusion

There are mainly three steps involved in proposed algorithm.

1. Image fusion in NSCT domain
2. Image fusion in wavelet domain
3. Fusion of above results



4.2. Proposed Algorithm

Consider two perfectly registered images.

1. Input two source images A and B.

2. Images undergo some preprocessing steps
   - Image De-noising, using wiener filter
   - Image Enhancement, using Adaptive histogram

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.

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

5. Combined Fusion

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

Using the equation,

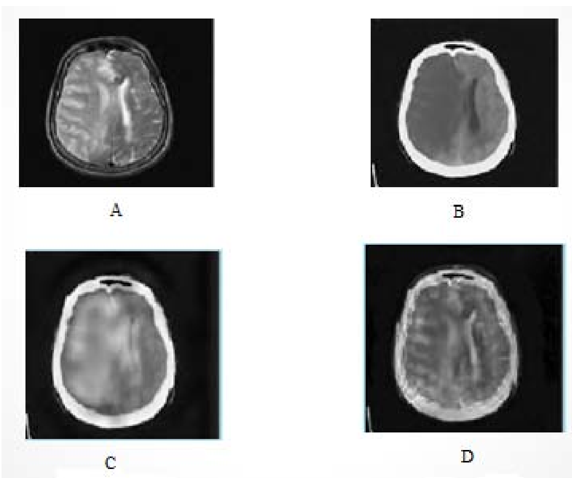
$$C = C/\text{mean } 2(C) * \text{std } 2(C)$$
$$F = F/\text{mean } 2(F) * \text{std } 2(F)$$

$$D = \begin{cases} C, & C > F \\ F, & \text{otherwise} \end{cases}$$

Thus get the final fused image in D.

Some general requirements for fusion algorithm are:

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



In Figure A and B are CT and MRI images of a person affected Alzheimer, C is Fused image based on Existing System and D is Fused image based on Proposed system.

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 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.

6. REFERENCES

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