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A Modified Three Level Fusion Technique for Multimodal Medical Image Fusion in Wavelet and NSCT Domain

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Abstract— Multimodal imaging is a medical imaging technique with applications in medical analysis. It is used for extracting complementary information from medical images. Nowadays with the rapid development in technology and modern instrumentation medical imaging has become a vital component for a large number of applications including diagnosis, research and treatment. Medical image fusion aims at improving image quality taken from different imaging method like CT and MRI. CT imaging provides information on dense structure whereas MRI provides information on soft tissues. Merging of two techniques will result in better interpretation of data.This paper presents a novel approach for multimodal medical image fusion by combining the NSCT domain with wavelet domain. Performance evaluation of proposed image fusion method based on similarity measures and entropy realizes an efficient method for accurate analysis of multimodal images.

Index Terms— Multimodal medical image fusion, Non-subsampled contourlet transform, Wavelet Transform, Adaptive Histogram Equalization, Wiener filter, Phase Congruency, Directive Contrast.

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1 INTRODUCTION

In the recent years, advancement in image processing has played a crucial role in the field of medicine. Medical imaging finds profound attention due to it effective contribution in health care. Many types of imaging techniques such as Computed Tomography(CT), Magnetic Resonance Imaging(MRI), radiation based imaging(SPECT and PET) used widely has helped in efficient disease identification and diagnosis thus leading to efficient treatment of various ailments. However each of these modalities along with their advantages has its own limitations. X-Ray and Computed Tomography provide information on dense structures like bones and implants but cannot detect physiological changes. Magnetic Resonance imaging helps in visualization of soft tissues but fails to detect fluid activity [1].

As a result, recent advancements in combining various imaging modalities to integrate information for obtaining more complete and accurate description of an object of interest are pursued. Image fusion techniques are employed to obtain multimodal images [4]. Multimodal imaging helps in reduce storage cost by reducing storage to a single fused image rather than multiple images.

This paper proposes a novel image fusion framework for combining CT and MRI images based on non subsampled transform and wavelet fusion technique. The proposed methodology combines these two techniques and preserves more details from source images and thus improves the quality of fused images. Experimental results indicate that the proposed framework can provide a better fusion outcome compared to traditional fusion method employing only Non-subsampled contourlet transform (NSCT).

The rest of the paper is organized as follows. Multimodal imaging, NSCT and wavelet fusion are explained in Section 2. In Section 3 proposed fusion framework is introduced. Experimental results and performace evaluation are discussed in Section 4. Finally, concluding remarks are presented in Section 5.

2 PRELIMINARIES

This section provides a brief description of concepts on which the proposed framework is based.

2.1 Multimodal Imaging

Medical images help in providing visual representation of physiological activities for clinical analysis and medical intervention. Improving the quality of medical images leads to better medical diagnosis and treatment. Multimodal images are images formed from fusion of medical images from various modalities like CT, MRI etc.

A multi-modal imaging system is a medical imaging system that combines optical, magnetic and radioactive properties. Using different methods to study human tissue at the same time allows analysis of multiple aspects of the same area. The image should display abnormalities present, its size, location and changes in metabolic activity. Multimodal imaging with two or more imaging modalities allows integration of the strengths of individual modalities, while overcoming their limitations to obtain a more complete and accurate description of an object [1]. Multimodal neuro-imaging along with image fusion is finding extensive application in analyzing brain functions both in seemingly healthy individuals and in individuals who have suffered various neurological disorders.

2.2 Image Fusion

Fusion in image processing is a technique combining relevant information from two or more images into a single image. The resulting image will be more informative than the input images. Objective of image fusion is to combine information from multiple images of the same scene into single image retaining

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important and required features of the original image. Many methods exist to perform image fusion [10] [15]. The very basic one is the high pass filtering technique. Later techniques are based on Discrete Wavelet Transform, uniform rational filter bank, and Laplacian pyramid.

Medical Image Fusion has become a common term used within medical diagnostics and treatment. The term is used when multiple images of a patient are registered and overlaid or merged to provide additional information. Fused images may be created from multiple images from the same imaging modality, or by combining information from multiple modalities, such as magnetic resonance image (MRI), computed tomography (CT), positron emission tomography, and single photon emission computed tomography [1]. For accurate diagnoses, radiologists must integrate information from multiple image formats.

2.3 Wavelet Fusion

Wavelet transforms can decompose a signal into several scales or segments that represent different frequency bands, and at each scale, the position of signal's instantaneous structures can be determined approximately. Wavelet transforms are developed to overcome various limitations of Fourier transform. Wavelet based method provides a method to blend two multimodal images and try to extract the salient features from them. A wavelet is a waveform of an effectively limited duration that has an average value of zero. Wavelet transform has received considerable attention in the field of image processing due to its flexibility in representing non-stationary image signals and its ability in adapting to human visual characteristics. Wavelet transforms are the most powerful and the most widely used tool in the field of image processing [4][7].

Wavelet based image fusion combines two images by merging the wavelet decomposition of the two original images using fusion methods applied to approximation coefficients and detail coefficients [11]. The source images are transformed to the wavelet domain with the function wfusimg(), where the parameters for fusion are specified. Then a decision mask is built in same way as in Laplacian fusion.In the next step the fused image is constructed from its decision mask [7]. Finally the fused image is obtained by applying an inverse wavelet transform.

Fusion rule implemented is the Maximum Selection Scheme which is a fusion scheme based on discrete wavelet transform. This schenme picks the coefficients in each subband with the largest magnitude [7][15].The syntax of the function wfusimg() is given as:

XFUS=wfusimg(X1,X2,WNAME,LEVEL,AFUSMETH,DFUSMETH)

where XFUS returns the fused image XFUS obtained by fusion of the two original images X1 andX2. Each fusion method, defined by AFUSMETH and DFUSMETH, merges in a specific way[11], the decompositions of X1 and X2, at level LEVEL and using wavelet WNAME.

AFUSMETH and DFUSMETH define the fusion method for approximations and details, respectively.

2.4 Non-Subsampled Contourlet Transform

Nonsubsampled contourlet transform (NSCT) is a transform developed with the motivation to construct a flexible and efficient transform targeting applications where redundancy is not a major issue. The NSCT is a fully shift-invariant, multiscale, and multidirection expansion that has a fast implementation [6].

NSCT, based on the theory of contourlet transform [5][6], 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 [1][6].

In NSCT based multimodal image fusion source images are decomposed using NSCT transform [6]. Two fusion rules based on phase congruency(PC) and directive contrast(DC) are used to combine the low frequency and high frequency components respectively [1][2][8].Phase congruency provides a contrast and brightness-invariant representation of low-frequency coefficients. It selects and combines contrast- and brightness-invariant representation contained in the low-frequency coefficients. Using directive contrast, the most prominent texture and edge information are selected from high-frequency coefficients and combined in the fused ones [1]. Finally the fused image image is obtained by applying an inverse NSCT.

2.5 Preprocessing Techniques

The two preprocessing techniques used in the proposed method are image denoising using Wiener filter and image enhancement using Adaptive histogram localization.

Wiener filter provides a 2-D adaptive noise removal by filtering an image using pixelwise adaptiver filtering, using neighborhoods of size m-by-n. Function weiner2() filters a grayscale image that has been degraded by constant power additive noise [9].Adaptive histogram equalization is used to improve contrast in images. Function adapthisteq() enhances the contrast of a graysale image by transforming the values using contrast limite adaptive histogram equalization [12].

3 PROPOSED FUSION FRAMEWORK

Proposed method realizes on NSCT, wavelet transform and fusion rules for multimodal medical image fusion which takes a pair of source image denoted by A and B and to generate a composite image. A general image fusion scheme using proposed method is shown in Figure 1. The CT and MRI images are applied as inputs to obtain output as a fused image. The procedure is as follows and it is shown in Figure 1.

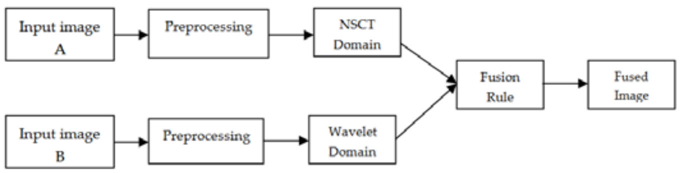


Fig. 1. Block Diagram of Image Fusion Scheme using Three Level Fusion Rule

Consider two perfectly registered source images A and B. The proposed image fusion approach consists of the following steps:

Step 1: From the dataset select a CT image and MRI image to be fused. Preprocessing of the source images are performed for denoising and image enhancement using wiener filter and adaptive histogram equalization[9][12].

A1=wiener2(A,[3 3]) and B1=wiener2(B,[3 3])
A1=adapthisteq(A1) and B1=adapthisteq(B1)

Step 2: First level Fusion - Perform *l*-level NSCT on the source images to obtain one low-frequency and a series of high-frequency sub-images at each level and direction θ, i.e,

$$A:\{\mathcal{C}_\ell^A,\mathcal{C}_{l,\theta}^A\} \text{ and } B:\{\mathcal{C}_\ell^B,\mathcal{C}_{l,\theta}^B\}$$

where C_l^* are the low-frequency sub-images and $C_{l,\theta}^*$ represents the high-frequency sub-images at level in the orientation [1].

Step 3: Fusion of Low-frequency sub-images: The low-frequency sub-images represent the approximation component of the source images. The simple averaging methods can be used for fusion. However, due to reduced contrast a high quality fused image cannot be obtained.Hence a method based on the phase congruency is used which is given as [1].

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

Step 4: Fusion of High-frequency Sub-images: The high-frequency sub-images represent details component of the source image. A modified method based on directive contrast is applied for fusion [1].

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

Step 5: Perform *l*-level inverse NSCT on the fused low-frequency $C^F{}_l$ and high-frequency and $C^F{}_{(l,\theta)}$ subimages, to get the first level fused image F[1].

Step 6: Second level fusion - Perform wavelet fusion on the input images to get second level fused image C[7][11].

C = wfusimg (A,B,'sym4',5,'max','max')

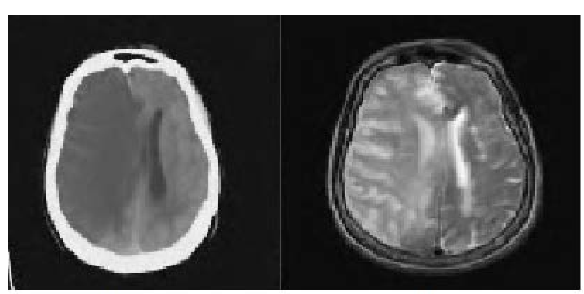
Step 7: Third level fusion - Combine the NSCT image and wavelet image to obtain final fused image. The mean and standard deviation values of C and F are considered and based on a threshold value D the higher values are captured to construct the output image.

C = (C/mean2(C))*std2(C)
F = (F/mean2(F)) * std2(F)
D(C>F) = C(C>F)

EXPERIMENTAL RESULTS AND ANALYSIS

4.1 Results

The test data consist of MRI and CT images. The proposed algorithm for the fusion of MRI and CT images is tested and compared to the fusion framework using NSCT. The MRI and corresponding CT images are downloaded from [1]. The source images and fusion results are displayed in Figure 2 and Figure 3. Proposed method combines NSCT domain with wavelet domain.



(a) (b)

Fig.2. Input images (a) CT image (b) MRI image

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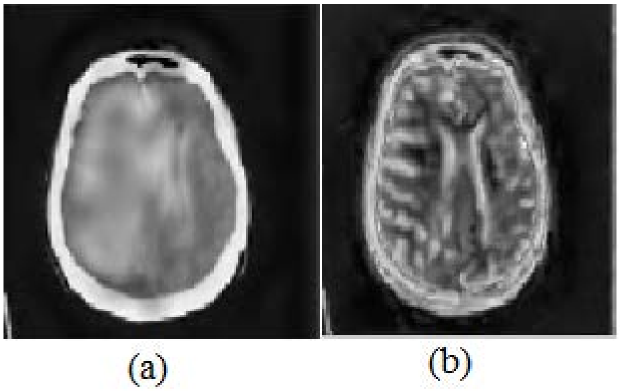

Fig.3. Fused output images (a) Image fusion using NSCT (b) Proposed fusion method

4.2 Performance Evaluation

Comparison of the two method shows proposed method to be better than fusion using only NSCT domain in terms of various performance measures like Structural Similarity Index measure (SSIM) and Entropy (EN). The values are tabulated in table1.

Structural Similarity Index measure is used for measuring image quality. The equation ssimval = ssim(A,ref) computes the structural similarity index value for an image A using ref as the reference image[13].

Entropy is defined as a statistical measure of randomness that can be used to characterize the texture of the input image. E = entropy(I) returns E, a scalar value representing the entropy of grayscale image I [14]. High value of ssim and entropy implies that fused image is more informative.

TABLE 1
PERFORMANCE EVALUATION

	Fusion Method	
Parameters	Fusion using NSCT	Proposed fusion
SSIM	0.81107	0.97793
ENTROPY	0.025759	0.55426

5 CONCLUSION

In this paper, a modified approach of multimodal medical image fusion scheme using a combination of NSCT and Wavelet domain is proposed. In the proposed algorithm, first, each of source images are decomposed using NSCT, then the coefficient are fused using modified fusion rule and then reconstructed by performing the inverse NSCT. In the second level fusion wavelet method is used for fusion of the source images. The final level fusion combines the NSCT fused images and wavelet fused images to get the output.The performance analysis shows that the proposed method produce better fused output. The superiority of the proposed algorithm is compared with NSCT fusion method and the performance is evaluated with the qualitative analytical measurement of mutual information between input and output images, entropy and structural similarity. The performance measures proven that, the proposed method is better method to obtain more information in fused image.

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