Study of Fusion Techniques of CT Scan and MR Images

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Abstract-Medical image fusion has been used to derive useful information from multimodality medical image data. The main motivation is to get most relevant information from sources into a single output, which plays an important role in medical diagnosis. Medical imaging modalities such as computerized tomography (CT), magnetic resonance imaging (MRI), have been developed and widely used for clinical diagnosis. These two types of images contain important information that can be diagnosed a brain diseases accurately and effectively. Fusion of two different medical images into a single image is highly in demand. This paper discusses various fusion techniques that can be used for fusing multimodality medical images in which non-subsampled contourlet transform (NSCT) is best of all the fusion techniques.

Index Terms- Image Fusion, Contourlet transform, Discrete Curvelet Transform, Non-Subsampled Contourlet Transform, Wavelet transform

I. INTRODUCTION

Image fusion plays an important role in medical field as it helps doctor to recognize the disease. The image fusion is the process of combining two or more images. The fused image gives better results as fusion criterion is to minimize error between fused image and input image. Different fusion techniques have been used in image fusion. They are magnetic resonance image (MRI), computed tomography (CT), positron emission tomography (PET) and Single positron emission computed tomography (SPECT).This techniques provide different information. CT provides images as dense like structure with which physiological changes cannot be detected easily whereas in MRI images the soft pathological tissues can be visualized better but cannot provide dense structure. For this reason functional and anatomical medical images are needed to be combined for better visualization and for accurate diagnosis. As a result medical image fusion is an effective way to provide solution to generate information from medical image fusion. This fusion technique provides accurate diagnosis, analysis and also helps in reducing the storage cost by reducing storage to a single fused image [1]. Various image fusion techniques such as spatial domain and frequency domain techniques have been implemented. Spatial domain techniques results poor performance as it produces edge distortion in fused image. Image Techniques are categorized into three stages. They are pixel level, feature level and decision level fusion. In medical image fusion we employ the pixel level fusion due to the advantages like containing the original measured quantities, computationally efficient and easy implementation. The pixel level deals with information associated with each pixel. In feature level fusion, source images are segmented into regions and these features are used for fusion. In decision level image fusion, the objects in the source images are first detected and then by using some suitable fusion algorithm, the fused image is generated. 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

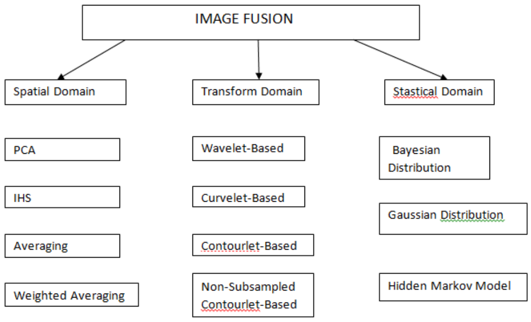

Fig.1 Categories of image fusion methods[1]

The categories of image fusion methods is shown in Fig.1. There are many different methods in image fusion process. Fusion schemes, such as averaging, weighted averaging and Principal Component-Analysis (PCA), are performed solely in the spatial domain. Despite the easy implementation, these methods pay the expenses of reducing the contrast and distorting the spectral characteristics .These problem is solved by transform domain[1] .The transform domain employs the properties like multi-resolution decomposition. It decomposes images at different scale to several components, which account for important salient features of images. It gives a better performance than those performed in the spatial domain.

In this paper, we focus on the image fusion techniques in transform domain as statistical domain methods suffer from a significant increase of computational complexity the rest of the paper is organized as follows: section 2 explain image fusion techniques section 3 presents the non-subsampled contourlet Transforms Section 4 performance analysis.

II. IMAGE FUSION TECHNIQUES

Image fusion method can be divided into two groups– 1.Spatial domain fusion method 2.Transform domain fusion. Spatial domain fusion method directly deals with pixels of input images .The fusion methods are simple maximum, simple minimum, averaging, principal component analysis (PCA) and hue intensity saturation (HIS). In transform domain method image is first transferred into frequency domain. The Transform domain fusion methods are wavelet Transform, curvelet Transform, contourlet Transform, nonsubsampled contourlet Transform.

GuihongQu, Dali Zhang, 2001,"Medical image fusion by wavelet transform modulus maxima"[2][3].In these paper, a method for multimodality medical image fusion is proposed. 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. The image fusion scheme of this study includes the decomposition of the input images, calculating the wavelet transform modulus maxima, fusion strategy, and reconstruction .the new fusion image is as shown in Fig.2

First, the input images which are to be fused is decomposed by forward wavelet transformation. In such case, each image is decomposed into the same levels using a periodic discrete wavelet transform. The wavelet transform decomposes each image into low- and high-frequency subband images. The third step is the combination of the information from each image by fusion rules.

Low-frequency subbands related to the common part of the images and high-frequency corresponds to the region boundaries or edges. As mentioned above, the job of image fusion is to combine the complementary information carried by multimodality images.

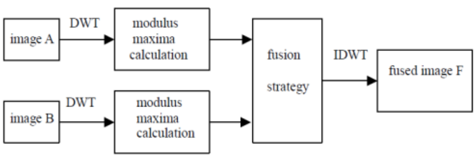

Fig.2 Image fusion scheme by wavelet transform modulus maxima [3]

The advantages of the image fusion algorithm based on the wavelet transform modulus maxima are: (i) both edge features and component information of the objects from different modalities are preserved in the fused image effectively; (ii) features at different levels and bandwidths are extracted for fusion.

However, it is contended 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.

F. E. Ali, I. M. El-Dokany, A. A. Saad," Curvelet Fusion of MR and CT Images"[4][5] .If there is any discontinuity along the curved edge that will affect all the wavelet coefficients. So there is need of a better algorithm to represent the curved shapes efficiently, in such condition Curvelet Transform is used .The fused image using the curvelet-based image fusion method gives almost the same detail as the original panchromatic image, because curvelet represent edges better than wavelets. It gives the same colour as the original multispectral images. It helps in shape detection of the fused image. But it has limited availability of wavelet transform leads to curved shapes of the fused image. The second generation of Curvelet transform is shown in Fig: 3. Firstly, the 2D FFT is applied to the source image to obtain Fourier samples. After that a discrete localizing window smoothly localizes the Fourier transform near the sheared wedges obeying the parabolic scaling. Then, the wrapping transformation is applied to re-index the data. Finally, the inverse 2D FFT is used to obtain the discrete Curvelet transform (CVT) coefficients.

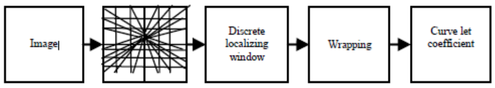

Fig. 3 The second generation of Curvelet transforms[4]

Curvelet can solve the blurring of edges and details in wavelet image fusion, but it has no good performance of the local variation of the image.

L. Yang, B.L. Guo, W. Ni, "Multimodality medical image fusion based on multiscale geometric analysis of contourlet transform" [6]-[7] The wavelet transform has limitations such as limited directions (only three directions, horizontal, vertical, diagonal) and non-optimal-sparse representation of images. In order to solve these limitations, the new multiscale transforms i.e. Curvelet , Contourlet, etc. has been introduced in image fusion. The contourlet transformation is a multidirectional and multiresolution image expression method. Contourlet transformation has good direction sensitivity, and catches accurately the image edge information. Block diagram of the contourlet-based image fusion algorithm is shown in fig 4. Here images A and B denote the input source images (i.e CT image and MR image) which is to be fused, F is the final fused image. All the input source images to be fused should perfectly registered, so that the corresponding features can coincide pixel to pixel [11]. The source images A and B are decomposed using contourlet transform. For1-level contourlet decomposition, the input images are decomposed into low passsubband and highpass subbands in different directions and scales. The lowpass subband is an approximation of the original image; while the highpass subbands show high frequency details in different directions and scales. The laplacian pyramid (LP) and Directional filter bank (DFB) filtering process are then iterated on the lowpass subband .

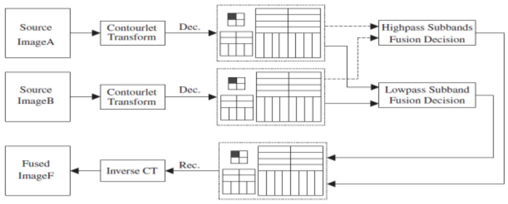

Fig. 4 Block diagram of the contourlet-based image fusion algorithm [6]

The Contourlet transform lacks the shift invariance because of the need for up sampler and down sampler, which usually cause the Gibbs effect. The contourlet transform has a major drawback, which is that its basis images are not localized in the frequency domain. The new Contourlet transform with shift invariance, called non-subsample contourlet transform (NSCT) has been proposed [6].CT provides good Directional Sensitivity; provide accurate image edge information, but Lacks Shift Invariance.

Qiang Zhang, Bao-long Guo "Multifocus image fusion using the nonsubsampled contourlet transform"[8] In contourlet transform, it can achieve better expression than discrete wavelet transform, especially for edges and contours. The Contourlet transform uses a double filter bank structure to get the smooth contours of images. Double filter bank consist of the Laplacian pyramid (LP) which is first used to capture the point discontinuities, and then a directional filter bank (DFB) is used to form those point discontinuities into linear structures.But, due to the down sampling and up sampling, the contourlet transform is lack of shift-invariance and results in ringing artifacts. The shift-invariance is required in image analysis applications, such as edge detection, contour characterization, image fusion. In NSCT, the multiscale analysis and the multidirection analysis are also separated, but both of them are shift-invariant. First, then on subsampled pyramid (NSP) is used to obtain a multiscale decomposition by using two-channel nonsubsampled 2-D filter bands. Second, then on subsampled directional filter bank is used to split band pass sub-bands in each scale with different directions. Since there is no down sampling in pyramid decomposition, low-pass sub-band has no frequency aliasing. The band width of low-pass filter is larger than $\pi/2$. Hence, the nonsubsampled contourlet transform offers better frequency characteristics than the original contourlet transform.

III THE NON-SUBSAMPLED CONTOURLET TRANSFORMS

A Non-Sub sampled Contourlet Transform (NSCT) is based on the theory of Contourlet Transform which is a kind of multi-scale and multi-direction computation framework of the discrete images[7]-[10].These method is also based on non-subsampled contourlet transform and directive contrast. Two different rules are used for fusion, by which more information can be preserved in the fused image with improved quality. The phase congruency is used to the low frequency bands and directive contrast is used as the fusion measurement for high-frequency bands. The main property of NSCT is to provide a multidirectional, multiscale, shift invariant image decomposition that can be efficiently implemented by means of the fusion techniques or algorithms. 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 other algorithms

3.1 Non-Subsampled Pyramid Structure (NSP)

NSP conserved the main multiscale property of nonsubsampled contourlet transforms [9].It is met by combining the directional filter banks and Laplacian pyramid. The pyramidal filter bank structure plays important role in the compression applications as a result of production of very little redundancy by the pyramidal filter bank with the contourlet transform. Two channel non-subsampled 2D filter banks can be used to achieve the multiscale property in the NSCT domain

3.2 Non-Subsampled Directional Filter Bank (NSDFB)

The upsamplers and the downsamplers are disregarded from the directional filter bank to contain the nonsubsampled directional filter bank.[7][8]The nonsubsampled directional filter bank produces a tree structured filter bank. NSDFB offers the NSCT with the multi-direction property and provides us with more precise directional details information.

Combination of NSDFB and NSP: The NSCT is the mixture of NSP and NSDFB.NSCT is fabricated very carefully such that it does not disturb the upper stages of the pyramid because applying directional response at lower and higher frequencies may cause aliasing due to the tree structured format of the NSDFB.

3.3 Directive Contrast

The directive contrast is useful for fusion of high frequency coefficients of the input images[]. For the better interpretation of the image selection of high frequency coefficients are necessary. The bright and sharp regions of the image are generally symbolized by the high frequency coefficients of an image. Directive contrast produce accurate result.

3.4 Phase Congruency

The phase congruency is used for fusion of low frequency coefficients of input images. It yields the contrast and brightness invariant representation of the low frequency coefficients of the image. It conveys the luminance and contrast invariant feature extraction in the low frequency coefficients of the image. It is also beneficial for selecting and combining the brightness and the contrast invariant of the low frequency coefficients of the image. The main use of the phase congruency is in feature perception of the image based on local energy model, which needs the important features of the image at points of pixels.

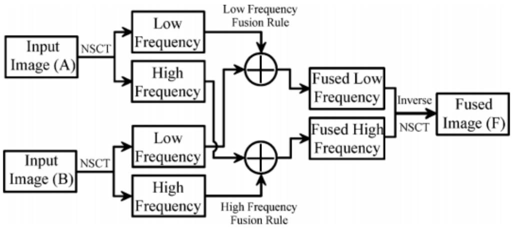

Fig. 5. Block diagram of NSCT multimodal medical image fusion framework.[10]

NSCT has a property of shift-invariant version of CT (Contourlet transform) and has some excellent properties including multilevel and multidirectional properties. NSCT provides a better representation of the contours[7]. CT employs the Laplacian pyramid for multiscale decomposition and the DFB for directional decomposition. To reduce the frequency aliasing of CT and to reach the shift invariance, NSCT eliminates the down samplers and the up samplers during the decomposition and the reconstruction of the image. It is built upon the non-subsampled pyramid filter banks and the non-subsampled Directional filter banks, by applying this transform we will get low and high frequency component of input image. Apply different level of transform to CT and MRI image.

A high frequency component of CT and MRI is fused based on Energy level. Fused low frequency is nothing but MRI and CT low frequency components. Then apply inverse NSCT to get a reconstructed panel.

IV. PERFORMANCE ANALYSIS

The aim of image fusion is to process the significant parts of source image. For performance evaluation we can use quantitative measures in which we evaluate fusion on the basis of parameters of fused image such as information Entropy, Peak Signal to Noise Ratio (PSNR), Mutual information (MI) and structural similarity index. These performance metrics are introduced as follows

i) Peak Signal to Noise Ratio:

PSNR is defined as ratio between the maximum possible power of a signal and power corresponding to noise the fidelity of its representation. The PSNR is used to calculate the similarity between two images. The PSNR between the reference image R and the fused image F is calculated as

PSNR=$10\log_{10}\left(\frac{MAX_I^2}{RMSE}\right)$, where RMSE is root mean square error

ii)Normalized Mutual Information

Mutual information (MI) is a quantitative measure of the mutual dependence of two variables. It shows measurement of the information shared by two images. Mathematically, MI between two discrete random variables U and Vis defined as

$$MI(U,V) = \sum_{u\in U}\sum_{u\in V} p(u,v)\log_2\frac{p(u,v)}{p(u)p(v)},$$

Where is the joint probability distribution function of U and V whereas p(u) are the marginal probability distribution function of U and V respectively. The quality of the fused image with respect to input images A (CT image) and B (MR image) can be expressed as,

$$Q_{MI} = 2\left[\frac{MI(A,F)}{H(A)+H(F)} + \frac{MI(B,F)}{H(B)+H(F)}\right]$$

where $H(A), H(B) and H(F)$ is the marginal entropy of images CT image, MR image, and Fused respectively

iii) Structural Similarity based Metric

Structural similarity (SSIM) is designed by modeling any image distortion as the combination of loss of correlation, radiometric and contrast distortion. Mathematically, SSIM between two variables U and V is defined as

$$SSIM(U,V) = \frac{\sigma UV}{\sigma U\sigma V}\frac{2\mu U\mu V}{\mu^2 U+\mu^2 V}\frac{2\sigma U\sigma V}{\mu^2 U+\mu^2 V}$$

Where $\mu U, \mu V$ are mean intensity and $\sigma U, \sigma V, \sigma UV$ are the variances and covariance respectively. A SSIM for the image fusion assessment and is defined as

$$Q_S = \begin{cases} (w)SSIM(A,F|w) + (1-(w))SSIM(B,F|w), ifSSIM(A,B|w) \geq 0.75 \\ \max[SSIM(A,F|w), SSIM(B,F|w)], ifSSIM(A,B|w) < 0.75 \end{cases}$$

ωwhere is a sliding window of size, which moves pixel by pixel from the top-left to the bottom-right corner and (ω) is the local weight obtained from the local image salience.

iv) Edge Based Similarity Measure

The edge based similarity measure gives the similarity between the edges transferred in the fusion process. Mathematically, $Q^{AB/F}$ is defined

ω

$$Q^{AB/F} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[i, j^x + \omega_{i,j}^y\right|\quad]}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[Q_{i,j}^{AF}\,\omega_{i,j}^x + Q_{i,j}^{BF}\,\omega_{i,j}^y\right]}$$

where A, B and F represent the CT image, MR image, and fused images respectively. The definition of $Q^{AF} \wedge Q^{BF}$ are same and given a

$$Q^{AF}_{i,j} = Q^{AF}_{g,I,j} Q^{AF}_{\alpha,I,j}$$

$$Q^{BF}_{i,j} = Q^{BF}_{g,i,j} Q^{BF}_{\alpha,i,j}$$

Where Q^{F}_{g} and Q^{F}_{α} are the edge strength and orientation preservation values at location (i,j) respectively for images CT image and MR image . The dynamic range for $Q^{AB/F}$ is [0,1] and it should be as close to 1 as possible for better fusion. Table:1 shows the evaluation of different methods for CT-MRI images.

Table: I Evaluation of different methods for CT-MRI images

Algorithm	**PSNR**	$Q^{AB/F}$	Q_{MI}	Q_S
Wavelet Transform[1]	21.19	0.6669	0.8812	0.7551
Discrete Curvelet Transform [2]	25.26	0.7058	0.9407	0.7625
Contourlet [3]	25.23	0.7424	1.0380	0.7968
NonSubsampled Contourlet Transform-1 [4]	38.09	0.7457	1.0367	0.7965
NonSubsampled Contourlet Transform-2[5]	39.14	0.7538	1.0471	0.8166
NSCT[7]	41.66	0.7560	1.0813	0.8726

CONCLUSION

This paper explains the different related works based on fusion techniques used for multimodal medical images. The comparative analysis of image fusion techniques allows in selecting the best fusion method. Wavelet transform fusion algorithm is not good at edges and textured region and it captures limited directional information. Curvelet transform fusion algorithm has no good performance of the local variation of the image. Contourlet transform is lack of shift invariance which usually causes the Gibbs effect. NSCT provides a property such as multidirectional, multiscale, shift invariant image. Compare to the other fusion algorithm NSCT has the higher the value of the PSNR,$Q^{AB/F}$,Q_{MI},Q_S and therefore one can obtain better visualization of the fused image.

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