Medical Image Fusion Using Bandlet Transform

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Abstract- *This paper represents a novel design and control Medical image Fusion using Bandlet transform is proposed. Bandlet transform can take advantage of the geometrical regularity of image structure and represent sharp image transitions such as edges efficiently in image fusion. For reconstructing the fused image, the maximum rule is used to select source images' geometric flow and Bandlet coefficients. Experimental results indicate that the Bandlet-based fusion algorithm represents the edge and detailed information well and outperforms the Curvelet-based fusion algorithm, especially when the abundant texture and edges are contained in the source images.*

Keywords- Bandlet transform, Medical image fusion, edges and textures

I. INTRODUCTION

Image fusion is the combination of two or more different images to form a new image by using a certain algorithm [1]. The combination of sensory data from multiple sensors can provide more reliable and accurate information.Image fusion technique has been widely employed in many applications such as computer vision, surveillance, medical imaging, and remote sensing. Nowadays, Medical imaging plays a significant role in everyday clinical use. There are a number of different imaging modalities that each shows specific aspect of the human body. Each of modalities such as Magnetic Resonance Imaging (MRI), Computed Tomography (CT), etc., provides limited and complementary information. As an instance, CT can indicate bones and dense tissue with great details. However, it provides little information about soft tissue, in contrast to MRI which displays soft tissue with high resolution. Therefore, CT/MRIfused image can simultaneously visualize bones and soft tissue. The image fusion methods generally are separated to *1)* pixel-,*2)* feature-, and *3)* decision-level categories [12]. In more detail, a pixel-level fusion algorithm (PLFA) directly combines information derived from pixels of different images to obtain the fused image; hence it would have the least data loss [13-15]. In feature-level algorithms, different features of the source images are combined to form the feature vector of the fused image [16-17]. Finally, the decision based methods can be counted as the most abstract level of fusion, since they combine the information of source images according to some decision rules [18-19]. Here, we focus on PLFAs for appropriate accuracy. Most of these approaches were based on combining the Multi Scale Decompositions (MSDs) of the source images. MSD-based fusion schemes provide much better performance than the simple methods studied previously [5]. Due to joint information representation at the spatial-spectral domain, the Discrete Wavelet Transform (DWT) becomes the most popular approximation in image fusion. The human visual system is especially sensitive to local contrast changes, i.e., edges. Rapid contrast changes contain extremely useful information for the human observer. Unfortunately, wavelets cannot take advantage of the geometrical regularity of image structures [6]. Sharp image transitions such as edges are expensive to represent, although one could reduce their cost by taking into account the fact that they often have a piecewise regular evolution across the image support.

D. L. Hall and J. Llinas et al.has proposedMultisensor data fusion systems that combine information from multiple sources and sensors in order to achieve inferences that cannot be achieved with a single sensor or source. Applications of data fusion for Department of Defense (DoD) applications include automatic target recognition (ATR), Identification-Friend-Foe-Neutral (IFFN), and battlefield surveillance and situation assessment. The use of data fusion for these applications is appealing. Conceptually, the use of a broad spectrum of sensors should improve system accuracy, decrease uncertainty, and make these systems more robust to changes in the targets and environmental conditions.

Multi-sensor Image Fusion in Remote Sensing has been proposed by C. Pohl and J. L. Van Genderen.With the availability of multi-sensor, multi-temporal, multi-resolution and multi-frequency image data from operational Earth observation satellites the fusion of digital image data has become a valuable tool in remote sensing image evaluation. Digital image fusion is a relatively new research ® held at the leading edge of available technology. It forms a rapidly developing area of research in remote sensing. This review paper describes and proposed mainly pixel based image fusion of Earth observation satellite data as a contribution to multi-sensor integration oriented data processing.

C. Liu, Z. Jing, G. Xiao, and B. Yang, Chin et al. has proposed a novel region-segmentation-based fusion algorithm for infrared (IR) and visible images is presented. The IR image is segmented according to the physical features of the target. The source images are decomposed by the NSCT, and then, different fusion rules for the target regions and the background regions are employed to merge the NSCT coefficients respectively. Finally, the fused image is obtained by applying the inverse NSCT. Experimental results show that the proposed algorithm outperforms the pixel-based methods, including the traditional wavelet-based method and NSCT-based method.

In this paper, medical image fusion using Bandlet transform is proposed.Bandlet transform is an analysis tool which aims at taking advantage of sharp image transitions in images. A geometric flow, which indicates directions in which the image grey levels have regular variations, is used to form Bandlet bases that lead to optimal approximation rates for geometrically regular images and are proven to be efficient in still image compression, video compression, and noise-removal algorithms [8−10].

The remainder of this paper is lined up as follows. In section 2, Introduced the proposed methodology. Section 3 was discussed on the experimental results and ultimately, Section 4 was discussed on making conclusions.

II. PROPOSED METHODOLOGY

A general Image fusion scheme using Bandlet transform is shown in Fig.1. The first step of image fusion is to decompose source images using Forward transform. The source images taken in this section are MRI image and CT image. Once images are decomposed using Forward transform and coefficients are obtained, select an appropriate fusion rule to combine the coefficients of source images. Merging coefficients is an important step in image fusion. Now reconstruct the image using the Inverse transform.

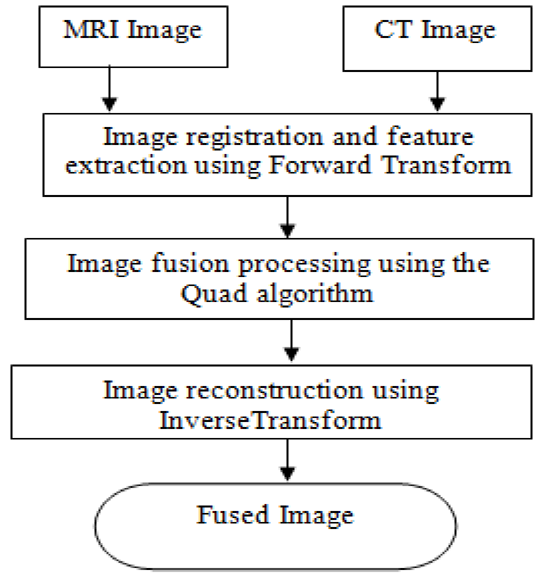


Fig 1:General ImageFusion scheme

Proposed Method:

In the Bandlet-based fusion algorithm, Bandlet transform is used as a MSD tool for images. It can extract the features of original images well, such as edges and texture, so that more information is provided for fusion.

The fusion framework using Bandlet transform is shown in below figure. The operational procedure for the proposed Bandlet-based image fusion approach is given as follows.

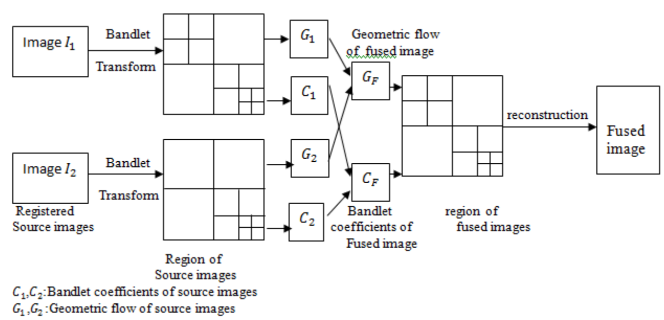


Fig 2: Fusion framework using Bandlet transform.

1) The two source images in the fusion are geometrically registered to each other.
2) Compute the image sample values along the flow lines in each region Ω_i of the partition.
3) Geometric flow $G_j(i)$ where j = 1, 2, · · · , N in each region Ω_i and bandlet coefficients $C_j(x, y, i)$ where j = 1, 2, · · · , N corresponding to the geometric flow are computed. N is the total number of source images,
4) Process the fusion rules. For the geometric flow, fusion with the maximum rule b

$C_j(x, y, i)$ is the Bandlet coefficient of j[th] source image at the pixel (x, y) and $(x, y)\in\Omega_i$.

5) Process the fusion rules.

For the geometric flow, fusion with the maximum rule

$$G_F(i) = \begin{cases} G_1(i), & if\ \ G_1(i) \geq G_2(i) \\ G_2(i), & if\ G_1(i) < G_2(i) \end{cases} \qquad (1)$$

For the Bandlet coefficients, fusion with the maximum absolute value rule

$$C_F(x,y,i) = \begin{cases} C_1(x,y,i)\ , & if\ abs\big(C_1(x,y,i)\big) \\ & \geq abs\big(C_2(x,y,i)\big) \\ C_2(x,y,i), & if\ abs\big(C_1(x,y,i)\big) \\ & < abs\big(C_2(x,y,i)\big) \end{cases} (2)$$

In expressions (1) and (2), $G_F(i)$ denotes the geometric flow in the region Ω_i of the fused image, $C_F(x, y, i)$ is the Bandlet coefficient of fused image at the pixel (x, y) and $(x, y) \in \Omega_i$.

The performance evaluation criteria of image fusion are still a hot topic in the research of image fusion [4]. Besides visual observation, objective performance evaluation criteria are used in this paper, such as the standard deviation, average gradient, entropy, and mutual information. To evaluate the performance of the proposed fusion algorithm, we compare with the maximum algorithm based on curvelet transform

III. EXPERIMENTAL RESULTS

In this proposed work, we are comparing our results with the curvelet transform by using parameters. Here we are using CT/MRI medical images with the size of 256×256 pixels.

The following parameters are

1. The mutual information [15] I_{AF} between the source image *A* and the fused image *F* is defined as follows:

$$I_{AF} = \sum_{af} p_{AF}(a,f) log \frac{p_{AF}(a,f)}{p_A(a)\, p_F(f)}$$

Where p_{AF} is the jointly normalized histogram of *A* and *F*, p_A and p_F are the normalized histogram of *A* and *F*, and *a* and *f* represent the pixel value of the image *A* and *F*, respectively.

The mutual information I_{BF} between the source image *B* and the fused image *F* is similar to I_{AF}. The mutual information between the source images *A*, *B*, and the fused image F is the sum of I_{AF} and I_{BF}, i.e.

$$M_F^{AB} = I_{AF} + I_{BF}$$

2. The metric $Q^{AB/F}$ [16] is defined as follows:

$$Q^{AB/F} = \frac{\sum_{n=1}^{N}\sum_{m=1}^{M}(Q^{AF}(n,m)W^A(n,m) + Q^{BF}(n,m)W^B(n,m))}{\sum_{n=1}^{N}\sum_{m=1}^{M}(W^A(n,m) + W^B(n,m))}$$

Where

$Q^{AF}(n,m) =$
$Q_g^{AF}(n,m)Q_\alpha^{AF}(n,m);\ Q_g^{AF}(n,m) and\ Q_\alpha^{AF}(n,m)$

are the edge strength and orientation preservation values, respectively; *n*, *m* represent the image location; and *N*,*M* are the size of images, respectively. $Q^{BF}(n,m)$ is similar to $Q^{AF}(n,m). W^A(n,m) and\, W^B(n,m)$ reflect the importance of $Q^{AF}(n,m)$ and $Q^{BF}(n,m)$, respectively. The dynamic range of $Q^{AB/F}$ is [0 1], and it should be as close to 1 as possible.

3.The metric Q_0 between the source image *A* and the fused image *F* is defined as follows:

$$Q_0(A,F) = \frac{2\sigma_{af}}{\sigma_a^2 + \sigma_f^2} \cdot \frac{2\bar{a}\bar{f}}{\bar{a}^2 + \bar{f}^2}$$

Where σ_{af} represents the covariance between *A* and *F*; σ_a, σ_f denote the standard deviation of *A* and *F*; and $\bar{a}, \bar{f}$ represent the mean value of *A* and *F*, respectively. $Q_0(A, B, F)$ is the average between $Q_0(A,F)$ and $Q_0(B,F)$, i.e.,

$$Q_0(A,B,F) = (Q_0(A,F) + Q_0(B,F))/2$$

Note that $-1 \leq Q_0 \leq 1$, and it should be also as close to 1 as possible.

4.The metric $Q_W$among images *A*, *B*, and *F* is defined as follows:

$$Q_W(A,B,F) = \sum_{w\in W} c(w)\big(\lambda(w)Q_0(A,F|W) + \big(1-\lambda(w)\big)Q_0(B,F|w)\big)$$

Where $\lambda(w)$ represents the relative salience of *A* compared to *B* in the samewindow *w*, and $c(w)$ denotes the normalized salience of the window *w*.

5.The metric Q_E is defined as follows:

$$Q_E(A,B,F) = Q_W(A,B,F) \cdot Q_W(A'B'F')^{\alpha}$$

Where A', B', F' are the corresponding edge images of *A*, *B*, *F*, respectively. Parameter α which is set to 1 in this paper reflects the contribution of the edge images compared to the original images.

6.Standard Deviation: The standard deviation (STD) reflects the contrast change of an image: the larger the value, the clearer the edge contour; the definition of STD is given as follows:

$$STD = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[f(i,j) - \hat{f}\right]^2}{M \times N}}$$

In the formula, *f* (*i*, *j*) represents the result fusion image, while *M*×*N* represents the image *f*, and $\hat{f}$ represents the mean value of *f*.

7.Entropy: Entropy (EN) measures the amount of information maintained by the fused image. The larger the entropy value is, the more information the result image has. EN is defined as

$$EN = -\sum_{0}^{255} P_i \log_2 p_i(x)$$

$P_i(x)$ is defined as the normalized histogram of the variable *x* and $\sum_0^{255} P_i(x) = 1$

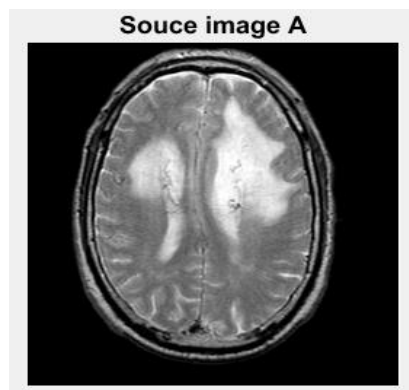
These seven metrics given above evaluate the amount of information transferred from source images into the fused image, but there exist differences among them. Mutual information reflects the statistical dependence of two random variables from information theory viewpoint. Especially for image fusion, it measures the similarity of image intensity distribution of the corresponding image pair. The metric $Q^{AB/F}$ evaluates the amount of edge information transferred from source images into fused image. The metrics Q_0, Q_W, and Q_E integrate characteristics of the human visual system. Themetric Q_0 evaluates the degree of distortion of the fused image. It combines three factors of image distortion related to the human visual system, i.e., loss of correlation, luminance distortion, and contrast distortion. The metric Q_W further takes the salience of information into account. The metric Q_E contains visual information and edge information, simultaneously. In addition, the larger value for the above metrics means the better fusion result.

The output images of the Bandlet tSransform are shown in the Fig.3

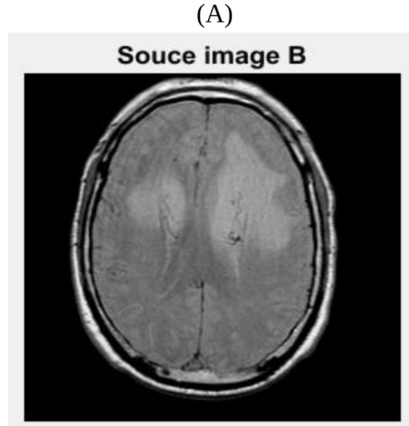
The Table1 gives the comparison of Curvelet and Bandlet Transform using the parameters shows which one is better image fusion. After seeing the results higher values indicates the better fusion results. Mutual information and Q_w better in Curvelet transform. Most of the image fusion parameters like Q_f, Q_0 and Q_e are better in the proposed Bandlet Transform

Table 1: Compression of parameters between Curvelet and Bandlet Transform

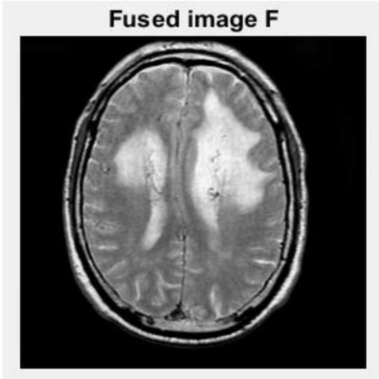
Method	MF	Q_f	Q_o	Q_w	Q_e
Curvelet Transform	**0.0616**	0.5224	0.1391	**0.4913**	0.0307
Bandlet Transform	0.0037	**0.5391**	**0.1611**	0.3198	**0.0504**



(A)



(B)



(C)

Fig 3: (a) MRI image (b) CT image and (C) Fused Image using Bandlet transform

In Table 2 it can be observe that the proposed bandlet transform has the better standard deviation than the previous methods which were used for Image fusion.

Table 2: Comparison of different medical image fusion techniques

S.No	Author	Technique used	Parameters	
			Entropy	standard deviation
1	R. Singh, A. Khare	Daubechies complex wavelet Transform	5.9915	32.92
2	Vikrant Bhateja	CASCADE OF WAVELET AND CONTOURLET TRANSFORM DOMAINS	6.9414	74.1232
3	Sneha Singh	Nonsubsampled shearlet Trasform	5.343	87.186
4	Bhavana. V, Krishnappa. H.K	Discrete Wavelet Transform	5.6237	…..
5	Tania Sultana, Md. Dulal Hossain, Md. Karam Newaz	Stationary wavelet transforms	…..	63.2723
6	Xuan Liu, Yue Zhou, Jiajun Wang	shearlet transform	6.8029	56.7671
7	**G.Prathibha,A.Udaya kumar**	**Proposed Bandlet transform**	0.93544	**121.7516**

IV. CONCLUSION

Bandlet Transform is an efficient analysis tool to take advantage of sharp image transitions in images and can take the image feature well, especially the abundant texture and edges. From the visual observation, the Bandlet-based fused image has clear edge and texture, image features from source images are extracted and reserved well. Objective performance evaluation criteria also prove that Bandlet-based fusion algorithm can offer better performance than the curvelet fusion algorithm. The Bandlet-based algorithm will have a bright future in fusion field, especially when abundant texture features are contained in the source images. Because the Bandlet Transform is newly introduced into the image fusion field, much work is needed. From our experiment, we can expect the following extension of research in this area. 1) Other fusion rules could be employed, not only the maximum rule. 2) The combination of geometric flow and Bandlet coefficients for fusion could be considered. 3) Fast algorithm of Bandlet Transform needs further investigation

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