Investigation of Image Fusion using Curvelet Transform

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ABSTRACT

Image fusion is the process of extracting meaningful visual information from two or more images and combining them to form a new image. In medical image fusion, multiple medical images, such as computed tomography (CT) and magnetic resonance (MR) images are fused into a new image to improve the information content for diagnoses. 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 structures, it is expected that the curvelet transform would be better in their fusion. Global Energy Merging scheme is a region-based analysis approach comparing to all other methods this method produces fused image having very high Edge and curve details.

Keyword : Curvelet Transform, Peak Signal To Noise Ratio, Tiling, Ridgelet Transform, Root Mean Square Error, Subband Filtering.

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1. INTRODUCTION

Image fusion is important in many different image Processing fields such as satellite imaging, remote sensing and medical imaging. The study in the field of image fusion has evolved as a server for the advance in satellite imaging and then it has been extended to the field of medical imaging. With the development of multi-sensors, it is possible to obtain data from different sensors. Because of the different properties of multi-sensors, these images might provide totally different information. Several fusion algorithms have been proposed extending from the simple averaging to the curvelet transform.

Algorithms such as the intensity- hue- saturation (IHS) and the wavelet transform have proved to be successful in satellite image fusion. IHS belongs to colour image fusion algorithms. The wavelet transform for image fusion has also succeeded in both satellite and medical image fusion applications.

The basic limitation in the wavelet transform is in the fusion of curved objects. So the application of the curvelet transform for curved object image fusion would result in better fusion techniques. MR and CT imaging are of main concern for diagnostic purposes efficiency. A few attempts for curvelet fusion have been made in the field of satellite image fusion but no attempts in medical image fusion have been made using the curvelet transform.

The main objective of medical imaging is to obtain a high resolution image with as much details as possible for the sake of diagnosis. It is known that there are several medical imaging

Both techniques give special sophisticated characteristics of the organ to be imaged. So, it is expected that fusion of MR and CT images of the same organ would result in an integrated image of much more details. Researchers have made few attempts for the fusion of MR and CT images. Most of these attempts are directed towards the application of the wavelet transform for this purpose. Due to the limited ability of the wavelet transform to deal with images with curved structures, the application of curvelet image fusion is proposed.

The curvelet transform is based on the segmentation of the whole image into small overlapping tiles and then the Ridgelet transform is applied to each tile. The purpose of the segmentation process is to approximate curved lines by small straight lines. The overlapping of tiles aims at avoiding edge effects. The Ridgelet transform itself is a 1-D wavelet transform applied in the Radon domain on each tile. The Radon transform is mainly presented as a tool for shape detection, especially of curved objects. Mainly the Curvelet transform was proposed for image denoising.

The paper is organized as follows. In section II, a new energy fusion method is proposed. Some relative equations and the detailed algorithm are given about this method.

2. Global Energy Method Based On Region

The curvelet transform is based on the segmentation of the whole image. The low frequency band at each level can be segmented. Then Global Energy Method is performed. After all the processes above, a final fused image will be obtained by applying Inverse curvelet transform to the acquired coefficient matrix.

3. Wavelet Fusion

The most common form of transform type image fusion is the wavelet transform fusion due to its simplicity and its ability to preserve the time and frequency details of the image. A schematic diagram for the fusion of two images using the wavelet transform is depicted in Fig.(1). It can be defined considering the wavelet transform ω of two registered input images $I1\ (x , y)$ and $I2\ (x , y)$ together with the fusion rule φ.

There are several wavelet fusion rules that can be used for selecting the wavelet coefficients. The most frequently used rule is the maximum frequency rule which selects the maximum coefficients from the wavelet transformed images. Then, the inverse wavelet transform ω^{-1} is computed, and the fused image $I(x , y)$ is reconstructed:

$$I(x , y) = \omega^{-1} (\varphi (\omega(I (x , y)),\omega(I (x , y)))) \quad (1)$$

The wavelet transform concentrates on representing the image in multiscales and it's appropriate to represent linear edges. For curved edges, the accuracy of edge localization in the wavelet transform is small. So, there is a need for an alternative approach with high accuracy of curve localization such as the curvelet transform.

4. The Curvelet Transform

The curvelet transform has evolved as a tool for the representation of curved shapes in graphical applications. Then, it was extended to the fields of edge detection and image denoising. Recently, some authors have proposed its application in image fusion. The algorithm of the curvelet transform can be summarized in the following steps:

A) The image is split up into three subbands using the additive wavelet transform.

B) Tiling is performed on subbands 1 Δ and 2 Δ.

C) The discrete Ridgelet transform is performed on each tile of the subbands $\Delta 1$ and $\Delta 2$.

A schematic diagram of the curvelet transform is depicted in Fig.(2)

A detailed description of these steps is presented below.

A. Subband Filtering

The purpose of this step is to decompose the image into additive components each of which is a subband of the image. This step isolates the different frequency components of the image into different planes without down sampling as in the traditional wavelet transform. The *"a trous"* Algorithm given below is implemented for this purpose.

Given an image P, it is possible to construct the sequence of approximations:

f1(P)=P1, f2(P1)=P2, f3(P2)=P3, ... fn(Pn-1)=Pn (2)

$$H = \frac{1}{26}\begin{vmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 4 & 4 & 1 \end{vmatrix}$$

To construct this sequence, successive convolutions with a certain low pass kernel are performed. The functions f1, f2 and f3 mean convolution with this kernel.

The wavelet planes are computed as the differences between two consecutive approximations Pl-1 and Pl. *i.e*,

$$w_l = P_{l-1} - P_l \qquad (3)$$

where P_0=P is the original image.

Thus, the reconstruction formula is given by :

$$P = \sum_{l=1}^{n} W1 + Pr \qquad (4)$$

where P_r is the residual image.

B. Tiling

Tiling is the process by which the image is divided into overlapping tiles. These tiles are small in dimensions to transform curved lines into small straight lines in the subbands $\Delta 1$ and $\Delta 2$. The tiling improves the ability of the curvelet transform to handle curved edges. The purpose of the segmentation process is to approximate curved lines by small straight lines. The overlapping of tiles aims at avoiding edge effects.

C. Ridgelet Transform

The Ridgelet transform belongs to the family of discrete transforms employing basis functions. It is complicated to some extent. To facilitate its representation mathematically, it can be viewed as a wavelet analysis in the Radon domain. The Radon transform itself is a tool for shape detection. So, the Ridgelet transform was primarily a tool for ridge detection or shape detection of the objects in an image.

The Ridgelet basis function is given by:

$$\Psi_{a,b,\theta} = a^{-1/2} p\left(\left(\frac{x1\cos\theta + x2\sin\theta - b}{a}\right)\right) \qquad (5)$$

Thus, the Ridgelet coefficients are represented b y:

$$R_f(a,b,\theta) = \iint_{-\infty}^{\infty} \Psi_{a,b,\theta}(x_1,x_2)\, f(x_1,x_2)\,dx_1 dx_2 \qquad (6)$$

This transform is invertible and the reconstruction formula is given by:

The Radon transform for an object f is given by :

$$R_f(\theta,t) = \iint_{-\infty}^{\omega} f(x_1,x_2)\,\delta(x_1\cos\theta + x_2\sin\theta - t)\,dx_1 dx_2 \qquad (7)$$

Thus, the Ridgelet transform can be represented as follow:

$$R_f(a,b,\theta) = \int_{-\infty}^{\omega} R_f(\theta,t)\, a^{-1/2} p\left(\frac{(t-b)}{a}\right) dt \qquad (8)$$

Hence, the Ridgelet transform is the application of a one-dimensional wavelet transform to the slices of the Radon transform where the angular variable θ is constant and t is varying. A schematic diagram of the Ridgelet transform is shown in Fig. (3). To make the Ridgelet transform discrete both the Radon transform and the wavelet transform have to be discrete.

5. The Proposed Fusion Algorithm

It is known that different imaging modalities are employed to depict different anatomical morphologies. CT images are mainly employed to visualize dense structures such as bones. So, they give a general shape of objects and fewer details. On the other hand, MR images are used to depict the morphology of soft tissues. So, they are rich in details. Since these two modalities are of a complementary nature, the objective is to merge both images in a single image to obtain as much information as possible.

A Curvelet based approach is introduced for this purpose. It is summarized as follows:

(1) The MR and CT images are registered.

(2) The curvelet transform steps are performed on both the MR and CT images.

(3) The maximum frequency fusion rule is used for the fusion of the Ridgelet transforms of the subbands Δ1 and Δ2 for both MR and CT images.

(4) An inverse curvelet transform is performed on MRI image and the fused subbands Δ1 and Δ2 .

These steps are expected to merge the details in both images into a single image with much more details.

GEM algorithm is used for different levels of decompositions.

GEM Algorithm steps

The following algorithm performs the fusion Process

1. Initialization: define the area size A which will be used around each location p; n=-1.

2. Input: image F1 and F2, set X=F1 and Y=F2

3. while n<N DO n=n+1; X,Y →DWT→ $D_{LL\,n}$, D_{LHn} , D_{HLn} , D_{HHn} set X= D_{LLn} ,Y= D_{LLn} and go to 3

4. Image Tiling

5. Ridgelet transform

6. Fused image: Select : for each location p at (x,y) in the transformed tiles compute the following region energy values using the equation

$E^{v}_{ijn}(P) = \sum_{P\in A} W(P)\, D^{v}_{ijn}(p))^2$

Where

$E^{X}_{ijn}(P)$; $E^{Y}_{ijn}(P)$ with ij = LL, LH, HL, HH

Merge: firstly low frequency band is calculated

$e^{v}_{lln}(P) = \max(E^{X}_{lln}(P), E^{Y}_{lln}(P))$

$D^{V}_{LLn}(P) = D^{X}_{LLn}(P)$ IF $e^{v}_{lln}(p)$ come from X

else $D^{V}_{LLn}(P) = D^{Y}_{LLn}(P)$

7. Then high frequency bands are calculated:

When $M_{ijn}(p) \geq \alpha$

Do

$D^{v}_{ijn}(P) = W^{X}_{ijn}(P) * D^{X}_{ijn}(P) * W^{Y}_{ijn}(P) * D^{Y}_{ijn}(P)$

When $M_{ijn}(p) < \alpha$

Do

$e^{v}_{ijn}(P) = \max(E^{X}_{lln}(P), E^{Y}_{lln}(P))$

$D^{V}_{ijn}(P) = D^{X}_{ijn}(P)$ IF $e^{v}_{lln}(p)$ come from X, else

$D^{V}_{ijn}(P) = D^{Y}_{ijn}(P)$

8. While n ≠ -1

Apply Inverse Curvelet Transform to transformed tiles.

Obtaining $D_{LL(n-1)}^{W}$;

n=n-1 and go to 8

9. Output: fused image Z= D_{LLn}^{W}

6. Performance Measures

a. Root Mean Square Error (RMSE)

As a quality measure, the RMSE (Root Mean Square Error) is used. It is expressed as follows :

$$RMSE=\left(1/MN\sum_{n=1}^{N}\sum_{m-1}^{M}(x_R(n,m)-x_F(n,m))^2\right)^{1/2}$$

Where x_R is the ideal reference x_F the obtained fused image, and M, N are the dimensions of the images. Root mean square error indicates how much error the fused image x_F conveys about the reference x_R .

Thus, the lower the RMSE between x_F and x_R ,the more likely resembles the ideal x_R .

The mean-square error function is commonly used because:

- It is easy to compute,
- It is differentiable implying that a minimum can be sought,
- It corresponds to "signal energy" in the total error, and
- It has nice properties *vis à vis* Parseval's theorem.

b. Peak Signal To Noise Ratio(PSNR)

The PSNR is defined as follows :

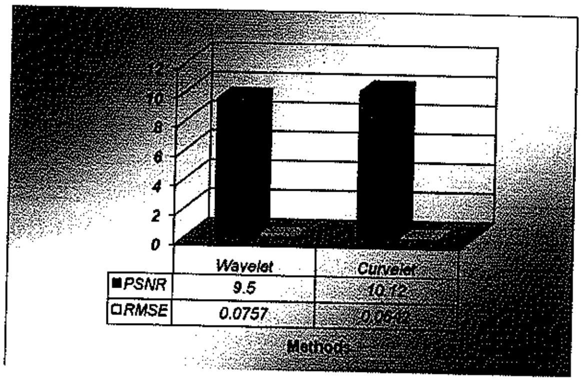
PSNR =10×log $(f_{max})^2$/ $RMSE^2$)

where f_{max} is the maximum gray scale value of the pixels in the fused image. The higher the value of the PSNR, the better the fusion performance. The RMSE between the fusion result and both the MR and CT images is estimated and two values of PSNR for both curvelet and wavelet fusion results are obtained.

7. Experimental Results

CT and MR scans of the brain are used as input images shown in Figs. (4) and (5), respectively. The wavelet fusion result is given in Fig. (6) And the curvelet fusion result is given in Fig.(7). From the fusion results of figs. (6) and (7). It is clear that the curvelet fusion result has a better visual quality than the wavelet fusion result.

These values reflect the ability of the curvelet transform to capture features from both the MR and CT images. From these results, it is clear that the proposed algorithm has succeeded in obtaining better results than the wavelet transform from both the visual quality and PSNR points of view.



Comparison Chart for Wavelet and Curvelet

8. Conclusions

The paper has presented a new trend in the fusion of MR and CT images using the curvelet transform. A comparison study has been made between the traditional wavelet fusion and the proposed curvelet fusion. The experimental study shows that the application of the curvelet transform in this fusion is superior to the application of the traditional wavelet transform. The obtained curvelet fusion results have higher PSNR values than the wavelet fusion results. Also curved visual details are better in the curvelet fusion results than in the wavelet fusion results.

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