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AN IMAGE FUSION USING WAVELET AND CURVELET TRANSFORMS

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Abstract: *This Image fusion is a data fusion technology which keeps images as main research contents. It refers to the techniques that integrate multi-images of the same scene from multiple image sensor data or integrate multi images of the same scene at different times from one image sensor. The image fusion algorithm based on Wavelet Transform which faster developed was a multi-resolution analysis image fusion method in recent decade. Wavelet Transform has good time-frequency characteristics. It was applied successfully in image processing field. Nevertheless, its excellent characteristic in one-dimension can't be extended to two dimensions or multi-dimension simply. Separable wavelet which was spanning by one-dimensional wavelet has limited directivity. This paper introduces the Curvelet Transform and uses it to fuse images. The experiments show that the method could extract useful information from source images to fused images so that clear images are obtained. In this paper we put forward an image fusion algorithm based on Wavelet Transform and the Curvelet Transform. Low and high frequency coefficients are choosen according to different frequency domain after Wavelet and the Curvelet Transform. In choosing the low-frequency coefficients, the concept of local area variance was chosen to measuring criteria. In choosing the high frequency coefficients, the window property and local characteristics of pixels were analyzed. Finally, the proposed algorithm in this article was applied to experiments of multi-focus image fusion and complementary image fusion.*

Keywords*: Image Processing Curvelet Transform, Image Fusion, Wrapping Algorithm, Wavelet Transform*

1. INTRODUCTION

Image fusion is the process of merging two images of the same scene to form a single image with as much information as possible. 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 to serve the advance in satellite imaging and then, it has been extended to the field of medical imaging. Several fusion algorithms have been proposed extending from the simple averaging to the curvelet transform. The wavelet fusion algorithm has succeeded in both satellite and medical image fusion applications. The basic limitation of the wavelet fusion algorithm is in the fusion of curved shapes. Thus, there is a requirement for another algorithm that can handle curved shapes. So, the application of the curvelet transform for curved object image fusion would result in better fusion efficiency.
The main objective of medical imaging is to obtain a high resolution image with as much details as possible for the sake of diagnosis. MR and the CT techniques are medical imaging techniques. Both techniques give special sophisticated characteristics of the organ to be imaged. So, it is expected that the fusion of the MR and the CT images of the same organ would result in an integrated image of much more details. Due to the limited ability of the wavelet transform to deal with images having curved shapes, the application of the curvelet transform for MR and CT image fusion is presented. The rest of paper is organized as follows. Section 2 discrete Wavelet Transform. Section 3 Curvelet Transform. Section 4 Image fusion. Section 5 conclusion.

2. DISCRETE WAVELET TRANSFORM

The discrete wavelet transform (DWT) is use to apply the wavelet transform to digital world. Filter banks are used to approximate the behavior of the continuous wavelet transform. The signal is decomposed with a high-pass (HP) filter and a lowpass (LP) filter. The coefficients of these filters are computed using mathematical analysis and made available filter banks decompose the signal into two different component. That is high- and low-frequency components. The low-frequency component usually contains most of the frequency of the signal. This is called the approximation. The high-frequency component contains the details of the signal. Wavelet decomposition can be implemented using a two-channel filter bank. The main idea is that perfect reconstruction filter banks implement series expansions of discrete-time signals.

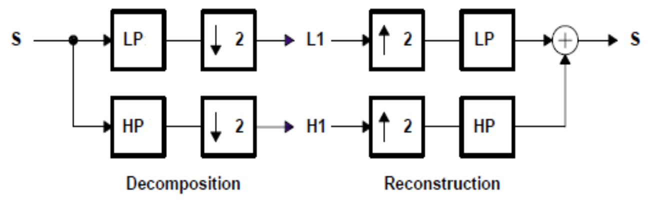

Figure 1. Discrete Wavelet Transform

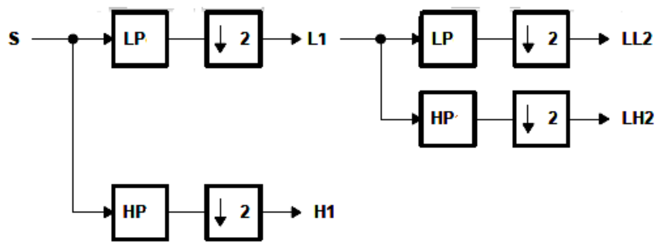

Figure 2. Two Level Wavelet Decomposition

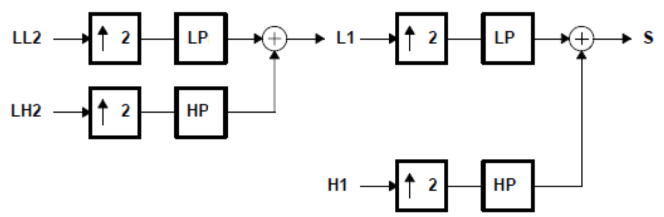

Figure 3. Two Level Wavelet Reconstruction

2.1 Wavelet Decomposition of Images

Row by row wavelet decomposition is perform and then column by column. For instance, here is the procedure for an N x M image. You filter each row and then down-sample to obtain two N x (M/2) images. Then filter each column and subsample the filter output to obtain four (N/2) x (M/2) images. Of the four sub images obtained as seen in Fig. 4, the
one obtained by low-pass filtering the rows and columns is referred to as the LL image.
The one obtained by low-pass filtering the rows and high-pass filtering the columns is referred to as the LH images. The one obtained by high-pass filtering the rows and low-pass filtering the columns is called the HL image. The sub image obtained by high-pass filtering the rows and columns is referred to as the HH image. Each of the sub images obtained in this fashion can then be filtered and sub sampled to obtain four more sub images. This process can be continued until the desired sub band structure is obtained.

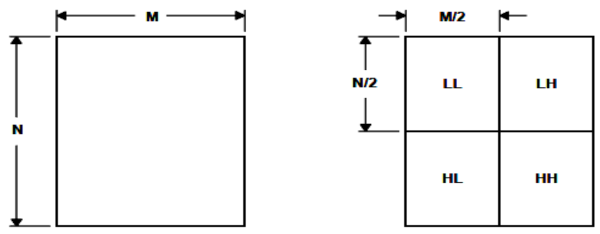

Figure 4. Original Image One-Level 2-D Decomposition

Three of the most popular ways to decompose an image are: pyramid, spacl, and wavelet packet, as shown in Fig.5

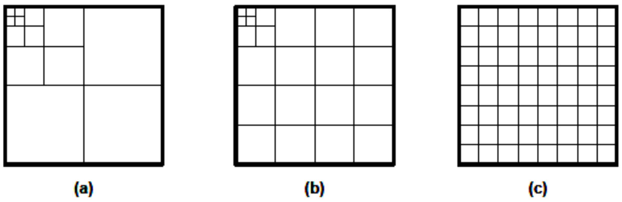

Figure 5. Three Popular Wavelet Decomposition Structure On Image: (a) pyramid, (b) spacl, (c) wavelet packet

- In the structure of pyramid decomposition, only the LLsub image is decomposed after each decomposition into four more sub images.
- In the structure of wavelet packet decomposition, each sub image (LL, LH,, HL, HH) is decomposed after each decomposition.
- In the structure of spacl, after the first level of decomposition, each sub image is decomposed into smaller sub images, and then only the LL sub image is decomposed.

2.2 1-D Wavelet Transform

The discrete wavelets transform (DWT), which transforms a discrete time signal to a discrete wavelet representation. The first step is to discredited the wavelet parameters, which reduce the previously continuous basis set of wavelets to a discrete and orthogonal set of basis wavelets.

$\psi m,n(t) = 2m/2\ \psi(2mt - n)$ (1)
$m, n \in Z$ such that $-\infty < m, n < \infty$

The 1-D DWT is given as the inner product of the signal x(t) being transformed with each of the discrete basis functions.z

$Wm,n = < x(t), ym,n(t) >$; m, n Î ıZ (2)

The 1-D inverse DWT is given as:

$$x(t) = \sum_m \sum_n W_{m,n} \psi_{m,n}(t) \quad ; m, n \in Z \qquad (3)$$

2.3 2-D Wavelet Transform

The 1-D DWT can be extended to 2-D transform using separable wavelet filters. With separable filters, applying a 1-D transform to all the rows of the input and then repeating on all of the columns can compute the 2-D transform. When one-level 2-D DWT is applied to an image, four transform coefficient sets are created. As depicted in Fig.6(c), the four sets are LL, HL, LH, and HH, where the first letter corresponds to applying either a low pass or high pass filter to the rows, and the second letter refers to the filter applied to the columns.

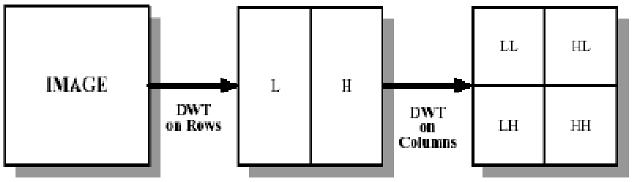

Figure 6. Block Diagram of DWT (a) Original Image (b) Output image after the 1-D applied on Row input (c) Output image after the second 1-D applied on row input

(a) (b) (c)

Figure 7. DWT for Lena image (a) Original Image (b) Output image after the 1-D applied on column input (c) Output image after the second 1-D applied on row input

The Two-Dimensional DWT (2D-DWT) converts images from spatial domain to frequency domain. At each level of the wavelet decomposition, each column of an image is first transformed using a 1D vertical analysis filter-bank. The same filter-bank is then applied horizontally to each row of the filtered and sub sampled data. One-level of wavelet decomposition produces four filtered and sub sampled images, referred to as sub bands. The upper and lower areas of Fig.6.b), respectively, represent the low pass and high pass coefficients after vertical 1D-DWT and sub sampling. The result of the horizontal 1D-DWT and sub sampling to form a 2DDWT output image is shown in Fig.6.(c).
We can use multiple levels of wavelet transforms to concentrate data energy in the lowest sampled bands. Specifically, the LL sub band in fig 5 (c) can be transformed again to form LL2, HL2, LH2, and HH2 sub bands, producing a two-level wavelet transform. The straight forward convolution implementation of 1D-DWT requires a large amount of memory and large computation complexity. An alternative implementation of the 1D-DWT, known as the lifting scheme, provides significant reduction in the memory and the computation complexity. Lifting also allows in-place computation of the wavelet coefficients. Nevertheless, the lifting approach computes the same coefficients as the direct filter-bank convolution.

3. 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..
The algorithm of the curvelet transform of an image P can be summarized in the following steps: The algorithm of the curvelet transform of an image P can be summarized in the following steps:

A. The image P is split up into three sub bands Δ1,Δ2 and P3 using the additive wavelet transform
B. Tiling is performed on the sub bands Δ1 and Δ2.
C. The discrete ridgelet transform is performed on each tile of the sub bands Δ1 and Δ2. A schematic diagram of the curvelet transform is depicted in Fig. 8.

Curvelet transform is a tool for representation of curved shapes in images. The concept of curvelet transform is based on the segmentation of the whole image into small overlapping tiles and then applying ridgelet transform on each tile. It is most suitable to work with medical images. Algorithm for first generation curvelet is given below:

1) Split the input image into 3 sub bands using additive wavelet transform.
2) Perform tiling on each of the three sub bands
3) Perform Discrete Ridgelet Transform on each of tile on all the sub bands.

Sub band filtering decomposes image into additive components which are the sub ands of the image. In order to decompose image Atrous algorithm is given by where Cj represents the low pass content of the image and Wj represents the high pass content.

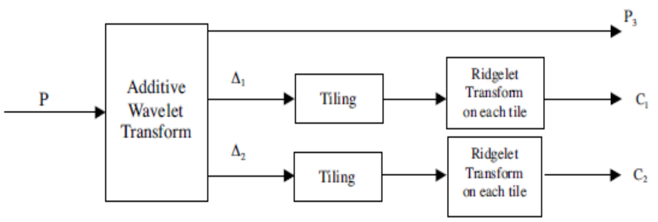

Figure 8. Discrete Curvelet Transform of Image P

Tiling involves dividing the sub bands 1 and 2 of the transformed image into overlapping tiles, resulting in smaller dimensions to transform the curved lines to straight lines thus avoiding the edge effects. Segmentation is performed to approximate curved lines into overlapping tiles. Discrete Ridgelet transform is performed on the segmented tiles. This is done by applying 1D discrete wavelet transform to the slices of the radon transform. Ridgelet transform helps in shape detection. The first generation curvelet transform is more complex involves a series of steps. Due to its complexity, the second generation curvelet is much preferred. Thus Second generation does notuse the ridgelet transform, and hence reduces the redundancy.

1. Wrapping Algorithm

i. Perform FFT on the original image.

ii. Divide FFT into collection of tiles
iii. For each tile apply
a. Translate tile to the origin.
b. Wrap parallelogram shaped support of tile around the rectangle with center as the origin as shown in Fig.9.
c. Take inverse FFT of wrapped one
d. Add curvelet array to collection of curvelet coefficients.

Figure 9.Support of wedge before (left) wrapping and After Wrapping

2. Inverse Wrapping Algorithm

i. For each curvelet coefficient array
a. Take FFT of the array.
b. Unwrap rectangular support to original orientation shape.
c. Translate it back to the original position
d. Store the translated array
ii. Add all the translated curvelet arrays
iii. Take inverse FFT to reconstruct the image.

4. IMAGE FUSION

The most important issue concerning image fusion is to determine how to combine the sensor images. There are several image fusion techniques have been proposed. The primitive fusion schemes perform the fusion right on the source images. Pixel-by-pixel gray level average of the source images is the very simple fusion technique. This simplistic approach often has serious side effects such as reducing the contrast.
With the introduction of pyramid transform in mid-80, some more sophisticated approaches began to emerge. We get the better results if the fusion was performed in the transform domain. The pyramid transform appears to be very useful for this purpose. Multi resolution decomposition is performing on each source image. Integration of all decompositions done to form a composite representation. Reconstruct the fused image by performing an inverse multiresolution transform.
Several types of pyramid decomposition or multiscale transform are used or developed for image fusion, such as, Laplacian Pyramid, Ratio-of-lowpass Pyramid, Morphological Pyramid, Gradient Pyramid and more recently, with the development of wavelet theory, the multi-scale wavelet decomposition has begun to take the place of pyramid decomposition for image fusion. Actually, the wavelet transform can be considered to be one special type of pyramid decompositions. It retains most of the advantages for image fusion but has much more complete theoretical support.

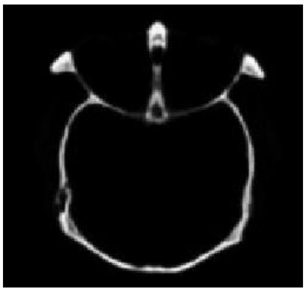

Figure 10. CT Image

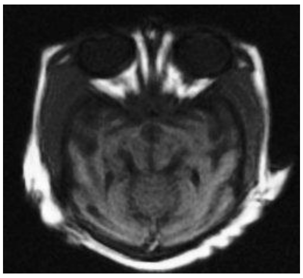

Figure 11. MRI Image

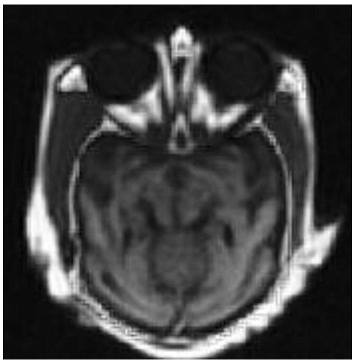

Figure 12. Fused image

In medical, CT and MRI image both are tomographic scanning images. Both images have different features. Fig.10. shows CT image, in which image brightness related to tissue density, brightness of bones is higher, and some soft tissue can't been seen in CT images. Fig.11. shows MRI image, here image brightness related to amount of hydrogen atom in tissue, thus brightness of soft tissue is higher, and bones can't be seen. There is complementary information in these images. We use Curvelet Transform and fused medical images.Fig.12. Shows the fused image.

5. QUANTITATIVE ANALYSIS

Quantitative analysis is carried out for comparison of different image fusion methods based on discrete wavelet transform and fast discrete curvelet transform. In this paper, 5 different parameters are used as follows:

1. Entropy

The entropy of an image is a statistical measure of randomness that can be used to characterize the texture of the input image. It represents richness of information content in an image. The value of entropy should be large for better information in an image.

2. PSNR

The PSNR (Peak Signal-to-Noise Ratio) is the most commonly used as quality of reconstruction of fused image. It represents the peak signal to noise ratio, so the value of PSNR must be high for less noise in an image. It is defined as,

$$PSNR = 10\log_{10}(255^2/MSE)$$

Where, 255 is the maximum pixel value of the image when the pixels are represented using 8-bit per sample.

3. RMSE

The RMSE represents the root mean square error which describes the difference in the pixel values between the corresponding pixels of the two images. The value of RMSE must be small for better fused image. For two MxN images S and F, where image S is considered a source image and I is the fused image.

$$RMSE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[S(i,j)-I(i,j)]^2}{M\times N}$$

4. Mean

The mean represents the average of pixel values of an image. So, the value of Mean should be high for better contrast in an fused image.

5. Standard deviation (STD)

Standard deviation is the square root of variance, reflects the spread in the data. It represents the deviation of pixel values from mean, so the value of STD should be high for better contrast of an image.

6. CONCLUSION

This paper puts forward an image fusion algorithm based on Wavelet Transform and Curvelet Transform. It includes multi resolution analysis ability in Wavelet Transform, also has better direction identification ability for the edge feature of awaiting describing images in the Curvelet Transform. This method could better describe the edge direction of images, and analyzes feature of images better. MRI image provides much greater contrast between different soft tissues of body than CT image. Brightness of bones is higher in CT images but soft tissues can't be seen. Fusion image provides both characteristics of CT and MRI in the single image.

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