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Curvelet Based Image fusion techniques for Medical Images

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Abstract—Image fusion integrates multiple images of the same scene from multiple image sensor data. It has acquired an integral role in medical field. This paper introduces the various means image fusion based on transform domain image processing. Wavelet and Curvelet transform techniques are used for fusion of medical images scanned via different modalities. Each of the methods are evaluated under a performance evaluation criteria.

Keywords— Image Fusion, CT Scanned Images, MRI Scanned Images, Discrete Wavelet Transform, Curvelet Transform, Image Registration, Performance evaluation metrics, entropy, Peak Signal to Noise Ratio, Mean Square Error

I. INTRODUCTION

Multimodal Image fusion is a technique used to merge the picture details obtained by two or more images captured by different methodologies into a single image. Thus the resultant image derived from the image process will contain information than any of the input images. The individual images taken are of the same scene but taken from multiple sensors or of multimodality or taken at different instants of time. Thus fusion of images allows the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. Image Fusion techniques play important role in medical imaging, microscopic imaging, remote sensing, computer vision and robotics. In medical imaging applications, if we combine both the CT and MRI scanned images of the brain then we will get a resultant image in which both hard tissue like skull bones and the soft tissue like the membranes covering the brain can be clearly visible. In medical field, different techniques used to examine the inner body parts have their own merits and demerits. In the CT scanned image of the brain is given in hard tissue like the skull bone is clearly seen but the soft tissue like the membranes covering the brain are less visible. In the MRI scanned image of the same brain we observe the soft tissue like the membranes covering the brain can be clearly seen but the hard tissue like the skull bones cannot be clearly seen. Image fusion techniques are used as a tool to combine the important information from both the modalities and provide a more complete and a more detailed image of the human body parts scanned. Image fusion techniques are categorized into sub-types based upon the domain of processing the image. The two broad categories include spatial domain method and transform domain method. The first category, spatial domain fusion method basically applies the rules of fusion in spatial domain and hence modifies each and every pixel value directly to achieve desired result. Averaging method, Brovey method, principal component analysis (PCA), Intensity Hue saturation (HIS) and high pass filtering etc. are included in this category. The disadvantage of these methods is that they tend to produce spatial distortion and spectral distortion in the fused image. In transform domain methods the image is first transferred into another domain, say frequency domain and all the fusion operations are performed on the transform of the image and then the inverse transform is performed to get the resultant image. Spatial distortion can be very well handled by frequency domain approaches on image fusion. The multi resolution analysis which is based on transform domain methods like discrete wavelet transform has become a very useful tool for analyzing remote sensing images, medical images etc.

II. WAVELETS & DISCRETE WAVELET TRANSFORMS

A Wavelet is a waveform of effectively limited duration with zero average value. They tend to be irregular and asymmetric, have finite energy and hence are suited for analysis of transient signal. [4] Sharp changes in a signal are better analyzed with an irregular wavelet than with a smooth sinusoid, just as some food is better handled with fork than a spoon.

Wavelets can be described by using two functions namely the scaling function f(t) or father wavelet and the wavelet function $\psi(t)$ or mother wavelet.[7][8] A number of basis functions can be used as the mother wavelet for Wavelet Transformation. The mother wavelet undergoes through translation and scaling produces various wavelet families which are used in the transformation. The

International Journal for Research in Applied Science & Engineering Technology (IJRASET)

wavelet families are given by following equation numbered 1,

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), (a,b \in R), a > 0 \quad \ldots\ldots \; (1)$$

The Discrete Wavelet Transform has the property that the spatial resolution is small in low-frequency bands but large in high-frequency bands. This is because the scaling function is treated as a low pass filter and the mother wavelet as high pass filter in DWT implementation. [4]

The wavelet transform decomposes the image into low-high, high-low, high-high spatial frequency bands at different scales and the low-low band at the coarsest scale which is shown in figure 1(a). The low-low image has the smallest spatial resolution and represents the approximation information of the original image. The other sub-images, on the contrary show the detailed information of the original image.

There are different levels of decomposition which are shown in Figure 1. After one level of decomposition, there will be four frequency bands, as listed above. The next level decomposition is just applied to the LL band of the current decomposition stage, which forms a recursive decomposition procedure. Thus, N-level decomposition will finally have 3N+1 different frequency bands, which include 3N high frequency bands and just one LL frequency band. [12]

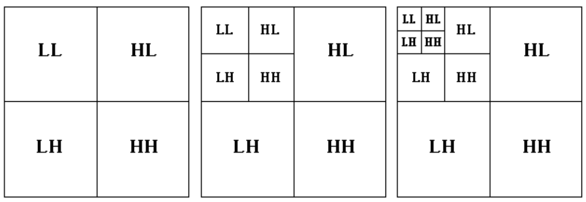

Fig. 1. Wavelet Transform (a) Single Level decomposition
(b) Two level decomposition (c) three level decomposition

III. IMAGE FUSION USING DWT

A. Preprocessing for Image Fusion

The multimodal images which are needed to be fused need to be processed prior to application of fusion algorithm. [8] The pre-processing includes image registration, image resizing and histogram equalization.

Image registration is the process of transforming different sets of data into one coordinate system. Data may be multiple photographs from different sensors, times or viewpoints. Registration is necessary in order to be able to compare or integrate the data obtained from these different measurements. Image registration algorithms used is feature-based algorithm. One of the images is referred to as the reference and the others are referred to as the target images. Image registration involves spatially registering the target image(s) to align with the reference image.

If the sizes of the images might vary so before fusion, the images are needed to be resized so that both the images are of the same size. This is done by interpolating the smaller size image by rows and columns duplication.

The next step which follows this is equalization of the histograms of the images so that the contrast of the image is enhanced and that both the images have similar range of values for wavelet coefficients.

B. Image Fusion Algorithm for DWT

The steps in the algorithm for image fusion using DWT as shown in Figure 2 are as follows:

1) Read the input images (MRI scanned image & CT scanned image). Resample and register both these images.
2) Apply 2D-discrete wavelet transform to these images which decompose it into four sub-bands (LL, LH, HL and HH).
3) The Wavelet coefficients obtained from both the images, called as approximation coefficients, horizontal detail coefficients, vertical detail & diagonal detail coefficients are fused various rules for fusion.
4) The final fused image is reconstructed by applying inverse discrete wavelet transform to fused image.

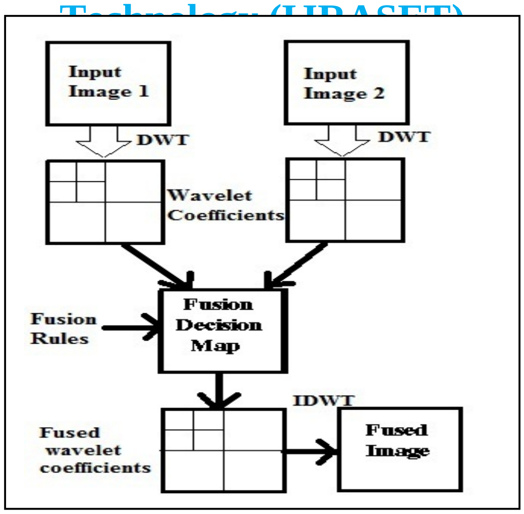

Fig. 3. Block diagram of Image Fusion process using DWT

C. Fusion Rules

By application of Wavelet Transforms to the images we obtain the Wavelet Coefficients which are called as approximation coefficients, horizontal detail coefficients, vertical detail & diagonal detail coefficients. [10]These corresponding coefficients of each of the image are to be fused together in a particular manner. Out of the many rules available we have chosen the Minimum-Maximum rule for fusion which adds the minimum of approximation coefficients & maximum of detail coefficients.

IV. CURVELET TRANSFORM BASED FUSION

A. Need for Curvelets:

The wavelet transform concentrates on representing the image in multi-scale and it is appropriate to represent linear edges. For curved edges, the accuracy of edge localization in the wavelet transform is low. Normally, when a wavelet transformation alone is applied the results are not so useful for analysis. Since medical images have several objects and curved shapes. So, there is a need for an alternative approach which has a high accuracy of curve localization, it is expected that the curvelet transform would be better in their fusion.

B. Image Fusion by Discrete Curvelet transform Method

Curvelet Transform is a new multi-scale representation most suitable for objects with curves developed by Candès and Donoho.

The curvelet transform can be decomposed with four steps:

1) Sub-band Decomposition: The image is filtered into sub-bands by applying a sub-band filter banks. This step divides the image into several resolution layers. Each layer contains details of different frequencies: P_0 indicates the low-pass filter and Δ_1, Δ_2, Δ_3 etc are the band-pass (high-pass) filters. So the original image can be reconstructed from the sub-bands by the following equation,

$$f = P_0(P_0 f) + \sum_s \Delta_s(\Delta_s f) \quad (2)$$

2) Smooth Partitioning: Following the sub-band decomposition, each of the sub-band filtered image is then partitioned into blocks of NxN (N- blocks in horizontal direction & N-blocks in vertical direction) where, N= 2^S and s= 1, 2, 3…..etc. After the partitioning of the image each sub-block is multiplied by a smoothing function W_Q. The partitioning makes the analysis of local line or curve singularities easier.

The grid of dyadic squares is defined in the following manner:

$$Q_{(s,k_1,k_2)} = \left[\frac{k_1}{2^s}, \frac{k_1+1}{2^s}\right] \times \left[\frac{k_2}{2^s}, \frac{k_2+1}{2^s}\right] \in Q_s ,$$

where Qs indicates all the dyadic squares of the grid.

Let W be a smooth windowing function with 'main' support of size $2^{-s} \times 2^{-s}$. It is a nonnegative smooth function and it expands the number of coefficients. For each square, W_Q is a displacement of W localized near Q. Multiplying $\Delta_s f$ with W_Q ($\forall Q \in Qs$) produces a smooth dissection of the function into 'squares'. The energy of certain pixel (x_1,x_2) is divided between all sampling windows of the grid.

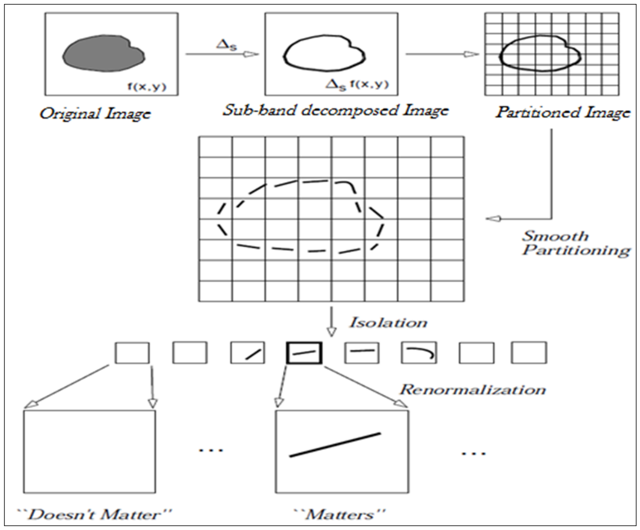

Fig. 4. Few steps of Image Fusion procedure using DCT

3) *Renormalization :* Renormalization is nothing but centering each dyadic square to the unit square [0,1]×[0,1]. This is done by the operation shown by the following. Each of the dyadic square is scaled by 2^s.

$$(T_Q f)(x_1, x_2) = 2^s f(2^s x_1 - k_1, 2^s x_2 - k_2)$$

For each *Q*, the operator T_Q is defined as:

$$g_Q = T_Q^{-1} h_Q$$

4) *Ridgelet Analysis:* Before the Ridgelet Transform we need to perform the ridgelet tiling. The $\Delta_s f$ layer contains objects with frequencies near domain $|\xi| \in [2^{2s}, 2^{2s+2}]$. We expect to find ridges with width $\approx 2^{-2s}$. Windowing creates ridges of width $\approx 2^{-2s}$ and length $\approx 2^{-s}$. The renormalized ridges has an aspect ratio of width ≈ length^2. Now these ridges can be encoded ridges efficiently using the Ridgelet Transform**.**

Ridgelet Transform divides the frequency domain to dyadic coronae $|\xi| \in [2^s, 2^{s+1}]$. It samples the *s*-th corona at least 2^s times in the angular direction, whereas in the radial direction, it samples using local wavelets.

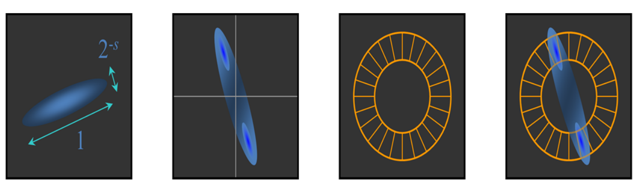

Fig. 5. Ridgelet Transform Procedure

V. PERFORMANCE EVALUATION OF IMAGE FUSION TECHNIQUES

Quantitative performance of the various Image Fusion techniques in Transform domain can be done by the following metrics. [3]

A. Entropy:

Entropy measures amount of information contained in an image. [7][12] Higher entropy value of the fused image indicates presence of more information and improvement in fused image. If L indicates the total number of grey levels and p= $\{p_0, p_1, ... p_{L-1}\}$ is the probability distribution of each level, Entropy is defined as,

$$E = \sum_{i=0}^{L=1} p_i \log(p_i) \qquad (6)$$

B.Mean Square Error:

MSE between an image, X, and an approximation, Y, is the squared norm of the difference divided by the number of elements in the image. If i and j are pixel row column indices, M and N are the number of rows and columns, MSE is defined by

$$MSE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[X_{ij} - Y_{ij}]^2}{MN} \qquad (7)$$

C. Peak Signal to Noise Ratio:

PSNR is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation.

$$PSNR = 20log_{10}\left(\frac{2^B - 1}{MSE}\right) \qquad (8)$$

D. Structural Similarity (SSIM) Index :

It is the method for measuring the similarity between two images. The SSIM index measures image quality based on an initial uncompressed or distortion-free image as reference.

If we consider two image windows of common size N×N and if μ_x is the average of x; μ_y is the average of y; σ_x is the variance of x; the σ_y is the variance of y; the σ_{xy} is covariance of x and y; $c_1= (K_1L)^2$ & $c_2=(K_2L)^2$ are two variables to stabilize the division with weak denominator ; L is the dynamic range of the pixel-values, then the SSIM is given as

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \qquad (9)$$

E.Normalized Cross Correlation:

Normalized cross correlation (NCC) used to find out similarities between fused image and registered image is given by the following equation

$$NCC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij}B_{ij})}{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij})^2} \qquad (10)$$

VI. RESULTS

Various image fusion algorithms were applied to the pair of medical images (human skull in this case) which were collected by 2 different modalities CRT Scanning & MRI scanning. The wavelet transform technique was first applied and then the curvelet transform technique was applied to the set of images. After the synthesized images were obtained, the performance evaluation of the images was done based on the quantitative metrics mentioned above. The synthesized images are shown in Figure 6. The Table I displays the results for the various performance metrics like entropy, SSIM, PSNR, MSE etc. for various image fusion techniques.

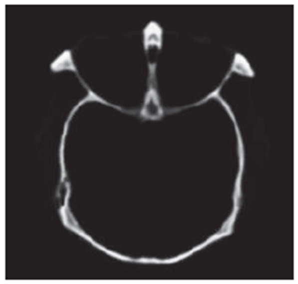

Fig 6.a CT Scanned Image of Skull

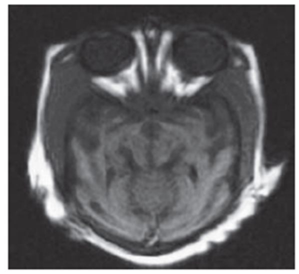

Fig 6.b MRI Scanned Skull Image

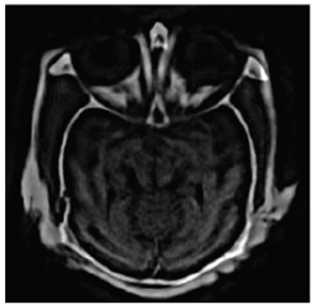

Fig 6.c DWT Fused Image of Skull

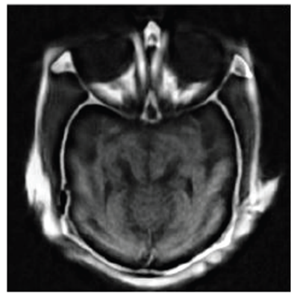

Fig 6.d DCT Fused Image of Skull

TABLE I.

Image fusion rule	***Performance metrics***			
	PSNR (dB)	***Entropy (bits)***	***SSIM***	***NCC***
CT scanned	-	5.617	-	-
MRI scanned	-	6.178	-	-
DWT Fused image	16.39	7.281	.713	.776
Curvelet Fused	18.57	7.672	.845	.895
Combined DWT & DCT	19.64	7.713	.893	. 901

VII. CONCLUSION

The image which is synthesized from the two varied modalities has the merits of both CT scanned as well as MRI scanned images. In this paper, the comparison of various transform based fusion techniques was performed. The Entropy, Peak signal to Noise Ratio, SSIM, NCC have been used as image fusion evaluation criterion for quantitative analysis of image fusion results The results of which are shown above. The Matlab fusion results indicate that the Curvelet based fusion method produced higher entropy, higher PSNR, higher SSIM & higher NCC compared to Wavelet based technique. But it was also indicated that the Combination of DWT and DCT produced highest values of performance metrics. The comparative analysis of image fusion techniques allows in selecting the best fusion method and therefore one can obtain better visualization of the fused image.

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