Multimodality Image Fusion by Using Activity Level Measurement and Counterlet Transform

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Abstract—In this paper we propose multimodality Medical Image Fusion based on counterlet transform. The objective of image fusion is combine two images to produce single image that provide more information. In this paper, we propose multimodality Image Fusion (MIF) method, this is done on activity level measurement &counterlet transform. Multimodality image fusion technology can be used in medical field by doctors to diagnose the disease. Main issue in multimodality image fusion is how to fuse two or more images of different modalities & how we get more clear and accurate information. In this paper to fuse the image firstly we decompose the source image. The low-frequency subbands (LFSs) are fused by using the novel combined ALM (Activity level mesurement), and the high-frequency subbands (HFSs) are fused according to their 'local average energy' of the neighborhood of coefficients.

Then inverse contourlet transform (ICNT) is used to apply on the fused coefficients to get the fused image. Experimental results demonstrate that the proposed scheme is evaluated by various quantitative measures like Mutual Information, Entropy and Spatial Frequency etc. The purpose of this paper is to replace the wavelet transform with counterlet transform to make image much smoother and to increase the efficiency of the fusion method and quality in the Image.

Keyword:- *Image Fusion, Contourlet Transform, Activity level mesurement, Mutual Information, Entropy.*

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I INTRODUCTION

Now a days development in technology is rapidly increases with modern instrumentations.Now a days number of medical image modalities have become available, to provide support to the physicians on their clinical diagnosis. Different medical imaging techniques may provide complementary information and occasionally redundant information. Different modalities techniques of medical imaging reflect different information of human organs and tissues.

The combination of different types of techniques medical images can often lead to additional clinical information which is not apparent in the separate images.

An image fusion process combines two or more images in one single image without losing the information. Main objective is to merge the complementary and redundant information from different images sources into one fused images which is more accurate and clear. Basically there are two types of image fusion systems. First, Single sensor image fusion system in which we use one sensor that capture multiple images and then fuse them into one image. Imaging sensor has few limitations like it does not work in bad environment like clicking an image in fog and rain. Second, Multisensor image fusion system in which we use multiple sensor devices mainly we use infrared cameras which has capability to work in bad environmental conditions. For image enhancement, one needs to improve the visual quality of an image with minimal image distortion. Wavelet based transform are not well adapted for detection of highly anisotropic elements such as alignments in an image. There are three basic levels of image fusion. At the lowest level is Pixel image fusion which contains detailed information. Next is Feature level image fusion where we simply extract features of different images, and then fuse that features to get new image.At last decision level which consist of compact data. Decision level fusion is not suitable for general applications rather it is most effective for complicated systems with multiple true or false decisions.. All decision and control are decided according to the result of decision level image fusion. Magnetic Resonance Imaging (MRI), Ultrasonography (USG) ,Computed Tomography (CT), etc. gives high resolution images for medical image fusion with anatomical information. low-spatial resolution images with functional information provided by Position Emission Tomography (PET) and functional MRI (fMRI) , Single-Photon Emission Computed Tomography (SPECT) etc.

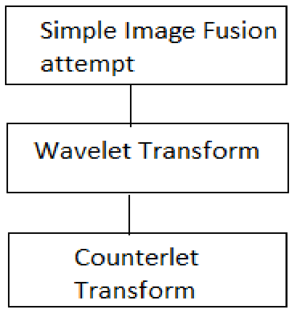

Figure 1. The flowchart of evolution of the image fusion

The major drawback of Discret Wavelet Transform in two dimensions is their limited ability in capturing directional information. In light of this, Do and Vetterli developed the Counterlet transform, based on an efficient two-dimensional multiscale and directional filter bank (DBF). 2D separate wavelet is only good at isolating the discontinuities at objet edges, but cannot effectively represent the line and the curve discontinuities. On the other hand, it can only capture limited

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directional information Counterlet transform not only possess the main features of DWT, but also provide a high degree of anisotropy and directionality. Counterlet transform allows different and flexible number of directions at each scale. There is one more problem with Wavelet Transform (WT) that is, it can efficiently preserve spectral information but cannot express spatial characteristics well. WT based fusion scheme cannot preserve the salient features in source images efficiently, and by any chance it can introduce some artifacts and inconsistency in the fused results. Contourlet Transform (CT) proposed by Minh N. Do and Vetterli is a true two dimensional image representation method. It is achieved by combining the LP and the directional filter bank (DFB). Compared with the traditional DWT, the CT is not only with multi-scale and localization, but also with mulitdirection and anisotropy.

II. COUNTERLET TRANSFORM

For image enhancement, there is need to improve the visual quality of an image with minimum image distortion. Wavelet based transform have few limitations, like they are not well adapted for the detection of highly anisotropic elements such as alignments in an image. Contourlet transform performs better for representing the image salient features such as lines, curves, edges and contours than wavelet transform because of its anisotropy and directionality. Hence it is good for multi-scale edge based color image enhancement. Compared with the traditional DWT, the CT is not only with multiscale and localization, but also with multidirection and anisotropy. So the CT can represent edges and other singularities along curves much more efficiently. The contourlet transform is based on the sub band decomposition. . In the, next step the Laplacian pyramid (LP) is first used to capture the point discontinuities, and after that a direction filter banks

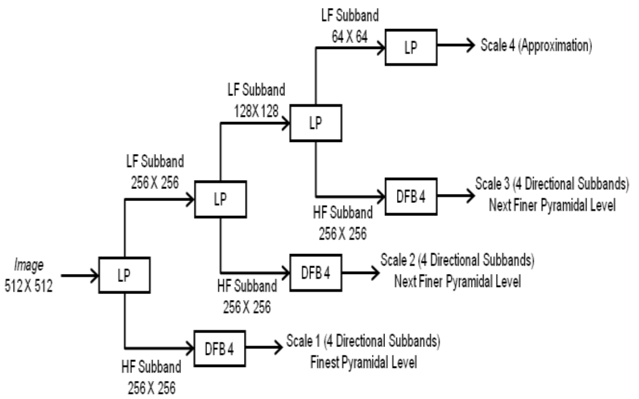

Figure 2. Flowchart of CNT for a 512 X 512 image.

(DFBs)issues.

CNT is used to link point discontinuities into linear structures.

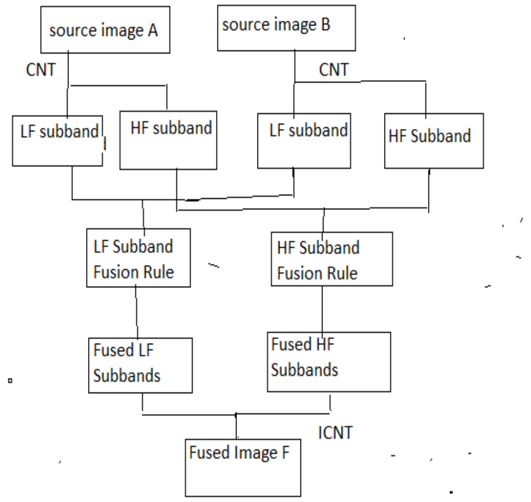

Figure 3.counterlet transform image fusion process

Pyramidal Directional Filter Bank (PDFB) which gives multiresolution. The PDFB contains Laplacian Pyramid (LP). Where Laplacian Pyramid captures the point discontinuities, with a Differential Filter Bank which links these discontinuities into linear structures. Laplacian Pyramid decomposition is first stage and after that Differential Filter Bank is used for next stage.

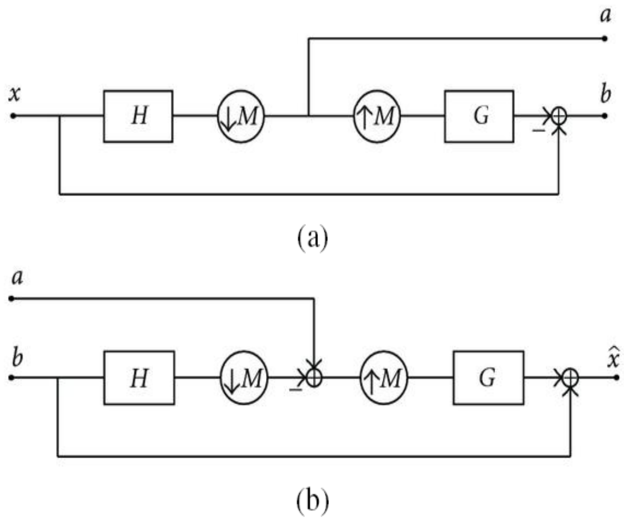

Figure 3. Laplacian pyramid scheme: (a) analysis and (b) synthesis.

Above figure shows the analysis and synthesis of Laplacian pyramid .In this input image x is First passing through low pass filter by analysis filter H and then down sampled to produce a coarse approximation a . After that interpolation is takes place and it passed through the synthesis filter G. The resulting image is subtracted from the original image *x* to obtain the band pass image b. This process can be iterated repeatedly inverse. LP is a multiscale decomposition.

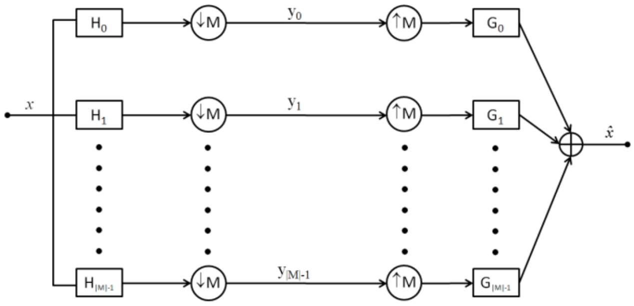

Figure 4. Construction of DBF.

To apply an *lj*-level DFB to the detail subspace *Wj* results in a decomposition with *2lj* directional subspaces in CNT as follows:

$$W_j = \bigoplus_{k=0}^{2^{l_j-1}} W_{j,k}^{l_j}$$

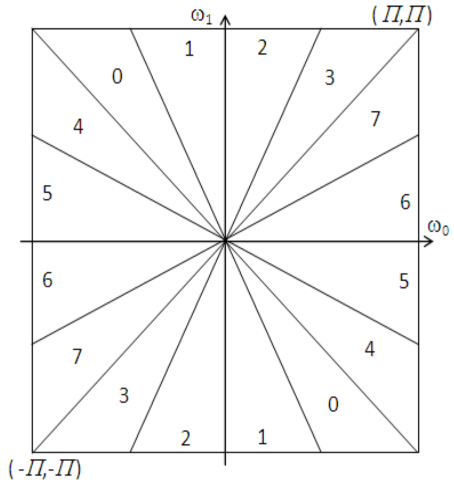

Figure 5. Frequency partition of CNT

A DFB is designed for capturing the high frequency content like smooth contours and directional edges.
In this *A*, *B* , *F* represents the two source images and the fused image ,respectively. *LTJ* indicates the LFS(Low frequency subband). *Hj,k* represents the HFS(High frequency subband). (*m,n*) denotes the spatial location of each coefficient. Preposed method:

A.Fusing Low Frequency Subband:-

Novel fusion based rule on a combined ALM,is used to fuse the LFSs coefficients by estimating each coefficient contribution to the fused image. If "a coefficient is large" and "its local information entropy is large", then the coefficient of low frequency sub band may contain more important information to the fused image. Consider f1(x(m,n)) and f2(x(m,n)) are two simple ALM(Activity level mesurement) representing "a coefficient is large", and "its local information entropy is also large", respectively, we have created, f(x(m,n)) as the new combined ALM which represents "a coefficient is large and its local information entropy is also large", which is more important for the fused image. f1(x(m,n)) is defined as follows:

$$f_1(x(m,n)) = \frac{|\, x(m,n)\,|}{max_{x(p,q)\in l_j^A}(|\, x(p,q)\,|)}$$

Similarly, f2(x(m,n)) is defined as follows:

$$f_2(x(m,n)) = \frac{I(x(m,n))}{min_{x(p,q)\in l_j^A}\ (I(x(p,q)))}$$

where, the 'local information entropy' of the coefficient x(m,n)is denoted by I(x(m,n)). The 'local information entropy' of a coefficient is calculated considering a M ×N neighborhood around the coefficient x(m,n), and is represented as follows:

$$I(x(m,n)) = -\sum p(x(m,n))\log_2 p(x(m,n))$$

where, p(x(m,n)) is the probability of occurrence of the coefficient x(m,n). Further we then compute f(x(m,n)) as follows:

$$f(x(m,n)) = \min\,(f_1(x(m,n)), f_2(x(m,n)))$$

Similarly, for a coefficient y(m,n)ϵ LB J , (j = 1, ..., J) we compute f1(y(m,n)), f2(y(m,n)) and f(y(m,n)). To get a fused coefficient z(m,n) of the subband LF J we follow the given rule:

$$z(m,n) = \frac{(x(m,n).f(x(m,n))) + (y(m,n).f(y(m,n)))}{f(x(m,n)) + f(y(m,n))}$$

B.Fusing High Fequency Subband:

The 'local average energy' of the neighborhood of the coefficient under consideration are fused by HFS(High frequency Subband)coefficients. For a coefficient x(m,n)ϵ HA j,k, (j = 1, ..., J); its' 'local average energy' EA(x(m,n)) is computed as follows:

$$E_A(x(m,n)) = \frac{1}{M\times N}\sum_{m=1}^{M}\sum_{n=1}^{N}(x(m,n))^2$$

where, M×N is the size of the neighborhood around the coefficient x(m,n).

Similarly for a coefficient y(m,n)ϵ HB j,k, (j = 1, ..., J); its' 'local average energy' EB(y(m,n)) is computed. To get a fused coefficient z(m,n) of the subband HF j,k we follow the following rule

$$Z(m,n) = \frac{(E_A(x(m,n).x(m,n))) + (E_B(y(m,n).y(m,n)))}{E_A(x(m,n)) + E_B(y(m,n)}$$

III.ALGORITHAM

Step1. First select two images.
Step2. Apply multi scale decomposition and Directional Filter Banks over registered images.

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Step3. Apply multi scale decomposition with Counterlet transformto get the LFSs and HFSs f or both images.
Step4. coefficients of LFSs are Fused by using ALM (Activity level mesurement) to get the fused LFS.
Step5. Similarly to get the fused HFSs, The HFSs coefficients are fused according to their 'local average energy'.
Step6. Apply inverse contourlet transform on the fused LFS and HFSs to get the final fused medical image.

IV.EXPERIMENTAL RESULT

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To evaluate the performance of the proposed MIF tecnique, various experiments were carried out on different modalities of defense images. Fig. 6(a)- and Fig. 6(b) shows two different sets of source images used in the experiments, and is denoted by A and B , respectively.
The image in Fig. 6(a) shows the visual image and the second image in Fig. 6(b) is the infra red image. Both image have different information. For example visual image do not have human presence, while infrared image shows the human presence. When we perform counterlet transform on both the images A and B we get fused image C with all the details information together.

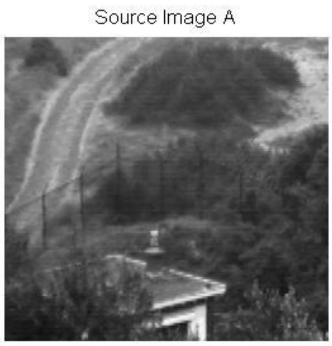

Figure 6 A. Input source image A

Figure 6 B. Input source image B

Figure 6 C. Output fused image

V.PERFORMANCE MEASURES

A. Standard Deviation (STD): Standard deviation measures the contrast in fused image. High contrast image would have high Standard deviation value.

$$STD = \sqrt{\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}(F(m,n) - MEAN)^2}$$

where $M \times N$ denotes the size of the image and $F(m,n)$ denotes the gray-value of the pixel of image F at position (m,n) and

$$MEAN = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N} |(F(m,n)|$$

B. Spatial Frequency (SF):
Spatial frequency can be used to measure the overall activity and clarity level of an image. Large SF value indicates better fusion result:

$$SF = \sqrt{RF^2 + CF^2}$$

where RF represents the row frequency and CF represents the column frequency:

$$RF = \sqrt{\frac{1}{M(N-1)}\sum_{m=0}^{M-1}\sum_{n=0}^{N-2}(F(m,n+1) - F(m,n))^2}$$

And

$$CF = \sqrt{\frac{1}{(M-1)N}\sum_{m=0}^{M-2}\sum_{n=0}^{N-1}(F(m+1,n)F(m,n))^2)}$$

where $M \times N$ denotes the size of the image and $F(m,n)$ indicates the gray-value of the pixel of image F at position (m,n).

c.Mutual Information (MI):-
MI measures the degree of dependence of the two images.
If the measureis high then it implies a better quality. Given two images xF and xR; MI is defined as :

$$MI = I(x_A ; x_B) + I(x_B ; x_F)$$

Where;

$$I(x_R ; x_F) = \sum_{u=1}^{L}\sum_{v=1}^{L} h_{R,F}(u,v) \log_2 \frac{h_{R,F}(u,v)}{h_R(u)h_R(v)}$$

where hR, hF are the normalized gray level histograms of xR and xF, respectively. The joint gray level histogram of xR and xF is denoted by hR,F, and L is the number of bins. xF and xR correspond to the fused and reference images, respectively. I(xR;xF) indicates how much information the fused image xF conveys about the reference xR. Thus, higher the mutual information between xF and xR, there are more chances that xF resembles the ideal xR.

D. Entropy (EN);-

Entropy can be used to measure the difference between two source images and the fused image. The entropy of an image is a measure of information content. Entropy is the average number of bits which have a need of quantize the intensities in the image. It is represented as follows :

$$EN = \sum_{g=0}^{L-1} p(g) \log_2 p(g)$$

where p(g) is the probability of grey-level g , and the range of g is [0,.....,L-1].High information content of image would have high entropy. High entropy of fused image indicates that the it contains more information than the original image sources.

VI. Proposed Software Design

Interactive software is developed to do the reliable monitoring and management of Fusion process. The system software is made using MATLAB .We are taking two images image A and image B after the process of Counterlet transform. We get one output fused image.

VII.CONCLUSION

With this we conclude that contourlet Transform can be used to fuse two dimensional images and represent them more efficiently, which makes the fused images more clear and more informative. Contourlet Transform overcomes the drawbacks of traditional Image Fusion schemes by using ALM. The Experimental results using this technique of IF show that it can preserve more useful information in the fused image with higher spatial resolution and less difference to the input images.

REFERENCES

1) H. H. Wang, “A new multi wavelet-based approach to image fusion”,
Journal of Mathematical Imaging and Vision, vol.21, pp.177-192, Sep 2004

2)Zong-hu,he and De-xiang,Zhang (2011) , “ Fusion of Polarimetric Image using Contourlet Transform ”, Consumer Electronics, Communications and Networks International Conference,pp 362-365.

3). Lu,Yue and Do,Minh N (2006) "A New Contourlet Transform with Sharp Frequency Localization." Image Processing International Conference ,pp1629-1632.

4) **“**The Application of Wavelet Transform to Multi-modality Medical Image Fusion” Anna Wang, Haijing Sun, and Yueyang Guan 2006.

5) S. Das, M. Chowdhury, and M. K. Kundu, “Medical image fusion based on ripplet transform type-I,” Progress In Electromagnetic Research B, vol. 30, pp. 355–370, 2011.

6) M. N. Do and M. Vetterli, “The contourlet transform: An efficient directional multiresolution image representation,” IEEE Transactions on Image Processing, vol. 14, no. 12, pp. 2091–2106, 2005.

7) Mandal, T., Jonathan Wu, Q. M. & Yuan, Y. (2009). Curvelet based face recognition via dimension reduction. *Signal Processing*, Vol. 89, No.12, pp. 2345-2353, ISSN 0165-1684.

8) Zhang, Z., Blum, R.S. A categorization of multiscale-decomposition-based image fusion schemes with a performance study for a digital camera application. Proc. IEEE, 1999, 87 (8):1315–1326.

9). S. Li and B. Yang. Mult ifocus image fusion using region segmentation and spatial frequency. Image and Vision Computing, 2008, 26 (7) :971-979.

10). G. Pajares, J. Cruz. A wavelet-based image fusion tutorial. Pattern Recognition, 2004, 37 (6): 1855-1872.

11)Susmitha Vekkot, and Pancham Shukla, “ Novel Architecture for Wavelet based Image Fusion” World Academy of Science, Engineering and Technology ,vol 6 ,no.7, pp . 372-377(2009)

12) Yi Yang ,Chongzhao Han ,Xin Kang and Deqiang Han “An Overview on Pixel-Level I mage Fusion in Remote Sensing,” Proceedings of the IEEE International Conference on Automation and Logistic,vol 6, no .4, pp .2339- 2344 feb (2007)

13)image code,” IEEE Transactions on Communications, vol. 31, pp. 532–540, 1983.

14) R. H. Bamberger and M. J. T. Smith, “A filter bank for the directional decomposition of images: theory and design,” IEEE Transactions on Signal Processing, vol. 40, no. 4, pp. 882–893, 1992.

15) G. H. Qu, D. L. Zhang, and P. F. Yan, “Information measure for performance of image fusion,” Electronic Letters, vol. 38, no. 7, pp. 313–315, 2002.

16) H. Tian, Y.-N. Fu, and P.-G. Wang, “Image fusion algorithm based on regional variance and multi-wavelet bases,” in Proc. of 2nd Int. Conf. Future Computer and Communication, vol. 2, 2010, pp. 792–795