ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 11, November 2013

Modified Approach of Multimodal Medical Image Fusion Using Daubechies Wavelet Transform

Kanisetty Venkata Swathi[1], CH.Hima Bindu[2]

[1]PG Student, ECE Department, QIS College of Engineering & Technology, Ongole, India[1]

[2]Assoc.Professor, ECE department, QIS College of Engineering and Technology, Ongole, India[2]

Abstract: The multimodal medical image fusion is an important application in many medical applications. This is used for the retrieval of complementary information from medical images. The MRI and CT image provides high resolution images with structural and anatomical information. The CT image is used in tumour and anatomical detection and MRI is used to obtain information among tissues. In this paper, we have proposed a new approach of multimodal medical image fusion on Daubechies wavelet transform coefficients. The fusion process starts with comparison of block wise standard deviation values of the coefficients. Here the standard deviation can be used to characterize the local variations within the block. The performance of proposed image fusion method is compared with existing algorithms and evaluated with mutual information between input and output images, entropy, standard deviation, fusion factor metrics. .

Keywords: Multimodal Medical Image Fusion, Daubechies Wavelet Transform.

I. INTRODUCTION

Image fusion is the process of integrating all relevant and complementary information from different source images into a single composite image without introducing any artifact or noise. Image fusion can be performed at three levels – pixel level, feature level and decision level. Pixel level fusion deals with information associated with each pixel and fused image can be obtained from the corresponding pixel values of source images. In feature level fusion, source images are segmented into regions and features like pixel intensities, edges or texture, are used for fusion. Decision level fusion is a high level fusion which is based on statistics, voting, fuzzy logic, prediction and heuristics, etc [1].

Medical image processing is a challenging and interesting area of research for scientists from last three decades with the invention of multimodal imaging sensors such as X-ray, CT(Computed Tomography), MRI(Magnetic Resonance Imaging) scanners etc. These inventions influenced the interest of researchers in medical imaging including a wide range of applications like denoising, registration, classification, segmentation and fusion [2].

The organization of this paper is as follows, the section II explains Daubechies Wavelet Transform. In section III the Methodology for proposed method and the implementation is explained. Finally in section IV the experimental results are shown.

Generally, pyramid and wavelet transforms are used for multiresolution image fusion. A detailed literature review on image fusion can be found in Section 2 (Background and Literature) of this paper.

II. DAUBECHIES CONTINUOUS WAVELET TRANSFORM

In general the Daubechies wavelets are chosen to have the highest number A of vanishing moments, (this does not imply the best smoothness) for given support width N=2A**,** and among the 2A−1possible solutions the one is chosen whose scaling filter has extremal phase [3]. The wavelet transform is also easy to put into practice using the fast wavelet transform. Daubechies wavelets are widely used in solving a broad range of problems.

DTCWT provides shift invariance and better directionality than real valued wavelet transforms [6]. Higher directionality and shift invariance properties of DTCWT make it suitable for image fusion.

The basic equation of multiresolution theory is the scaling equation.

$$\phi(x) = 2\sum_{k} a_k \phi(2x-k) \quad (1)$$

The construction of complex Daubechies wavelet transform is as in [11]. The generating wavelet w(t) is given by

$$\psi(t) = 2\sum_{n} (-1)^{\wedge} n.\bar{a}(1-n)\phi(2t-n) \quad (2)$$

Here and /(t) share the same compact support[N,N+1].

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 11, November 2013

I	Method		EN	STD	MI		FF
I 1	EM	DB2	5.99	32.92	4.10	0.62	4.72
	PM	**DB2**	**6.71**	**61.31**	**4.42**	**0.97**	**5.39**
I2	EM	DB2	6.30	72.97	1.92	2.59	4.52
	PM	**DB2**	**6.71**	**73.47**	**3.27**	**2.12**	**5.39**

Table 1: The fusion methods performance measures

Any function f(t) can be decomposed into complex scaling function and mother wavelet as:

$$f(t)=\sum_k c_k^{j0}\phi_{j0,k(t)} \sum_{j=j0}^{j\max-1} d_k^j \psi_{j,k(t)} \tag{3}$$

where j0 is a given resolution level. Where ak are the coefficients [4]. The ak can be real as well as complex valued and $\sum a_k = 1$.

The Daubechies complex wavelet transform has the following advantages:
(i) It has perfect reconstruction property.
(ii) No redundancy.
(iii) It is symmetric. This property makes it easy to handle edge points during the signal reconstruction.

However there are some other important properties of the Daubechies complex wavelet transform that directly influence the performance of image fusion.

III. PROPOSED METHOD

Proposed method uses Daubechies complex wavelet transform and standard deviation for multimodal medical image fusion [5]. A general image fusion scheme using proposed method is shown in Figure 1. The CT and MRI images are applying as inputs to obtain output as a fused image. The procedure is as follows and it is shown in Figure

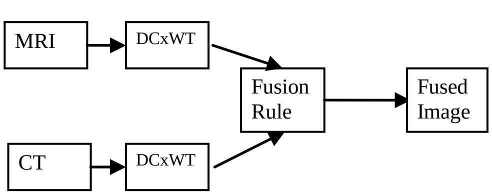


Figure 1. Block diagram of a general image fusion scheme using Daubechies wavelet transform.

Step1: The multimodal medical images A and B are decomposed into different levels using Daubechies complex wavelet transform [7] to obtain the low frequency (LL_A, LL_B) and high frequency (LH_A, HL_A, HH_A, LH_B, HL_B, HH_B) coefficients.

Step2: Divide the each sub band coefficients into K small blocks. For each pair of corresponding blocks the standard deviations $SD_A(k)$ and $SD_B(k)$ are computed for k=1,2…..K.

Step3: Thus, the block with a larger standard deviation value is chosen to construct the fused image coefficients [8]. The process is as follows.

$$f_{LL}(k)=\begin{cases} LL_A(k) & if SD_{LL_A}(k) > SD_{LL_B}(k) \\ LL_B(k) & if SD_{LL_A}(k) < SD_{LL_B}(k) \\ (LL_A + LL_B)/2 & Otherwise \end{cases} \tag{4}$$

Here the k= 1, 2…..k.

Apply the same technique for $f_{LH}(k), f_{HL}(k) and f_{HH}(k)$.

Step4: Apply inverse Daubechies transform on $f_{LL}(k), f_{LH}(k), f_{HL}(k) and f_{HH}(k)$ to obtain fused image.

IV. EXPERIMENTAL RESULTS

The test data consist of high resolution MRI and CT images. The spatial resolution of MRI and CT images are 160×160 pixels. The MRI and corresponding CT images are downloaded from [12]. The source images and fusion results are displayed in Figure 2 and Figure 3. The Proposed and Existing Method uses 2-level Daubechies Transform.
The PM (Proposed Method) is better than EM (Existing Method) in terms of various performance measures like Entropy (EN), Standard Deviation (STD), Mutual Information (MI) and Fusion Factor (FF).The values are tabulated in table1.

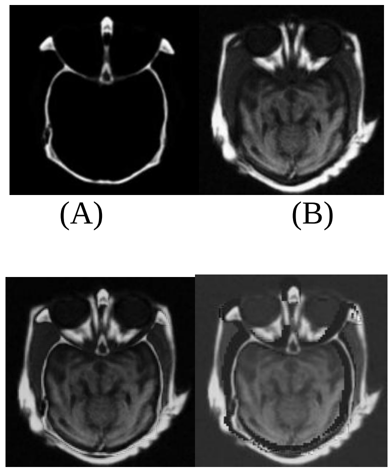
For two input images A, B and fused image F, fusion factor is defined
as

$$FF = I_{AF} + I_{BF} \tag{5}$$

where I_{AF} and I_{BF} are mutual information between source images and fused image. High value of fusion factor implies that fused image is more informative.

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

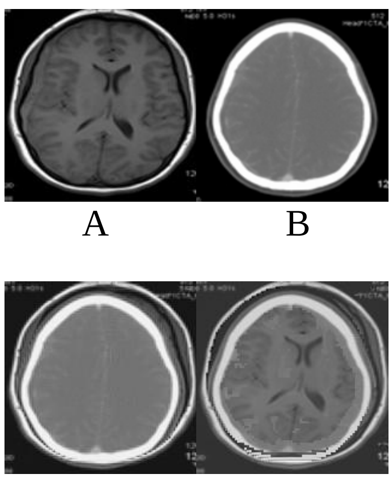
International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 11, November 2013



(A) (B)

(C) (D)

Figure 2**:** MRI and CT images (a) and (b) respectively(c) Existing Method (d) Proposed Method.



A B

Figure 3: MRI and CT images (a) and (b) respectively(c) Existing Method (d) Proposed Method

V. **CONCLUSION**

In this work, a modified approach of multi modal medical image fusion scheme using Daubechies complex wavelet transform is proposed. In the proposed algorithm, first, each of multimodal images are decomposed using DCxWT, then the coefficient are fused using modified fusion rule then the fused coefficients are reconstructed by performing the inverse DCxWT. The qualitative and quantitative analysis shows that the proposed method produce better fused output. The superiority of the proposed algorithm is compared with [9] and the performance is evaluated with the qualitative analytical measurement of mutual information between input and output images, entropy, standard deviation and fusion factor. The performance measures proven that, the proposed method is better method to obtain more information in fused image.

REFERENCES

[1] B.V. Dasarathy, “Information fusion in the realm of medical applications – a bibliographic glimpse at its growing appeal”, Information Fusion 13 , (2012) 1–9.
[2] S.P. Constantinos, M.S. Pattichis, E.M. Tzanakou, “Medical imaging fusion applications:” an Overview, in: Conference Record of the Thirty-Fifth Asilomar Conference on Signals, Systems and Computers, vol. 2, 2001, pp. 1263–1267.
[3] E. Kenneth, A.U. Rajendra, N. Kannathal, C.M. Lim, “Data fusion of multimodal Cardiovascular signals”, in: 27th Annual Conference of the IEEE Engineering in Medicine and Biology Society, 2005, pp. 4689–4692.
[4] A. Khare, U.S. Tiwary, “Daubechies complex wavelet transform based moving object tracking”, in: IEEE Symposium on Computational Intelligence in Image and Signal Processing, Honolulu, Hawaii, USA, 2007, pp. 36–40.
[5] R. Singh, M. Vatsa, A. Noore, “Multimodal medical image fusion using redundant wavelet transform”, in: Seventh International Conference on Advances in, Pattern Recognition, 2009, pp. 232–235.
[6] J.Tian and L.Chen, “Adaptive multi-focus image fusion using a wavelet based statistical sharpness measure”, Signal Processing, vol. 92, 2012 pp. (2137-46).
[7] Z.Lin, M.Chen, L.Wu, and Y.Ma, “The augmented Lagrange multiplier method for exact recovery of corrupted low-rank matrices”, UIUC Technical Report UILU,2009,pp.(1-20).
[8] H.Li, B.S.Manjunath, and S.K.Mitra, “Multisensor image fusion using the wavelet transform, Graphical Models and Image processing”, vol. 57, 1995 pp. (235-45).
[9] S.Li and B.Wang, “Multifocus image fusion using region segmentation and spatial frequency”, Image and Vision Computing, vol. 26, pp.971-79, 2008.
[10] S.G. Nikolov, P.R. Hill, D.R. Bull, C.N. Canagarajah, Wavelets for image fusion,in: A. Petrosian, F. Meyer (Eds.), “Wavelets in Signal and Image Analysis,Computational Imaging and Vision Series”, Kluwer Academic Publishers, Dordrecht, The Netherlands, 2001, pp. 213–244.
[11] A. Khare, U.S. Tiwary, Soft-thresholding for denoising of medical images – a multiresolution approach, International Journal on Wavelets, Multiresoultion and Information Processing 3 (4) (2005) 477–496.
[12] www.rad.usuhs.edu/medpix.com