ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

Developing an Efficient Algorithm for Image Fusion Using Dual Tree- Complex Wavelet Transform

Rohit Raj Singh, Ravi Mishra

IV Sem M.E Student, Dept. of ECE, FET-SSGI, Bhilai (C.G), India

Sr. Asst. Prof, Dept. of EEE, FET-SSGI, Bhilai (C.G), India

ABSTRACT: Image Fusion is an image processing technique for combining data from two or more images of the same frame into a single image which will retain all the important features of the input images. The objective of image fusion includes set of images taken from different domain of the same scene into a single output image which is more informative, valid, reliable and accurate as compared to each source images. Fusion techniques are important in detection and treatment of cancer in medical field, remote sensing and robotics. This paper focuses on developing an image fusion technique using Dual Tree Complex Wavelet Transform. The results showcase that the suggested algorithm has a more desirable visual quality than the base technique. Also the standard of the fused image has been estimated using a set of quality metrics.

KEYWORDS: Image fusion; DT-CWT; WT; Quantitative metrics; fusion rules

I. INTRODUCTION

Image fusion is a process which collects data from two or more images of the same frame into a singleimage which provides more detailed information compared to each single input image and can provide more valid and efficient result for the observers. Today, image fusion techniques are used in various fields such as remote sensing, optical microscopy, robotics and medical imaging [1]. There are many techniques for image fusion. These techniques can be categorized into two fundamental groups' namely spatial domain methods [1] and transform domain methods [2, 3]. For spatial domain techniques, we can refer to simple averaging methods, PCA [4], linear fusion. These techniques are easy but suffer from spatial deformation and do not present any spectral information. The stated drawbacks motivated us to use the transform domain methods. Discrete wavelet transform (DWT) has been widely used for image fusion recently, but it has some problems as it doesn't provide sufficient directional information and resulted in an image with shift variance and additive noise [5, 6]. As an alternative in the present work we propose a new scheme based on DT-CWT which provides approximate shift invariance and more directional information which first is introduced by Kingsbury. This transform overcomes the DWT limitations [7, 8]. After image decomposition using DT-CWT, we apply maximum selection and local energy to mix low and high frequency coefficients respectively [9, 10]. Then inverse DTCWT was applied on the fused coefficients to obtain the fused image. Finally the proposed method is compared with DWT and some spatial domain techniques such as simple averaging and PCA using various quantitative metrics such as SSIM, MI, entropy, STD and average gradient (AVG) where both qualitative and quantitative comparisons demonstrated that the proposed scheme has a superior performance. In this paper section 2 deals with the principle of the Dual Tree Complex Wavelet Transform. Section 3 involves different image quality metrics.

II. RELATED WORK

Uses Wavelet Transform based on maximum selection rule, good in area of Medical field for MRI [2]. Theeffectiveness of the fusion rule is determined by the objective evaluation of the fusion performance using parameters such as the entropy, mutual information and the SSIM based index. From the experiments conducted and human observation of the fused images we conclude that the proposed PCA - Max fusion algorithm is an efficient technique for fusing IR and visible spectrum images [4].The SIDWT scheme resulted in the most stable sequence, while DWT and Laplacian image pyramid fusion sequences exhibited flickering distortions, due to the shift variance of

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

the decomposition process [6]. Image fusion has been attracted more attention in recentdecades especially in multimodal domain. As each source image provides a limited aspect of information it's necessaryto combine them in such a way that carry complementaryinformation of each source images into the output fused image [12].

III. PRINCIPLE OF THE DUAL TREE COMPLEX WAVELET TRANSFORM

DT-CWT replaces single tree DWT structure with a dual tree real valued filters. The two parallel trees filters and down-sample the incoming input signal in the same way as DWT, but since there are two rather than one filtering tree, the aliasing effect that causes shift dependency in DWT get eliminated in DT-CWT. Discrete wavelet transform has been widely used in multi sensor image fusion, but it suffers from few major drawbacks such as poor directional selectivity and shift variance as discussed earlier in this paper. These mentioned problems were rectified by DT-CWT. At each level DT-CWT one of the trees produces the "real" part while the other tree produces the "imaginary" part of the complex wavelet coefficients. Filters in each tree are real-valued and the concept of complex coefficients only appears when outputs from the two trees are merged [11]. The inclusion of the second filter bank increases the redundancy of the transform to 2:1 for a 1D signal. A 2D dual-tree complex wavelet can be defined as $\psi(\mathrm{x},\mathrm{y})=\psi(\mathrm{x})\psi(\mathrm{y})$, where $\psi(\mathrm{x})$ and $\psi(\mathrm{y})$ are two complex wavelets, $\psi(\mathrm{x}) = \psi_h(x)+j\psi_g(x)$ and $\psi(\mathrm{y}) = \psi_h(y)+j\psi_g(y)$, $\psi_h(x)$ and $\psi_h(y)$ are real wavelet transforms of upper filter bank and lower filter bank, respectively. Then we get the following equations:

$$\psi(x,y)=[\psi_h(x)+j\psi_g(x)][\psi_h(y)+j\psi_g(y)]=\psi_h(x)\psi_h(y)-\psi_g(x)\psi_g(y)+j[\psi_g(x)\psi_h(y)+\psi_h(x)\psi_g(y)] \quad (1)$$

The real parts of six oriented complex wavelets of DT-CWT are as follows:

$$\psi i(x,y)=\frac{1}{\sqrt{2}}(\psi 1,i(x,y)-\psi 2,i(x,y)) \quad (2)$$

$$\psi i+3(x,y)=\frac{1}{\sqrt{2}}(\psi 1,i(x,y)+\psi 2,i(x,y)) \quad (3)$$

For i=1, 2 and 3 we have:

$$\psi 1,1(x,y)=\phi_h(x)\psi_h(y),\psi 2,1(x,y)=\phi_g(x)\psi_g(y) \quad (4)$$

$$\psi 1,2(x,y)=\psi_h(x)\phi_h(y),\psi 2,2(x,y)=\psi_g(x)\phi_g(y) \quad (5)$$

$$\psi 1,3(x,y)=\psi_h(x)\psi_h(y),\psi 2,3(x,y)=\psi_g(x)\psi_g(y) \quad (6)$$

where The imaginary parts of six oriented complex wavelets of DT-CWT are as follows:

$$\psi i(x,y)=\frac{1}{\sqrt{2}}(\psi 3,i(x,y)+\psi 4,i(x,y)) \quad (7)$$

$$\psi i+3(x,y)=\frac{1}{\sqrt{2}}(\psi 3,i(x,y)-\psi 4,i(x,y)) \quad (8)$$

For i=1, 2 and 3 we have:

$$\psi 3,1(x,y)=\phi_g(x)\psi_h(y),\psi 2,1(x,y)=\phi_h(x)\psi_g(y) \quad (9)$$

$$\psi 1,2(x,y)=\psi_g(x)\phi_h(y),\psi 2,2(x,y)=\psi_h(x)\phi_g(y) \quad (10)$$

$$\psi 1,3(x,y)=\psi_g(x)\psi_h(y),\psi 2,3(x,y)=\psi_h(x)\psi_g(y) \quad (11)$$

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

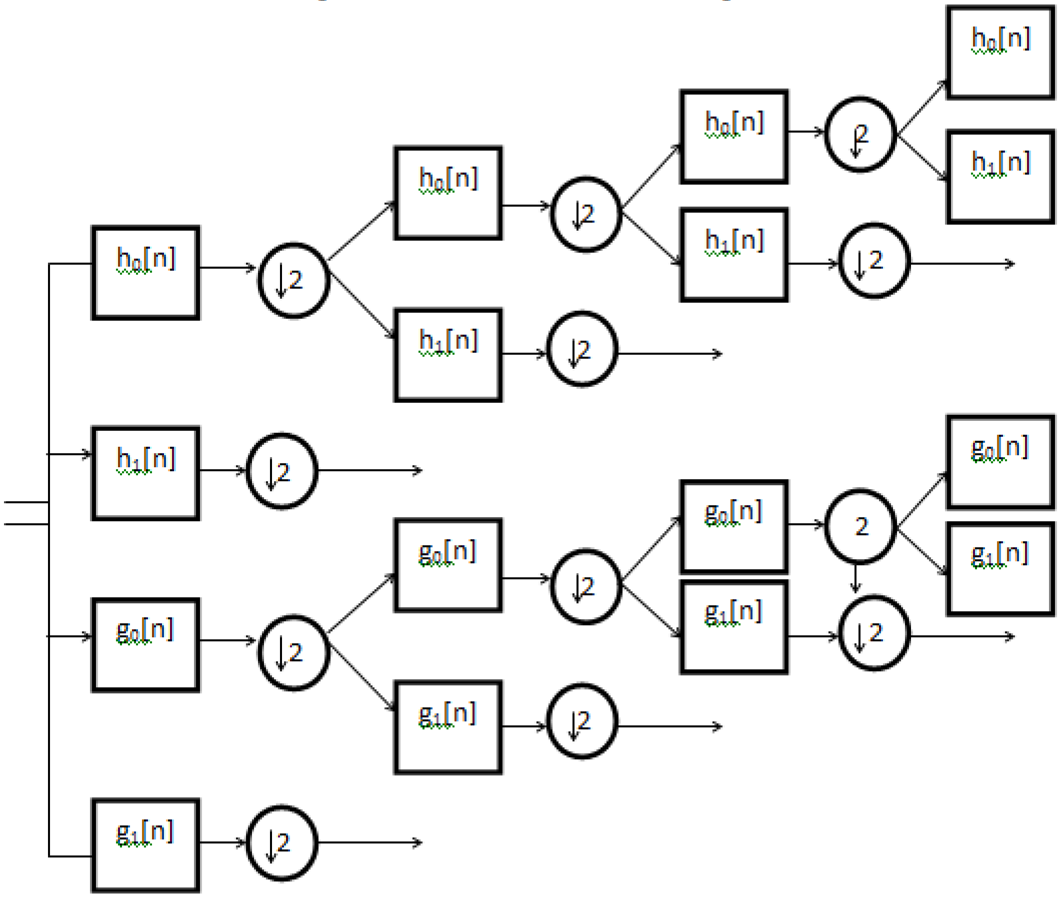

Fig.-1 DT-CWT Structure

In the above equations $\psi_h(x)$ and $\psi_g(x)$ denote the low pass filters of the upper filter bank and lower filter bank while, $\psi_h(y)$ and $\psi_g(y)$ represents the high pass filter of the upper filter bank and lower filter bank respectively. Each of the sub-band images contains the wavelet coefficients for both imaginary and real parts in the ±15degree, ±45degree and ±75degree directional edges in the original image [7].

It can be seen that the DT-CWT structure, comprise both real and complex coefficients. It is well known that DT-CWT technique is more suitable to visual sensitivity. Fusion policy involves the formation of a fused pyramid making use of DT-CWT coefficients which are taken from the decomposed pyramids of the input images.

Fusion Algorithm:

a) Decomposition: With the help of DT-CWT we start decomposing one of the input image and find approximated (LL, LH, HL) and detail [15^0,45^0,75^0, -15^0,-45^0 and -75^0] bands. Repeat the same process for all the given input images.
b) Pyramid formation: On the above obtained output decomposition is again done after the approximation thus it generates a series of different resolution pyramids.
c) Baseband Fusion: Low frequency, high low frequency information is present in the base band. Do masking on corresponding bands then denote these filtered bands as $A_p^k(i,j)$ and $B_p^k(i,j)$ for p_{th} direction band and k_{th} level. Take coefficient such that absolute value of filtered image at spatial location is high enough.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

$$F_p^k(i,j) = \{A_p^k(i,j),\ if\ A_p^{km} > B_p^{km}(i,j) \quad \{B_p^k(i,j), otherwise \tag{12}$$

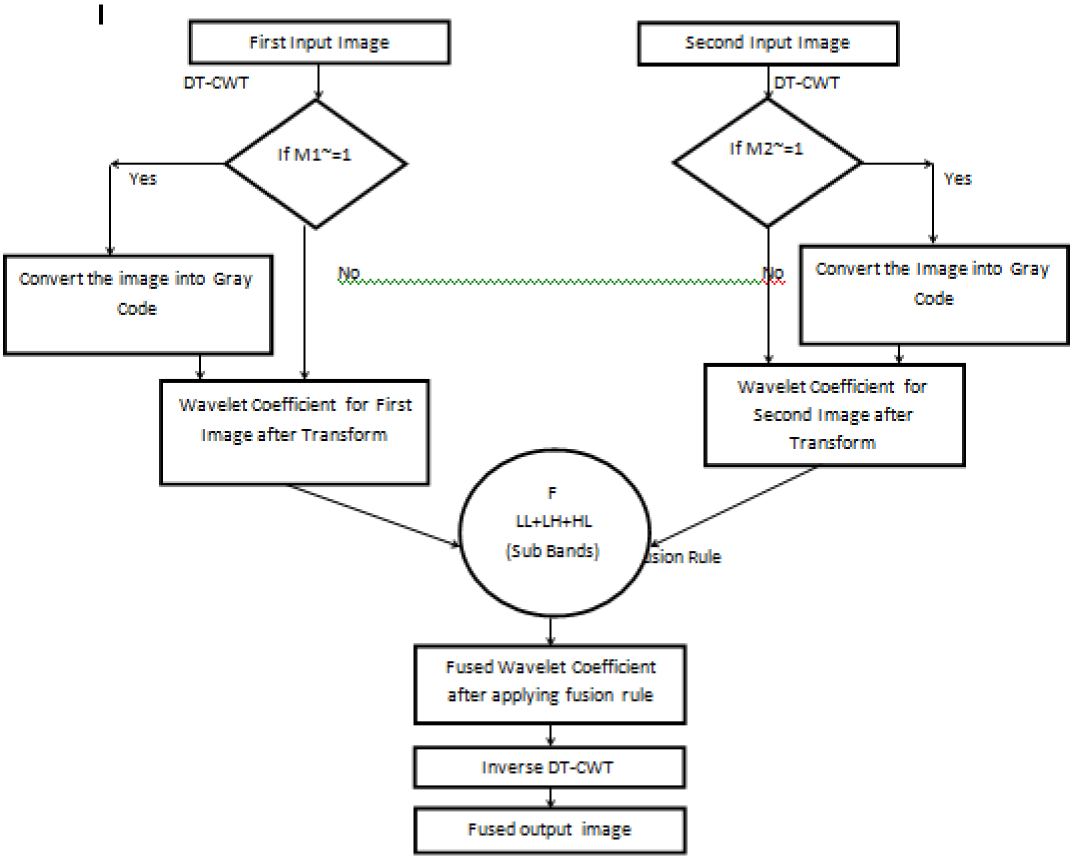

Fig.-2 DT-CWT based fusion

IV. QUANTITATIVE IMAGE QUALITY METRICS

Quality is a feature that measures recognized image deterioration i.e., in comparison with ideal image. Evaluation forms act as a crucial part in the evolution of image fusion techniques. It consist full Reference methods, where efficiency is measured in contrast with ideal image and No Reference Methods, i.e. no reference image. This paper deals with the full reference Methods. The metrics used are shown below in Table1. Assumptions used in the given equations are as, A is the image which is perfect, B is the resultant image, (i, j) is the pixel row and column index.

1) Mean Square Error (MSE)

$$MSE = \frac{1}{mn}\sum_{i=0}^{m}\sum_{j=0}^{n}(A_{ij} - B_{ij})^2$$

2) Peak Signal to Noise Ratio (PSNR)

$$PSNR = 10x\log_{10}(\frac{peak^2}{MSE})$$

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

3) Average Difference (AD)

$$AD = \frac{1}{mn}\sum_{i=0}^{m}\sum_{j=0}^{n}(A_{ij} - B_{ij})$$

4) Structural Content (SC)

$$SC = \frac{\sum_{i=0}^{m}\sum_{j=0}^{n}(A_{ij})^2}{\sum_{i=0}^{m}\sum_{j=0}^{n}(B_{ij})^2}$$

5) Normalized Cross – Correlation (NCC)

$$NCC = \frac{\sum_{i=0}^{m}\sum_{j=0}^{n}(A_{ij} \times B_{ij})}{\sum_{i=0}^{m}\sum_{j=0}^{n}(A_{ij})^2}$$

6) Maximum Difference (MD)

$$MD = \max(A_{ij} - B_{ij}), i = 0,1,2,....m; \ j = 0,1,2,....n$$

7) Normalized Absolute Error (NAE)

$$NAE = \frac{\sum_{i=0}^{m}\sum_{j=0}^{n}(A_{ij} - B_{ij})}{\sum_{i=0}^{m}\sum_{j=0}^{n}(A_{ij})}$$

8) Structural Similarity Index Metric (SSIM)

It compares local patterns of pixel intensities which have been normalized for luminance and contrast and it provides a quality value in the range [0, 1]. It consist parameters like K vector having constant value in SSIM index and L indicate the dynamic range of values. K= [0.01 0.03], L=255 by default. Thus the C1 and C2 will be

$$C_1 = K_1 \times L^2 \qquad C_2 = K_2 \times L^2$$

G is the Gaussian Filter Window in default and the input images are filtered using G generating μ1 and μ2.

$$\mu_1 = A.G \qquad \mu_2 = B.G$$

Thus $\sigma_1{}^2, \sigma_2{}^2, \sigma_{12}{}^2$ are calculated and are

$$\sigma_1{}^2 = A_{ij}{}^2.G - \mu_1{}^2 \qquad \sigma_2{}^2 = B_{ij}{}^2.G - \mu_2{}^2$$

$$\sigma_{12}{}^2 = A_{ij}B_{ij} - \mu_1 \times \mu_2$$

From these values the SSIM index is computed and

$$SSIM = mean(2 \times \mu_1\mu_2 + 2 \times \sigma_{12} + C_2 / (\mu_1{}^2 + \mu_2{}^2 + C_1 \times \sigma_1{}^2 + \sigma_2{}^2 + C_1))$$

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

9) Mutual Information (MI):
Comparison Shown in table 2 base on formula

$$MI(B,A) = \sum_{i,j} P_{BA}(i,j) \log[\frac{P_{BA}(i,j)}{P_B(i)P_A(j)}]$$

V. EXPERIMENTAL RESULTS

Methods	Image Quality Metrics							
	MSE	PSNR	AD	SC	MD	NAE	NCC	SSIM
Minimum	92.254	28.4809	6.6491	1	90	0.0694	0.948	0.91
SVD	258.761	24.001	-11.972	0.8276	173	0.1161	1	0.928
Average	42.95	31.8	-1.325	0.987	66	0.045	1	0.936
PCA	0.0232	46.194	3.7239	0.9877	90.85	0.0305	1	0.961
Maximum	112.543	26.982	3.0032	0.9952	80.94	0.0213	0.983	0.947
Proposed Method(DT-CWT)	0.0016	76.0896	-0.04	0.993	-0.04	0.00035303	1.003	1

Table 1[12]

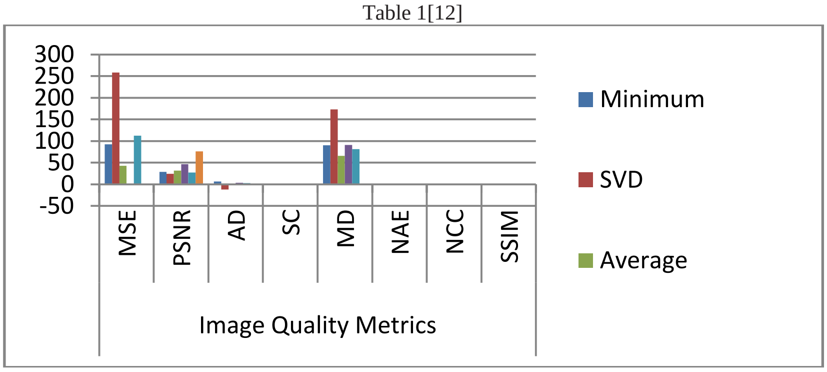

Fig.-3 Graph showing Comparison between Different Image Fusion Technique Image Metrics Values

(1) (2) (3)

(4) (5) (6)

Fig.-4Fused images using different algorithms ((1)-(6) are fused images, the methods used from (1) to (6) are: Average, Maximum, Minimum, PCA, SVD and Propose Method (DT-CWT)

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

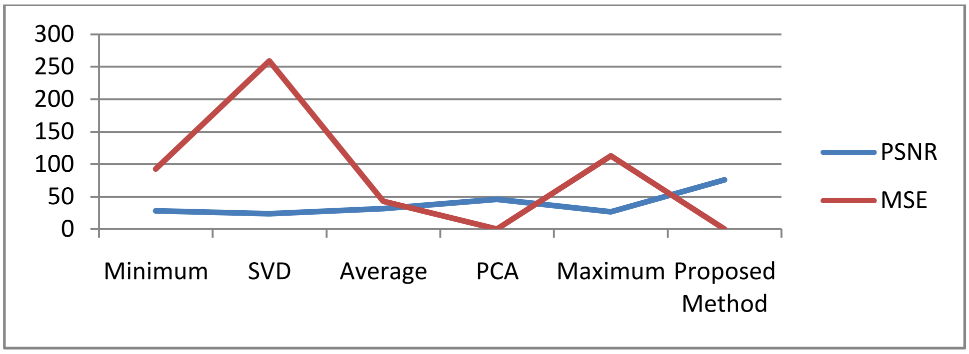

Fig.-5 Graph Showing relation between MSE and PSNR of different Image Fusion Technique

Methods	Image Quality Metrics
	Mutual Information (MI)
Average	5.6183
PCA	6.7862
DWT	6.0609
Proposed Method (DT-CWT)	6.512

Table 2[13]

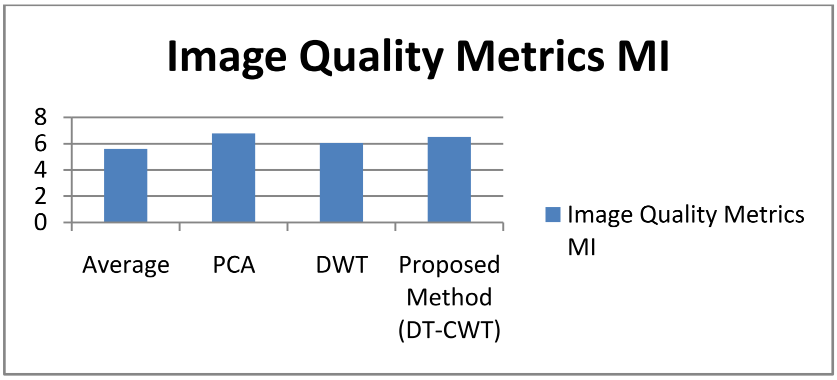

Fig.-5 Graph showing Comparison between Different Image Fusion Technique Image Mutual Information Value

VI. CONCLUSION& FUTURE WORK

Image fusion has drawn more attention in recent years. As each source image gives a limited amount of information it's necessary to mix them in such a way that they carry complementary information of each source images into the resultant fused image. From the above table of Quality metrics for different images it is clear that the DT-CWT based fusion is having a better result of PSNR when compared to other fusion technique, which shows that it is a better fusion technique as compared to other general techniques. Similarly if we check the MSE value, it is the least in DT-CWT. Thus it proves proposed method performs the better in comparison to other image fusion technique, since it reduces the drawback of shift invariance and it provides multiscale edge information and phase information. Visual analysis has also proved that the proposed method has a better performance compared to the other methods.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 4, April 2015

The proposed gives best result among previous techniques for image fusion, however it can also be extended for colour image fusion. There is a scope to develop robust joint segmentation algorithm and hence better feature level image fusion. This method can be further used to detect the accuracy of the any existing methodology.

REFERENCES

1. A. Goshtasby, 2-D and 3-D Image Registration for Medical, Remote Sensing, and Industrial Applications, Wiley Press, 2005.
2. H. Li, S. Manjunath, S. Mitra, Multisensor image fusion using the wavelet transform, Graphical Models and Image Processing 57 (3) (1995) 235–245.
3. S.G. Nikolov, P. Hill, D.R. Bull, C.N. Canagarajah, Wavelets for image fusion, in: A. Petrosian, F. Meyer (Eds.), Wavelets in Signal and Image Analysis, Kluwer Academic Publishers, The Netherlands, 2001, pp. 213–244.
4. S. Senthil Kumar and S. Muttan, PCA Based Image Fusion, Proceedings of SPIE, vol. 6233, pp.62331T-1 to 62331T-8.
5. Amolins, Krista, Yun Zhang, and Peter Dare. "Wavelet based image fusion techniques—An introduction, review and comparison." ISPRS Journal of Photogrammetry and Remote Sensing 62, no. 4 (2007): 249- 263.
6. Oliver Rockinger, "Image sequence fusion using a shift –invariant wavelet transform", International conference on image processing, vol.3, pp.228, October 1997.
7. N. Kingsbury. The dual-tree complex wavelet transform: a new technique for shift invariance and directional filters. In IEEE Digital Signal Processing Workshop, volume 86, 1998.
8. Kingsbury, N.G.: Shift Invariant Properties of the Dual-Tree Complex Wavelet Transform. Proceedings of International Conference, ICASSP'99, Phoenix, Arizona, USA, Vol. 1, Mar. 1999, pp. 1221–1224.
9. Hill, Paul R., Cedric NishanCanagarajah, and David R. Bull. "Image fusion using complex wavelets." In BMVC, pp. 1-10. 2002.
10. Lewis, John J., Robert J. O'Callaghan, Stavri G. Nikolov, David R. Bull, and NishanCanagarajah. "Pixel-and region-based image fusion with complex wavelets." Information fusion 8, no. 2 (2007): 119-130.
11. Sruthy S, Dr. LathaParameswaran, Dept. of Computer Science and Engineering AMRITA VishwaVidyapeetham , Coimbatore, India Ajeesh P Sasi Dept. of Electronics and Communication Engineering Caarmel Engineering College Pathanamthitta, "Image Fusion Technique using DT-CWT", India978-1-4673-5090-7/13/$31.00 ©2013 IEEE.
12. NegarChabi Faculty of Electrical and Computer Engineering, Shiraz University, Shiraz, IRAN, MehranYazdi Department of medical radiation, ShahidBeheshtiUniversity,Tehran,IRAN, Mohammad Entezarmahdi Department of nuclear medicine, Shiraz University of Medical Science,Shiraz,IRAN, "An efficient image fusion method based on dual tree complex wavelet transform", 2013 8th Iranian Conference on Machine Vision and Image Processing (MVIP) ©2013 IEEE.