International Journal of Engineering Science Invention
ISSN (Online): 2319 – 6734, ISSN (Print): 2319 – 6726
www.ijesi.org ||Volume 6 Issue 8|| August 2017 || PP. 01-09

A Novel Image Fusion Technique based on NSCT with EWGIF

*Harmanpreet Kaur[1], Navleen Kaur[2]
[1,2]*(Department of Computer Science & Engineering, ACET, Punjab, India)*
*Corresponding Author: *Harmanpreet Kaur*

Abstract : *Image fusion is an energetic area in digital image processing. Main goal of image fusion is always merge info through multiple pictures of exactly similar view in order to deliver the useful info. In this paper, a novel image fusion framework is proposed by the combination of NSCT as well as edge weakening guided image filter. Proposed algorithm could not just* maintain *the depth of multi-focus picture but could also restrain artefacts effectively by combining advantage of NSCT as well as EWGIF. Firstly original pictures are decomposed into low-frequency sub band as well as bandpass direction subband coefficients based on the nonsubsampled contourlet transform. Low-frequency subband coefficients are fused through VSF .on contrary bandpass direction subband coefficients are fused through cross contrast. After getting coefficient, fused image is obtained with the help inverse NSCT. Proposed system is performed on various parameters of image fusion with edge weakening guided image filter. The proposed system shows that image fusion is considerably improved with the EWGIF.*

Keywords: *Image Fusion, Edge Weakening Guided Image Filter (EWGIF), Visual Salient Features (VSF), Cross contrast (CC), NSCT method*

Date of Submission: 24-08-2017 Date of acceptance: 05-08-2017

I. Introduction

Image fusion is generally identified as a procedure where new picture can be generated through the integration of multi-focus pictures through a couple of input pictures [1]. Result procured via image fusion technique is much illuminating, suitable for purpose of human visual perception as well as image processing tasks [2] like segmentation, feature extraction and target recognition. Because of reasonably limited depth of focus of optical lenses in the digital camera, it's possible to get a photo which includes most of applicable information. One method to conquer this issue by applying multi-focus image fusion technique in which various pictures assorted with focus region are merged to obtain single pictures. Lately, the multi-focus image fusion techniques have been widely used in Object Targeting, Medical Imaging, Machine Vision, Object Recognition, and Military affairs, etc.

Image Fusion is a method which might be executed during diverse levels, namely as Pixel, Feature and Decision level of images [5, 6]. Pixel level is lowest level of image fusion as well as popular approach, associated with an area of the pixel merging the information on the input picture in a single picture. Feature level is middle level which determines and deals with the feature of information like point, edge, region, contour and direction obtain by extraction of the features. When this method is used along with decision levels fusion it provides better-fused picture. Decision level is highest level of image fusion. It extracts the information of the data from low level or middle-level fusion to build optimal decision. Before the fusion, data should be obtained to gain the absolute decision result, so that loss of information can't be ignored; meantime the cost is very high.

Essentially, Fusion methods are usually decomposed into 2 categories namely as spatial and transformed domain classification [5, 7]. Initial classification is spatial domain-based method; it deals directly with pixels or regions from clear regions with the spatial domain to compose fused pictures [8–13]. Second classification is transformed domain-based method; it deals directly along with the rate in which value of the pixel is adjusting in the spatial domain. Transform domain is firstly transforming the input picture to its frequency domain then these domains are merged with different rules. To get a final fused image, the inverse transformation of image fusion is applied [6, 14–17].

To achieve the better quality of the fused picture, numerous methods had been proposed to find a highly fused picture which splits into blocks regions with single pixels [8, 9, 11, and 13]. However, these techniques ordinarily have problems with block effects that considerably damage the fused image quality. Another form of a spatial domain-based method can recognize focused regions in single source picture. Furthermore fused pictures are converted into a single picture through replicating them [10, 12].

II. Traditional Approaches

2.1 Nonsubsampled Contourlet Transform

Nonsubsampled Contourlet Transform can be produced simply combined with NSPFB (nonsubsampled pyramids filter bank) and NSDFB (non-subsampled directional filter bank). NSPFB gives multi-scale decomposition and NSDFB provides directional. A NSPFB divides into low-pass subband as well as a band-pass subband. Then NSDFB breaks down bandpass subbed into numerous directional subbands as presented in below Fig. 1. Structure is iterated over and over again for the low-pass subband. Furthermore the construction of NSCT will be explained in further sections:

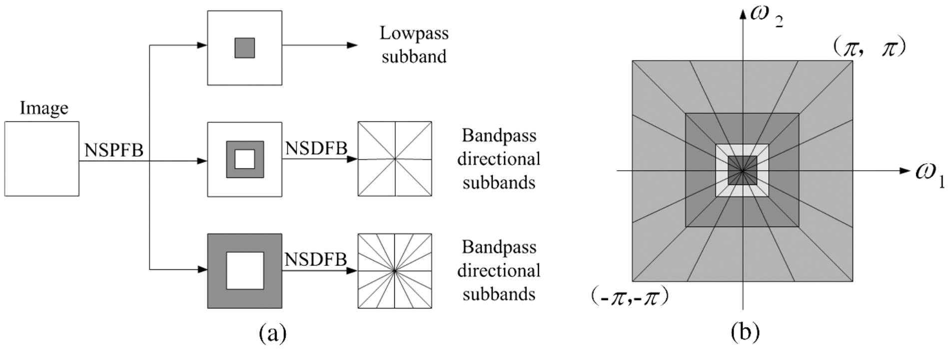

Fig: 1. Non-subsampled Contourlet Transform (NSCT): (a) Block Diagram (b) Resulting frequency distribution

2.1.1. Non-subsampled Pyramids Filter Banks

NSPFB is totally dissimilar from the previous contourlet transform. Building block of NSPFB is described as 2 channels of the nonsubsampled filter bank as well as it contains no down sampling or up sampling. Consequently, NSPFB is always shifting invariant. Absolute renovation state is offered just as:

$$H_0(z)\, S_0(z) + H_1(z)\, S_1(z) = 1. \tag{1}$$

$H_0(z)$ is definitely low-pass filter together with $H_1(z) = 1 - H_0(z)$; $S_0(z)$ and $S_1(z)$ seem to be low-pass and band-pass.

Non-subsampled pyramids can be produced simply with iteration of non-subsampled filter banks for achieving multi-scale decomposition. To the following level, many filters can be up-sampled simply by 2 in both dimensions. Hence, it satisfies the appropriate reconstruction condition. Up-sampled filtering ($H(\bar{z})$) has a similar difficulty in filtering using $H(z)$ with 'a trous' algorithm. Non subsampled pyramid filter banks are given by:

$$H_n^{eq}(z) = \begin{cases} H_1\left(z^{2^{n-1}}\right) \prod_{m=0}^{n-2} H_0\left(Z^m\right) & 1 \le n < 2^k \\ \prod_{m=0}^{n-1} H_0\left(z^{2^m}\right) & n = 2^k \end{cases} \tag{2}$$

Where z^m stands for $[z_1^m, z_2^m]$ .Non-subsampled pyramid decomposition has 3 stages as shown in fig 2:

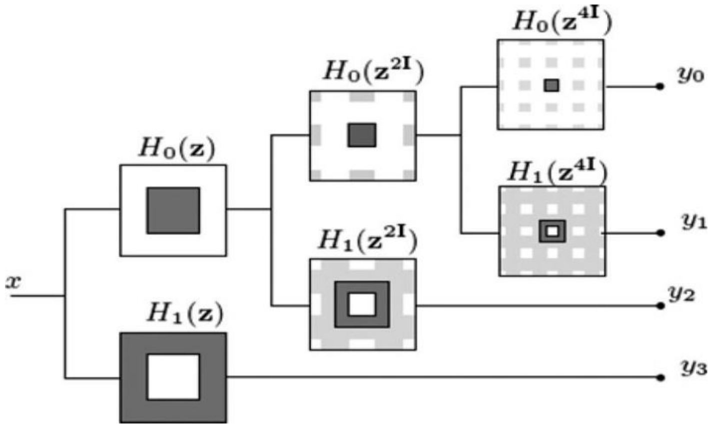

Fig 2: Nonsubsampled pyramid decomposition with three stages

2.1.2. Nonsubsampled Directional Filter Banks (NSDFB)

NSDFB is a shift-invariant release critically sampled DFB in the contourlet transform. Building block of NSDFB, yet another 2-channel non-subsampled filter bank. In further step, more filters are up-sampled with the help of a quincunx matrix distributed by:

$$Q = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

2.3. Fusion algorithm based on Visual Salient Features (VSF) and the Cross-Contrast (CC)

Fused picture p is regarded to be created via a set of original imagery p_1 and also p_2 which perfectly were registered. Image fusion is depending on NSCT and rules of image fusion carry out the significant role to quality the fused picture. For selection of BDS coefficients, CC method is used whereas for selection LFS coefficients, VSF are used. In the following sections a brief introduction of both coefficients is given:

2.3.1 Fusion rule of low frequency subband coefficients

Local Energy (LE) is describe the sharply goal in image fusion. Within multi-focus picture, area is sharp near the focus point and defocus areas are ambiguous. LE with defocused area has to be lesser than the area in focus. Therefore, all of us work with local source as visual salient feature (VSF) for making the LE source map, as proven in Eq. (3). In Eq. (3), m is the local area within the picture and also p(i, j) is the coefficient of picture element in the picture.

$$E = \sum_{(i,j)\in m} p^2(i,j) \tag{3}$$

Within picture, all the visual salient area is correctly analysed through contrast. In this paper, VSF is used to identify sharp areas in the picture as a feature of contrast. The contrast map is given in Eq. (4).

$$R = \frac{\frac{1}{x\times y}\sum_{i=-(x-1)/2}^{(x-1)/2}\sum_{j=-(y-1)/2}^{(y-1)/2} p(m+i,n+j)}{\frac{1}{X\times Y}\sum_{m=1}^{M}\sum_{n=1}^{N} p(m,n)} \tag{4}$$

The gradient is effectively identified by area in which texture is sharp within the picture, that's why gradient is used as VSF. At this point, Sobel gradient operator can be used for making entire gradient map, as given in Eq 5.

.

$$\begin{cases} \nabla_m p(m,n) = [p(m-1,n+1) + 2p(m,n+1) + p(m+1,n+1)] - [p(m-1,n-1) + 2p(m,n-1) + p(m+1,n-1)] \\ \nabla_n p(m,n) = [p(m-1,n-1) + 2p(m-1,n) + p(m-1,n+1)] - [p(m+1,n-1) + 2p(m+1,n) + p(m+1,n+1)] \\ G(m,n) = \sqrt{\Delta_m p(m,n)2 + \Delta_n f(m,n)\hat{}2} \end{cases} \tag{5}$$

2.3.2. Fusion rules of bandpass directional subband coefficients

Local contrast shows variation such as texture as well as edges which acquire recurrence information as well as intensity regarding picture together with back-ground of the picture, that's why real human visual device has sensitivity of changing local contrast around the picture. Fusion process will be able to precisely identify the contrast with the fused picture, to get fine visual conclusion. Since the cross-contrast is described in Eq. (6)

$$R_{j,l}(x,y) = \frac{\frac{1}{a\times b}\sum_{p=-(a-1)/2}^{(a-1)/2}\sum_{q=-(b-1)/2}^{(b-1)/2} S_{j,l}(x+p,y+q)}{\frac{1}{x\times n}\sum_{i=-(x-1)/2}^{(x-1)/2}\sum_{j=-(y-1)/2}^{(y-1)/2} S(m+i,n+j)} \tag{6}$$

Where $R_{j,l}(\mathrm{m,n})$ is Cross Contrast, a, b and m, n are the size of local area, but a × b is less than x × y. In this paper, the value of a and b is 3, and the value of m and n is 15.

2.4. Edge-weakening Guided Image Filter

The EWGIF is exclusively developed GIF for Image Fusion. The process of filtering requires Guidance picture G, original picture I, Resultant picture Z. Generally G and I are considered as equal picture. The former consideration is also used in this paper. For EWGIF, the essential prediction in which resultant picture Z is a linear transformation of the guidance picture G, as presented in (7):

$$\mathrm{Z(e)} = \alpha_{\mathrm{e}'}\,\mathrm{G(e)} + \beta_{\mathrm{e}'}, \forall \mathrm{e} \in w_r(\mathrm{e}') \tag{7}$$

Where $w_r(\mathrm{e}')$ reflects radius r centred at pixel e' in window w in which. $\alpha_{\mathrm{e}'}$and $\beta_{\mathrm{e}'}$are constant within$w_r(\mathrm{p}')$.

The filtering results must hold the areas of input picture in a way that, in most areas, the resultant and input differences must be effectively lower. Coupled with (7), Minimizing a cost functions$E(\alpha_{\mathrm{e}'}, \beta_{\mathrm{e}'})$ will be obtained through variables α as well as β that are explained as:

$$E(\alpha_{\mathrm{e}'}, \beta_{\mathrm{e}'}) = \sum_{e\in w_r(\mathrm{e}')}[(\alpha_{\mathrm{e}'}\,\mathrm{G(e)} + \beta_{\mathrm{e}'} - I(e))^2 + \lambda(\mathrm{e}')\alpha_{e'}^2] \tag{8}$$

In which λ(e′) is regularization parameter for achieving greater value of α .On contrary, standard GIF in which λ is to be consistent, λ(e′) in (8) is a variance-weighted parameter given in (9).

$$\lambda(e') = \in \left[\frac{1}{N}\sum_{q=1}^{N}\frac{\sigma_1^2(e')}{\sigma_1^2(q)}\right]^2 \quad (9)$$

Where ε is consistent component, number of total picture elements in a picture stands by N. Variance of picture element e with radius r *stands* $\sigma_r^2(e)$. According to the whole picture, λ(e′) measures the importance of picture element e'. The radii r is always set to 1 while measuring variance allows λ to detect edges more accurately.

Solving (8) as well as assume I = G, the values of α and β can be stated as:

$$\alpha_{e'} = \frac{\sigma_r^2(e')}{\sigma_r^2(e')+\lambda(e')} \quad (10)$$

$$\beta_{(e')} = (1-\sigma_{e'})\mu_r(e') \quad (11)$$

Where $\sigma_{e'}$ *and* $\mu_r(e')$ stands for variances and mean respectively. The resultant picture can be shown as:

$$Z(e) = \bar{\alpha}_e G(p) + \bar{\beta}_e \quad (12)$$

Where $\bar{\alpha}_e$ *and* $\bar{\beta}_e$ stands for average parameters within picture element *e:*

$$\bar{\alpha}_e = \frac{1}{|w_r(e)|}\sum_{q=w_r(e)}\alpha_e \quad (13)$$

$$\bar{\beta}_e = \frac{1}{|w_r(e)|}\sum_{q=w_r(e)}\beta_e \quad (14)$$

Where $|w_r(e)|$stands for no. of picture element in window, $w_r(e)$

Edge-weakening property: There are two extreme properties that analyse to obtain a representation of the edge-weakening property of EWGIF.

Property 1: First property has pixel e' is at an edge. Variance of the picture is significantly greater than 1. Due to this λ in (9), α in (10) is nearing 0 as well as β in (11) is reaching $\mu_{e'}$.

Property 2: Second property has pixel e' is at a flat area as well as value of σ^2 is significantly lower than 1. Due to this λ is nearing 0, β is nearing 0 and α is almost 1.

III. Proposed Algorithm

The Proposed Image Fusion Algorithm Using NSCT With EWGIF Is Summarized In The Given Steps.

Step 1: First, the original pictures are decomposed into a low and bandpass transformed coefficient

Step 2: Then, low and bandpass coefficients are merged with the help of various fusion rule.

Step 3: Furthermore, Fused picture is combined through employing inverse NSCT over merged coefficients.

Step 4: Moreover, apply the local variance based edge weakening guided image filter for edge sharpening.

Step 5: Conclusively, evaluate the parameters.

3.1. Flowchart

The flowchart of proposed algorithm is presented in the following block diagram:

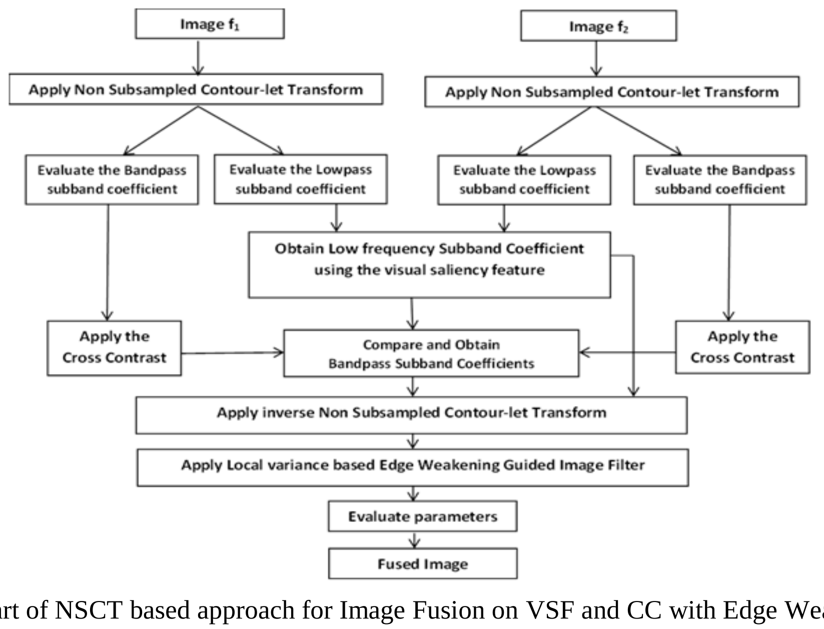

Fig. 3: Flow chart of NSCT based approach for Image Fusion on VSF and CC with Edge Weakening Guided Image Filter

5.2. Performance parameters

1) Information Entropy: The IE indicates quality with amount of average information included in picture. The value of information entropy is greater, which means the image has actually extra more abundant amount of information. Its definition is:

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

Where the probability of grey scale (g) is $p(g)$ and g is $[0,\ldots,\mathrm{L}-1]$ is the range.

2) Standard Deviation: SD usually means the dispersion degree regarding the average values as well as the gray values of pixels of the fused picture. The SD is larger which means the gray level is extra more dispersing degree. Its definition is:

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

Where *MEAN* is the average denoted by

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

3) Average grads: The AG indicates the clarity of the fused image, values of AG are larger than actually extract sharper fused image. Average gradient is shown as:

$$AG = \frac{1}{(M-1)(N-1)}\sum_{i=1}^{(M-1)(N-1)}\sqrt{\frac{(\frac{\partial f}{\partial x})^2+(\frac{\partial f}{\partial y})^2}{2}}$$

4) Spatial frequency: SF must be sensitive that reflect a picture which indicates the overall activity of the spatial domain as well as it gives larger value of SF which means fusion picture has given better quality of picture. The SF is computed as:

Row Frequency:

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

Column Frequency:

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

The Spatial Frequency of picture: $SF = \sqrt{(RF)^2+(CF)^2}$

5) Root mean squares cross entropy: RCE must be used to express the difference involving input picture and additionally fused picture. The value of RCE is smaller which means the value of fused image has obtained high info through original images as well as gives better effect of fusion. It's given as:

$$RCE = \sqrt{\frac{1}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N}[R(i,j)-F(i,j)]}$$

In which final-fused image has considered as F is; R reacted as original picture; $M\times N$ represent assize of the picture.

6) Fusion Factor: Considered 2 pictures A and B together with their fused picture F, Its definition as:

$$FF = I_{AF} + I_{BF}$$

Still High value associated with fusion factor does not imply that data via both the picture is usually symmetrically fused. Higher value of fusion factor shows that the fused picture provides quite good amount of info display in the picture.

7) Contrast Gain: CG is defined as the average contrast difference within original picture as well as fused picture. Higher CG indicates that given fusing technique is more effective than others.
Assume AC_F and AC_O are average contrasts of the fused picture and original picture respectively, then Contrast Gain can be computed as follows:

$$CG = AC_F - AC_O$$

IV. Result And Analysis

This section offers evaluation strategy considering the quality measures. MATLAB is used to perform these parameters.

4.1. Test Images and Statistical Parameters

Evaluation associated with multi-scale picture through employing NSCT utilizing EWGIF have more adequate quality measures in IE, SD, AG, SF, RCE, FF, CG. The below Table-I shows source Pictures and corresponding improved resultant Picture. Type of Picture is also mentioned.

S.No.	Source Picture 1	Source Picture 2	Resultant Picture	Type of Picture
1				Coloured Picture
2				Coloured Picture
3				Coloured Picture
4				Coloured Picture
5				Coloured Picture
6				Gray-Scale Picture

7				Gray-Scale Picture
8				Gray-Scale Picture
9				Coloured Picture
10				Gray-Scale Picture

Table-I: Table of Images

4.2. Analysis of proposed system

In proposed system examines pictures based on NSCT method with Edge weakening guided image filter on multi-focus images. We analyse calculate all the performance metrics as well as shows results of proposed system.

S.NO.	1	2	3	4	5	6	7	8	9	10
Information Entropy (IE)	7.8398	7.8381	7.8433	7.8381	7.8316	7.8550	7.8550	7.8550	7.8466	7.7517
Standard Deviation (SD)	4.0269	4.0260	4.0286	4.0260	4.0230	4.0345	4.0345	4.0345	4.0302	3.9923
Average Grads (AG)	4.9848	4.9831	4.9883	4.9831	4.9766	5.0000	5.000	5.000	4.9916	4.8967
Spatial Frequency (SF)	2.5583	2.5575	2.5600	2.5575	2.5544	2.5660	2.5660	2.5660	2.5617	2.5238
Root mean square cross entropy (RCE)	2.8000	2.7997	2.8006	2.7997	2.7985	2.8027	2.8027	2.8027	2.8012	2.7842
Fusion Factor (FF)	6.2433	6.1763	6.3816	6.1777	5.9380	6.8958	6.8966	6.8966	6.5209	4.0273
Contrast Gain (CG)	2.4987	2.4852	2.5262	2.4855	2.4368	2.6260	2.6261	2.6261	2.5536	2.0068

Table-II: shows the Various Metrics

The Table-II shows various metrics. Fig. 4 represents graph of proposed system analysis on multi-scale pictures with IE, SD, AG, SF, RCE, FF and CG parameters:

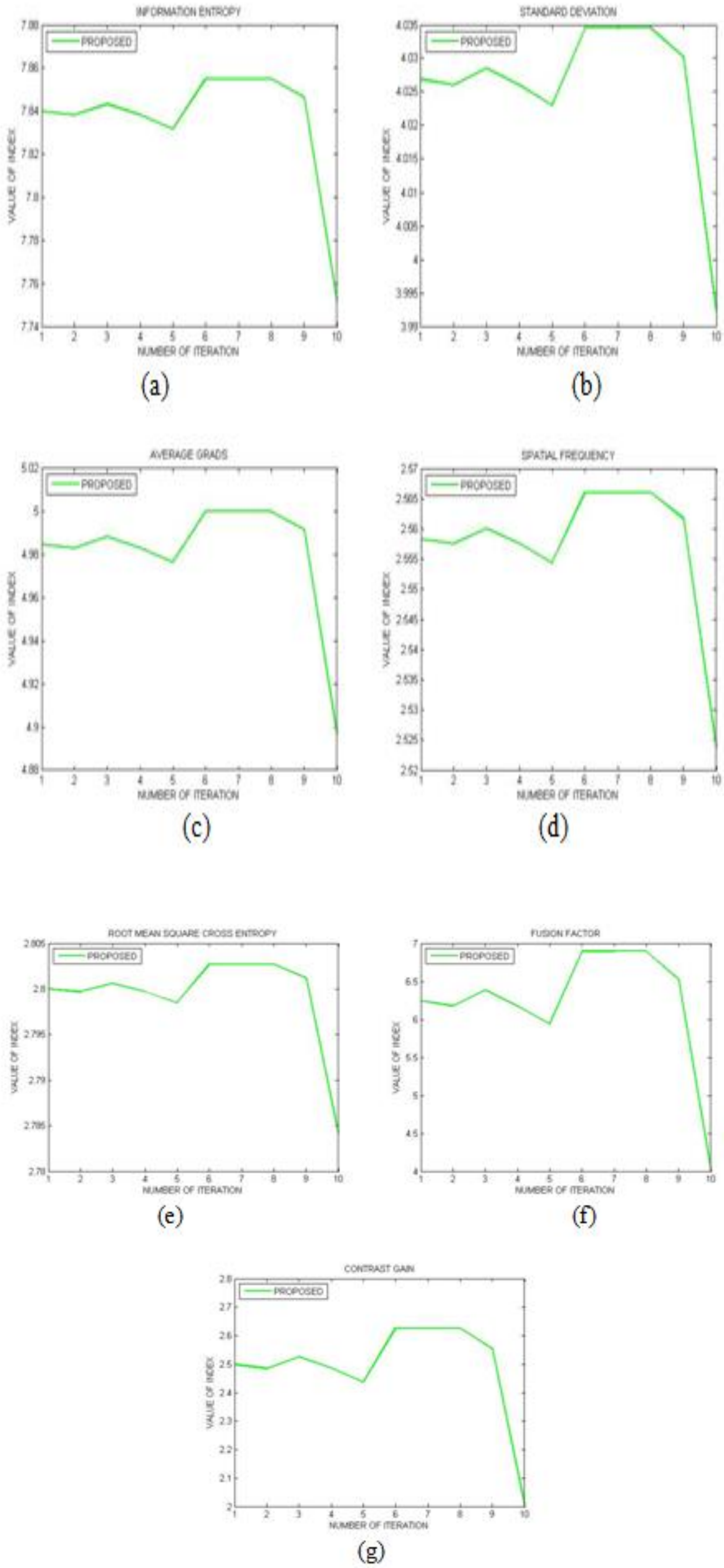

Fig. 4: Result of performing various parameter of NSCT transform with local variance based edge weakening guided image filter Fig. (a) Information Entropy (IE) (b) Standard Deviation (SD) (c) Average Grads (AG) (d) Spatial Frequency (SF) (e) Root mean square Cross Entropy (RCE) (f) Fusion Factor (FF) (g) Contrast Gain (CG)

V. Conclusion And Future Scope

Image fusion offers fantastic approach to get level of data while more than one picture as well as unify all of them into a one picture which can be even more informatics. Proposed an alternative fusion rules for unifying low subband as well as bandpass subband coefficients, that is the other part of the nonsubsampled contourlet transform after that it decomposed through employing inverse NSCT method for fusing low as well as bandpass coefficient bands within pictures in which outputs of various fusion rules depend on a dissimilarity measure of source pictures. Optimized method for fusing gives efficient performance evaluation with the help of EWGIF to maximize IE, SD, AG, spatial freq., Root mean squares cross entropy, Fusion Factor and Contrast Gain within final fused image. Upcoming Opportunity is in which it could be fused with respect to medical related colour photos within medical related terms.

References

[1]. Adu, J., Xie, S. and Gan, J., 2016. Image fusion based on visual salient features and the cross-contrast. Journal of Visual Communication and Image Representation, 40, pp.218-224.
[2]. Liu, Y., Liu, S. and Wang, Z., 2015. A general framework for image fusion based on multi-scale transform and sparse representation.Information Fusion, 24, pp.147-164.
[3]. Jiang, Y. and Wang, M., 2014. Image fusion with morphological component analysis. Information Fusion, 18, pp.107-118.
[4]. Guorong, G., Luping, X. and Dongzhu, F., 2013. Multi-focus image fusion based on non-subsampled shear let transform. IET Image Processing, 7(6), pp.633-639.
[5]. Adu, J., Wang, M., Wu, Z. and Zhou, Z., 2012. Multi-focus image fusion based on the non-subsampled contour let transform. Journal of Modern Optics, 59(15), pp.1355-1362.
[6]. Li, S., Yang, B. and Hu, J., 2011. Performance comparison of different multi-resolution transforms for image fusion. Information Fusion, 12(2), pp.74-84.
[7]. Chai, Y., Li, H.F. and Qu, J.F., 2010. Image fusion scheme using a novel dual-channel PCNN in lifting stationary wavelet domain. Optics Communications, 283(19), pp.3591-3602.
[8]. Aslantas, V. and Kurban, R., 2010. Fusion of multi-focus images using differential evolution algorithm. Expert Systems with Applications, 37(12), pp.8861-8870.
[9]. Li, S. and Yang, B., 2010. Hybrid multiresolution method for multisensor multimodal image fusion. IEEE Sensors Journal, 10(9), pp.1519-1526.
[10]. Huang, P.W., Chen, C.I. and Lin, P.L., 2009, October. Multi-focus image fusion based on salient edge information within adaptive focus-measuring windows. In Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference on (pp. 2589-2594). IEEE.
[11]. Zhang, Y. and Ge, L., 2009. Efficient fusion scheme for multi-focus images by using blurring measure. Digital signal processing, 19(2), pp.186-193.
[12]. Li, S. and Yang, B., 2008. Multifocus image fusion using region segmentation and spatial frequency. Image and Vision Computing, 26(7), pp.971-979.
[13]. N. Cvejic, D. Bull, N. Canagarajah, IEEE Sensors Journal 7 (5) (2007) 742.
[14]. Huang, W. and Jing, Z., 2007. Evaluation of focus measures in multi-focus image fusion. Pattern recognition letters, 28(4), pp.493-500.
[15]. De, I., Chanda, B. and Chattopadhyay, B., 2006. Enhancing effective depth-of-field by image fusion using mathematical morphology. Image and Vision Computing, 24(12), pp.1278-1287.
[16]. Gabarda, S. and Cristóbal, G., 2005. On the use of a joint spatial-frequency representation for the fusion of multi-focus images. Pattern Recognition Letters, 26(16), pp.2572-2578.
[17]. Petrovic, V.S. and Xydeas, C.S., 2004. Gradient-based multiresolution image fusion. IEEE Transactions on Image processing, 13(2), pp.228-237.
[18]. Li, S., Kwok, J.T. and Wang, Y., 2002. Multifocus image fusion using artificial neural networks. Pattern Recognition Letters, 23(8), pp.985-997.
[19]. Luo, R.C., Yih, C.C. and Su, K.L., 2002. Multisensor fusion and integration: approaches, applications, and future research directions. IEEE Sensors journal, 2(2), pp.107-119.
[20]. Nikolov, S., Hill, P., Bull, D. and Canagarajah, N., 2001. Wavelets for image fusion. In Wavelets in signal and image analysis (pp. 213-241). Springer Netherlands.